



SELINUS UNIVERSITY
OF SCIENCES AND LITERATURE

**SPATIOTEMPORAL ANALYSIS AND
REHABILITATION OF ALLUVIAL GOLD
MINING-AFFECTED AREAS IN BETARÉ-OYA,
CAMEROON (2021-2025) USING REMOTE
SENSING**

By **ZOUM FON ALAIN**

A DISSERTATION

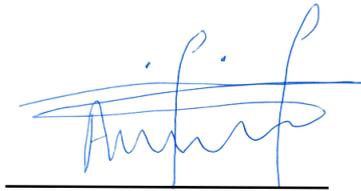
Presented to the
Department of Mining Engineering
Program at Selinus University

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In fulfillment of the requirements for the degree of
Doctor of Philosophy (PhD) in Mining Engineering

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DECLARATION

I, **Zoum Fon Alain**, Registration No: **UNISE3735IT**, in the Department of Mining Engineering, Faculty of Engineering and Technology, Selinus University hereby declare that, this work titled **“Spatiotemporal Analysis and Rehabilitation of Alluvial Gold Mining-Affected Areas in Betaré-Oya, Cameroon (2021-2025) Using Remote Sensing”** is my original work. It has not been presented in any application for a degree or any academic pursuit. I have acknowledged all borrowed ideas nationally and internationally through citations.



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ABSTRACT

This study investigates the spatiotemporal environmental impacts of alluvial gold mining in the Betaré-Oya, East Region of Cameroon from 2021 to 2025 using a mixed-methods approach combining remote sensing analysis, field observations, and community interviews. Sentinel-2 satellite imagery was analyzed to assess land degradation (Bare Soil Index), vegetation health (Normalized Difference Vegetation Index), water quality (Normalized Difference Water Index, Turbidity Index, Suspended Sediment Concentration), and land use/land cover (LULC) changes. Field observations (January to March, 2025) and Google Earth Pro imagery confirmed extensive deforestation, soil erosion, and water pollution in mining-affected areas. The BSI analysis revealed a significant increase in bare soil from 19.20% in 2021 to 38.23% in 2024. NDMI analysis showed a slight increase in moisture-deficient areas (bare soil) from 16.54% (2021) to 16.56% (2023) while greatly increases from 16.56% in 2023 to 24.68% in 2024. LULC classification indicated a decrease in dense vegetation and an increase in bare land and mine site areas. The study proposes a comprehensive rehabilitation strategy based on these findings, including soil stabilization, reforestation, water treatment, mine pit rehabilitation, community engagement, and long-term monitoring. Policy recommendations include stricter regulations, promotion of sustainable mining practices, and the establishment of a dedicated fund for mine closure and rehabilitation. Future research should focus on long-term monitoring of rehabilitation efforts, assessment of different rehabilitation techniques, and investigation of socioeconomic impacts. The findings highlight the urgent need for comprehensive and sustainable approaches to manage the environmental impacts of alluvial gold mining and ensure the long-term well-being of local communities and ecosystems in the Betaré-Oya region.

Keywords: Spatiotemporal analysis, Environmental impact, Rehabilitation, Alluvial gold mining, Betare-Oya,

DEDICATION

To the Zoum's family.

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LIST OF ABBREVIATIONS

ASM:	Artisanal Small-scale Mining
LULC:	Land Use Land Cover
GIS:	Geographic Information System
NDVI:	Normalized Difference Vegetation Index
NDWI:	Normalized Difference Water Index
NDMI:	Normalized Difference Moisture Index
BSI:	Bare Soil Index
TI:	Turbidity Index
SSC:	Suspended Sediment Concentration
GPS:	Global Positioning System
ASGM:	Artisanal Small-scale Gold Mining
CAOB:	Central African Orogenic Belt
USGS:	United State Geological Survey
NASA:	National Aeronautics and Space Administration
SNAP:	Sentinel Application Platform

CHAPTER 1

INTRODUCTION

1.1 Background of study

Mining has been a significant economic activity worldwide, contributing to industrial development, employment, and revenue generation (Hilson & Murck, 2000). However, its environmental and socio-economic impacts have raised major concerns, particularly in developing countries where regulation is weak (Weng et al., 2013). Among various forms of mining, alluvial gold mining is one of the most prevalent in tropical regions, especially in Africa, where semi-mechanized and artisanal small-scale miners extract gold from riverbeds and floodplains (D'Souza, 2020).

Betaré-Oya, located in the East Region of Cameroon, has emerged as a hotspot for alluvial gold mining due to its rich gold deposits (Ndjama et al., 2019). The mining industry in this region is largely dominated by semi-mechanized and artisanal small-scale mining (ASM), which provides livelihoods for thousands of people but also leads to severe environmental degradation, including deforestation, soil erosion, biodiversity loss, and water pollution (Tetsopgang et al., 2021). The lack of proper rehabilitation strategies has left abandoned mining sites exposed to further degradation, affecting both the ecosystem and local communities (Kouamé et al., 2022). The environmental impact of alluvial gold mining in Betaré-Oya is significant, particularly on land degradation, water pollution, and biodiversity loss. Studies have shown that excessive excavation of riverbanks leads to increased sedimentation, changes in river flow, and destruction of aquatic habitats (Lindahl, 2014). Additionally, the use of mercury and cyanide in alluvial gold concentration contaminates water sources, posing health risks to local populations (Esdaile & Chalker, 2018).

The introduction of remote sensing technology has transformed the monitoring and assessment of environmental changes caused by mining (Zhao & Han, 2018; Adamu & Lawal, 2019). It offers timely and accurate data, enabling the analysis of spatial and temporal patterns of land degradation, which is essential for developing effective rehabilitation strategies. Studies have demonstrated the effectiveness of satellite imagery in detecting land use and land cover (LULC) changes in mining areas (Zhou et al., 2017), providing critical insights for stakeholders to implement informed management practices. In addition Multispectral and thermal imaging for spatiotemporal analysis of mining impacts have widely been used in monitoring vegetation

health, and water quality over time, providing critical insights for rehabilitation planning (Jain et al., 2021).

Despite the evident environmental degradation, mine closure and rehabilitation remain a major challenge in many developing regions, including Betaré-Oya (UNEP, 2020; Barlas & Funtowicz, 2021). Effective reclamation and restoration strategies involve reforestation, soil remediation, and sustainable land-use planning (Miller et al., 2019; Smith & Watson, 2017). The use of remote sensing technologies, particularly Sentinel-2 and Landsat data, enables researchers to track vegetation recovery, soil erosion, and water contamination post-mining (Gessner et al., 2015; Vega & García-Ruiz, 2019).

Several studies have utilized remote sensing to map LULC changes resulting from alluvial gold mining activities in Betaré-Oya. For example, research employing Landsat imagery from 1987 to 2017 revealed significant environmental transformations, such as increased human settlements and expanded artisanal mining at the expense of vegetation cover (Kamga et al., 2017). Another study using Sentinel-2 imagery from 2018 to 2022 by Azinwi et al. (2024) highlighted the expansion of mining activities and their impact on local ecosystems. These findings underscore the critical need for continuous monitoring and the development of rehabilitation measures to mitigate environmental degradation.

Water quality assessments in Betaré-Oya have also indicated the adverse effects of mining activities (Babut et al., 2019). Analyses of surface water have shown increased turbidity and elevated concentrations of heavy metals, including mercury, which pose risks to aquatic life and human health (Chica & Walker, 2020). Additionally, studies have reported mercury contamination in sediments and fish, raising concerns about bioaccumulation and the potential health implications for local communities (Diop & Kamara, 2018).

Despite these insights, there remains a gap in research that integrates spatiotemporal analysis with rehabilitation efforts in the Betaré-Oya region. Existing studies have primarily focused on mapping changes without exploring the temporal dynamics of degradation or proposing concrete rehabilitation strategies. Addressing this gap is essential for developing comprehensive approaches to environmental management and restoration in mining-affected areas. Given these concerns, this study aims to conduct a spatiotemporal analysis of the land degradation, water quality, land use changes, and vegetation health in Betaré-Oya's mining-affected areas from 2021 to 2025. The research will integrate multispectral and thermal remote sensing techniques to assess environmental changes and propose strategies for effective mine rehabilitation.

1.2 Statement of the Problem

Alluvial gold mining has become a major economic activity in Betaré-Oya, East Cameroon, attracting both artisanal small-scale miners (ASM) and large mining companies. While this sector provides employment and contributes to the local economy, it also results in severe environmental degradation, including land degradation, deforestation, water pollution, and biodiversity loss. The uncontrolled expansion of mining activities, coupled with poor regulatory enforcement, has led to the abandonment of numerous mined-out sites without proper rehabilitation.

One of the most pressing environmental issues in Betaré-Oya is water pollution, as mining operations involve the direct discharge of sediments, heavy metals, and chemicals into rivers and streams. The use of mercury in gold extraction further exacerbates contamination, posing serious health risks to both miners and local communities who depend on these water sources for drinking, fishing, and agriculture.

Additionally, the region experiences rapid land cover changes, with vast areas of forest and farmland being converted into barren mining landscapes. Vegetation loss disrupts local ecosystems, reduces soil fertility, and increases erosion and flooding risks. Despite the clear evidence of environmental damage, rehabilitation efforts remain inadequate, and no comprehensive spatiotemporal analysis has been conducted to track environmental degradation and propose effective rehabilitation strategies. The lack of reliable environmental monitoring tools further hinders sustainable mining practices in the region. Traditional field-based assessments are costly, time-consuming, and geographically limited, making it difficult to obtain accurate and timely information on the environmental impacts of mining activities.

1.3 Research Objective

1.3.1 Main Research Objective

The main objective of this study is to conduct a spatiotemporal analysis of alluvial gold mining-affected areas in Betaré-Oya, Cameroon from 2021 to 2025 using multispectral and thermal remote sensing to assess land degradation, water quality, land use/land cover (LULC) changes, and vegetation health, while proposing a strategy for effective mine closure and rehabilitation.

1.3.2 Specific Research Objectives

1. Assess land degradation in alluvial gold mining-affected areas of Betaré-Oya from field-based assessment and satellite imagery analysis.

2. Examine vegetation health trends in the study area using multispectral and thermal remote sensing index (NDVI).
3. Analyze water quality changes in mining-impacted rivers and streams by integrating spectral indices and remote sensing data.
4. Monitor land use/land cover (LULC) changes for evaluating rehabilitation efforts implemented over time.
5. Propose effective mine closure and rehabilitation strategies based on the findings.

1.4 Research Questions

1.4.1 Main Research Question

How has alluvial gold mining affected land degradation, water quality, land use/land cover (LULC), and vegetation health in Betaré-Oya, Cameroon, from 2021 to 2025, and what strategies can be proposed for mine closure and rehabilitation?

1.4.2 Specific Research Questions

1. What is the extent of land degradation caused by alluvial gold mining in Betaré-Oya over the study period?
2. What are the trends in vegetation health, and how does mining impact ecosystem recovery?
3. How has water quality changed in mining-impacted rivers and streams, and what pollutants are present?
4. What are the spatiotemporal land use/land cover changes, and have there been any efforts of ongoing rehabilitation measures?
5. What mine closure and rehabilitation strategies can be implemented to restore degraded mining areas?

1.5 Significance of the Study

This research is significant in several ways, contributing to both scientific knowledge and policy-making for sustainable mining practices in Betaré-Oya, Cameroon.

1.5.1 Contribution to Environmental Monitoring and Remote Sensing Applications

The study employs multispectral and thermal remote sensing for spatiotemporal analysis, providing a scientific basis for monitoring environmental changes in mining-affected areas. By integrating Sentinel satellite data with GIS-based analysis, this research enhances existing methods for detecting land degradation, water pollution, and vegetation loss (Gimeno & Pérez, 2020).

1.5.2 Policy Implications for Sustainable Mining

The findings will offer data-driven insights to policymakers, regulatory agencies, and environmental managers to design and enforce sustainable mining policies. Identifying critical environmental risks will enable authorities to develop rehabilitation guidelines and enforce responsible mining practices.

1.5.3 Contribution to Mine Closure and Rehabilitation Strategies

By analyzing the effectiveness of past and present mine closure strategies, this study will propose evidence-based rehabilitation techniques for abandoned mining sites. This is essential for restoring soil fertility, vegetation cover, and water quality to pre-mining conditions.

1.5.4 Socioeconomic and Community Benefits

Mining communities in Betaré-Oya face serious environmental and health risks due to exposure to mercury, sedimentation, and deforestation (Esdaile & Chalker, 2018; Babut et al., 2019). By assessing water quality and land degradation trends, this study will provide critical information to local governments, NGOs, and community leaders on the need for environmental restoration efforts and alternative sustainable livelihoods for affected populations.

1.6 Scope and Limitations of the Study

1.6.1 Scope of the Study

This study focuses on spatiotemporal analysis of alluvial gold mining-affected areas in Betaré-Oya, Cameroon, from 2021 to 2025 using multispectral and thermal remote sensing data. The research assesses land degradation, water quality, land use/land cover (LULC) changes, and vegetation health while proposing strategies for mine closure and rehabilitation.

- **Geographical Scope:** The study area is Betaré-Oya, located in the East Region of Cameroon, a significant hub for semi-mechanized and artisanal small-scale gold mining (ASGM).
- **Temporal Scope:** The analysis covers a five-year period (2021–2025) to detect environmental trends and impacts.
- **Thematic Scope:** The research integrates remote sensing data (Sentinel multispectral and thermal imagery) and GIS tools (SNAP, ArcGIS, Google Earth Pro and Google earth engine) to analyze environmental changes and propose sustainable rehabilitation strategies.

1.6.2 Limitations of the Study

Despite its broad analytical scope, the study has some limitations:

- **Cloud Cover Issues:** The presence of persistent cloud cover in Betaré-Oya may obstruct satellite image acquisition, particularly for optical remote sensing.
- **Data Availability Constraints:** The study relies on publicly available Sentinel data, which may have spatial and temporal resolution limitations.
- **Field Validation Challenges:** While remote sensing techniques are effective, ground truthing (field data collection) is necessary to validate findings, which may be constrained by accessibility to all the mining-affected areas, and logistical challenges.
- **Uncertainty in Water Quality Assessment:** The use of remote sensing indices for water quality assessment may require supplementary in-situ water sampling for enhanced accuracy.

1.7 Study Area Description

Betaré-Oya is a key alluvial gold mining area located in the East Region of Cameroon. The area has been a major alluvial gold mining district for decades, contributing to land degradation, deforestation, and water pollution.

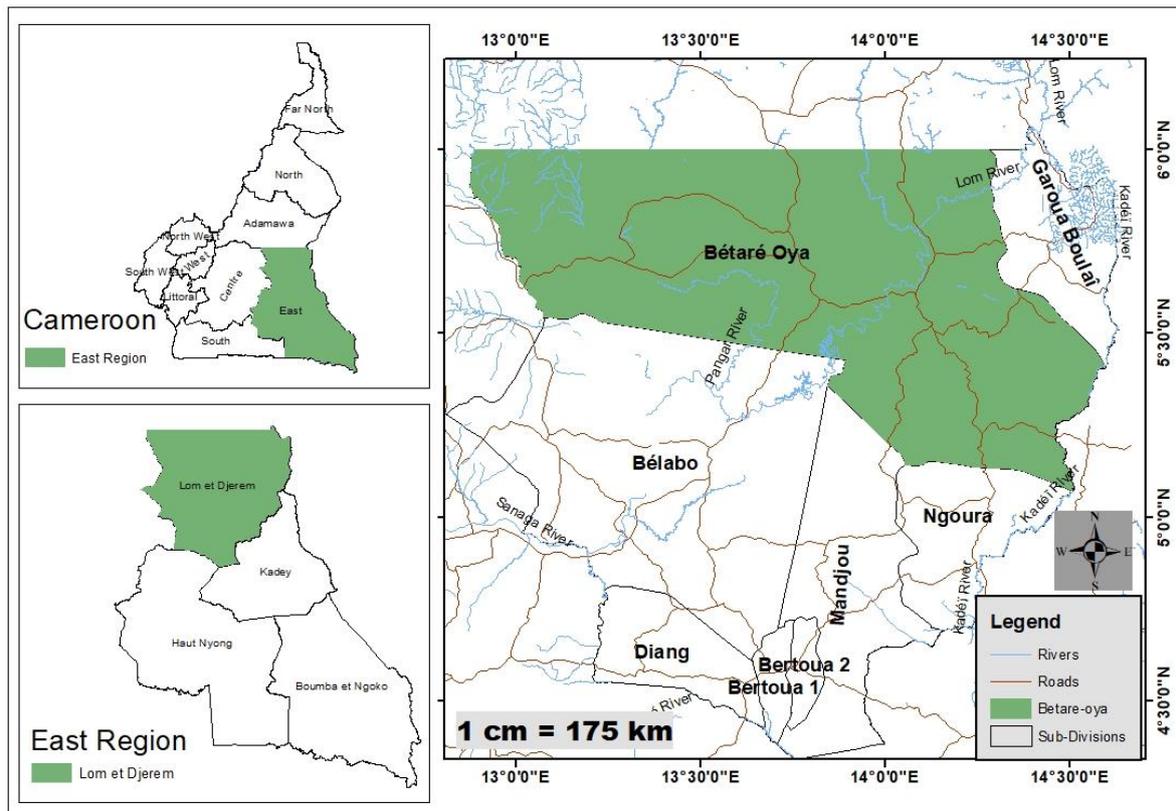


Figure 1.1: Location Map of study area

1.7.1 Geographical Location

Betaré-Oya is situated at approximately latitude 14°1'0.643"E and longitude 5°42'48.587"N (figure 1.1) in the Lom-et-Djerem Division of Cameroon's East Region. It is bordered by Ngoura, Belabo, and Garoua-Boulai and lies along the Lom River, a major water source that is heavily impacted by gold mining activities (Ndjigui et al., 2021).

1.7.2 Ethnic Groups and Population

The population of Betaré-Oya is diverse, with the Gbaya, Beti, and Baka ethnic groups being predominant. The Gbaya people, who are primarily agriculturalists and traders, form the largest community. The region also hosts migrant workers from other parts of Cameroon and neighboring countries who engage in artisanal mining (Tchindjang et al., 2018).

1.7.3 Climate and Rainfall Patterns

Betaré-Oya experiences a tropical humid climate with two major seasons:

Rainy Season: Extends from March to October, with peak rainfall occurring in July and September. Annual precipitation ranges between 1,500–2,000 mm (Yemefack et al., 2019).

Dry Season: Runs from November to February, characterized by hot temperatures (28°C–35°C) and reduced river flow, which influences mining activities.

1.7.4 Vegetation and Land Cover

The natural vegetation of Betaré-Oya consists of dense semi-deciduous forests, but extensive deforestation has occurred due to gold mining, agriculture, and logging (Sonwa et al., 2020). The main vegetation types include: Gallery forests along rivers and wetlands; Savannah woodlands in degraded mining zones; Farmland and secondary forests due to shifting cultivation

1.7.5 Socioeconomic Activities

The economy of Betaré-Oya is driven by artisanal gold mining, which employs thousands of miners. Other key activities include:

- **Subsistence agriculture:** Crops such as cassava, maize, and groundnuts are cultivated.
- **Fishing:** The Lom River provides fish but is heavily impacted by sedimentation from mining.
- **Timber extraction:** Logging companies operate in the region, contributing to forest degradation.

Gold mining has significantly altered the landscape and livelihoods of the local population, leading to environmental challenges such as deforestation, soil erosion, and water pollution (Tchindjang et al., 2018).

1.8 Definition of Terms

This section defines key terms and concepts used in the study to ensure clarity and consistency.

1.8.1 Spatiotemporal Analysis

Spatiotemporal analysis refers to the study of how spatial patterns change over time. In the context of this research, it involves the assessment of environmental changes (land degradation, water quality, and vegetation health) in Betaré-Oya over the period 2021–2025 using remote sensing and GIS techniques (Fisher et al., 2018; Wang & Liu, 2020).

1.8.2 Alluvial Gold Mining

Alluvial gold mining is the extraction of gold particles from riverbeds, floodplains, or sediments using manual or mechanized techniques. This process often leads to deforestation, riverbank erosion, and water pollution due to the release of mercury, sediments, and other contaminants (Aryee et al., 2003).

1.8.3 Remote Sensing

Remote sensing is the process of collecting information about the Earth's surface without direct contact, using sensors on satellites, drones, or aircraft. This study uses multispectral and thermal remote sensing to detect land degradation, vegetation changes, and water quality variations in mining-affected areas (Jensen, 2015).

1.8.4 Multispectral and Thermal Remote Sensing

Multispectral remote sensing captures reflected electromagnetic radiation in multiple wavelengths (visible, near-infrared, and shortwave infrared) to analyze land cover, vegetation health, and water bodies (Xie et al., 2008).

Thermal remote sensing detects land surface temperature (LST) variations, which can indicate soil moisture changes, mine-induced heat anomalies, and vegetation stress (Voogt & Oke, 2003).

1.8.5 Land Degradation

Land degradation refers to the deterioration of soil, vegetation, and water resources due to human activities such as mining, deforestation, and poor land management (He & Zhang, 2020). In Betaré-Oya, land degradation results from artisanal gold mining, which strips vegetation, causes erosion, and alters river courses (Lambin et al., 2001).

1.8.6 Land Use/Land Cover (LULC)

LULC refers to the classification of land based on its usage and physical cover. Land use includes agriculture, settlements, and mining, while land cover consists of forests, grasslands, and water bodies (Foody, 2002). Satellite imagery is used to analyze LULC changes over time.

1.8.7 Normalized Difference Vegetation Index (NDVI)

NDVI is a satellite-derived index used to measure vegetation health and biomass. It is calculated as: $NDVI = (NIR - RED) / (NIR + RED)$. Where NIR (near-infrared) and RED are reflectance values from satellite imagery. Higher NDVI values indicate healthy vegetation, while lower values suggest land degradation or deforestation (Tucker, 1979).

1.8.8 Normalized Difference Water Index (NDWI)

NDWI is used to detect water bodies and moisture content in an area. It is calculated as: $NDWI = (GREEN - NIR) / (GREEN + NIR)$. Higher NDWI values indicate water presence, while lower values suggest dry conditions or contamination (McFeeters, 1996).

1.8.9 Mine Closure and Rehabilitation

Mine closure refers to the process of shutting down mining operations in a way that minimizes environmental and social impacts (Laurence, 2006).

Rehabilitation involves restoring degraded mining sites through revegetation, soil stabilization, and water treatment to ensure ecological recovery.

1.8.10 Water Quality Indicators

Water quality is assessed using physical, chemical, and biological parameters, including:

- Turbidity (suspended sediments)
- Dissolved oxygen (DO) levels
- Heavy metal concentrations (e.g., mercury, arsenic)
- pH and conductivity

Remote sensing techniques such as NDWI and spectral analysis can help monitor water contamination in mining-affected rivers (Gholizadeh et al., 2016).

1.9 Organization of the Study

This dissertation is structured into five main chapters, each addressing different aspects of the research. Below is an overview of the content covered in each chapter:

Chapter 1: This chapter provides the background of the study, highlighting the impact of alluvial gold mining on the environment and the need for spatiotemporal analysis using remote sensing. It outlines the research problem, objectives, research questions, significance, scope, and

limitations of the study. Additionally, it provides a detailed description of the study area and defines key terms used in the research.

Chapter 2: This chapter reviews previous studies on alluvial gold mining and its environmental impact, with a focus on land degradation, water quality, and vegetation health. It also explores existing remote sensing techniques (multispectral, thermal, radar) used for monitoring mining activities, alongside past research conducted in Betaré-Oya and other mining-affected regions.

Chapter 3: This chapter outlines the research design, data sources, and analytical methods used in the study. It provides details on: The satellite datasets (Sentinel, Landsat) used for monitoring environmental changes. Spatiotemporal analysis techniques employed to assess land degradation, water quality, and vegetation health. The application of SNAP tool, Google Earth Pro, Google Earth engine and ArcGIS for image processing, classification, and change detection. Validation techniques, including field data collection and accuracy assessment of classified images.

Chapter 4: This chapter presents the findings of the study, including: Spatiotemporal trends in land use/land cover changes (deforestation, expansion of mining pits). Water quality analysis using spectral indices (NDWI, BSI) and field validation. Vegetation health assessment using NDVI. Impacts of mining on soil degradation and temperature anomalies based on thermal remote sensing. A discussion on the implications of the findings for environmental management and policy-making.

Chapter 5: The final chapter summarizes the key findings, highlights the study's contribution to knowledge, and suggests strategies for rehabilitating abandoned mining sites. It also outlines recommendations for future research on sustainable mining practices and environmental restoration in Betaré-Oya.

CHAPTER 2

LITERATURE REVIEW

2.1 Geological potential of Cameroon

Cameroon is underlain by Precambrian rocks, Cretaceous sediments, and Cenozoic sedimentary and volcanic formations. Much of the Precambrian is undifferentiated gneisses and migmatites. Meso- and Neoproterozoic rocks are exposed in the southeast of the country. Cretaceous sediments almost completely cover the Precambrian basement (Belinga, 2001). In northern Cameroon the Cretaceous sedimentary facies is mainly continental, while the Cretaceous in the coastal zone is mainly marine. A recent volcanic zone crosses Cameroon in a north-easterly direction. This line probably follows an important ancient structural zone. Finally, in the south of the country we have the Ntem group, which is the only area where archaic rocks are found, the most important being granites, gneisses and charnockites (Schluter, 2006).

The ore minerals present in the country are mainly: gold, diamond, bauxite, kyanite and rutile, tin, and cobalt. Gold deposits are found throughout the country, especially in the crystalline basement and epimetamorphic sequences. The highest concentrations are found in the east of the country, essentially along the borders with the Central African Republic and Chad. In this area, its association with the process of microcline formation with the base rock has been observed (Kamga et al., 2017). The same occurs for the extreme south, the north (Poli series) and the center (Lom series), based on the Congolese region, formed by a volcanic-sedimentary environment, and, finally in the west of the country, where rocks are found as mostly intrusive. The diamonds are associated with the Cretaceous fluviolacustrine formations of the "Series de Carnot", near the border with the Central African Republic and exploited using artisanal methods, although they are also associated with gold alluvium (Bakia, 2014). The Carnot series is composed of sandstones of Mesozoic age and fluvial origin that, in more recent deposit environments, could also have included lacustrine and marsh deposits from one end to the other (Delpomdor & Pr eat, 2015). Consequently, the Carnot sandstone includes various evolutionary levels of agglomerates, sandstone, argillite, and siltstones. The geomorphology of the present landscape is an important factor in the location and quality of diamond deposits that are exposed due to erosion (Chirico et al., 2010). Cassiterite occurs in a small deposit at Mayo Darl e in the northwest, near the Nigerian border. The mineralization occurs as porphyry-type stockwork veinlets with grades up to 0.3% SnO₂ and as vertical and horizontal high-grade (2–20% SnO₂) greisen veins within host alkali biotite granites, it is defined as alluvial cassiterite (Nwamba et

al., 2023). Economic concentration of nickel and cobalt appear in the east of the country, near Lomie in a small town called Nkamouna. The ore are associated with laterites and serpentine type rocks (Lambiv Dzemua et al., 2012). The feasibility report for the Nkamouna project has been submitted in 2011 by SRK Consulting, Knight Piésold, but to date no facility infrastructure are build (Africa Intelligence, 2022). Rutile is found in economical quantities at Akonolinga and is associated with micabearing schists, it depends of the Yaoundé series. The occurrence of rutile in the region east of Yaoundé (Nanga-Eboko and Akonolinga) and west of Yaoundé (Eseka-Pouma) is known in alluvial, eluvial and residual deposits since the last century. The rutile was exploited between 1935 and 1955 with a total production of 15,000 tons. The rutile is of high quality ($>95\%$ TiO_2) and occurs in various sizes (up to 5 cm of diameter) (Stendal, 2006).

2.2 Geology of the East Region

The East Region of Cameroon is characterized by a complex geological framework that includes Precambrian basement rocks, metamorphic formations, and mineral-rich belts. This region is known for its significant mineral resources, including gold, diamonds, and other valuable minerals, making it an important area for geological studies (Tchameni et al., 2006).

The East Region of Cameroon is predominantly part of the Central African Orogenic Belt (CAOB), which is composed mainly of Archean to Proterozoic rocks. The region features high-grade metamorphic rocks, granitoids, and supracrustal sequences (Nzenti et al., 1998). These geological formations are a result of multiple tectonic events, including the Pan-African orogeny.

The lithology of the East Region is dominated by Precambrian basement rocks, including gneisses, schists, and granites. The metasedimentary sequences contain quartzites, amphibolites, and migmatites, indicative of high-grade metamorphic processes (Toteu et al., 2004). The presence of greenstone belts also suggests potential for economic mineralization.

The structural framework of the East Region is controlled by Pan-African tectonics, leading to intense folding, faulting, and shearing. Major fault systems, including the Sanaga and Lom faults, influence the region's geological architecture (Ngako et al., 2003). These structures play a critical role in the emplacement of mineral deposits.

The East Region is one of Cameroon's richest in terms of mineral resources. Gold deposits are widespread, with artisanal and Semi-mechanized mining being the primary extraction method. Diamond occurrences are also common in alluvial deposits along major river systems (Yongue-

Fouateu et al., 2006). Other resources include bauxite and iron ore, which are yet to be fully exploited.

2.3. Overview of Betare-oya

Betare Oya is found in the East region of Cameroon in the Lom and Djerem Division. The area is characterized by two main hydrographic basins namely; Lom basin in the North West and Kadei basin in the South East. The geology of Betare Oya is dominated by volcano-sedimentary rocks of Neoproterozoic in the Lom metamorphize group (Eloung et al.,2020).

The climate is equatorial type with four seasons (2 dry seasons and 2 rainy seasons) with some variations which are particular to them due to the location at the foot of the Adamawa plateau. Humidity and cloud cover are relatively high and precipitation ranges from 1500 to 2000mm per year except in the extreme east and North regions where it is slightly less.

The Betare-Oya gold districts are watered by two main rivers: The Lom and the Pangar. These 2 rivers receive water from a large network of small rivers, the most important of which are Mba, Mari, Mbal, and Kpawara. The hydrologic regime of the river Lom in Betare-Oya is controlled by rainfall. The lower monthly flow rate is observed in February ($56\text{m}^3\text{s}^{-1}$), while the maximum flow rate is observed in October ($328\text{m}^3\text{s}^{-1}$) (Ngueyep et al., 2020).

The vegetation is dominantly of primary nature comprising of lowland tropical rainforest, which grows progressively thicker towards the south. The land area is sparsely cultivated and most of the natural vegetation is still intact (Manga et al., 2017).

The people of Betare Oya region heavily rely on artisanal gold mining for their livelihoods. It is a key source of income, often more lucrative than other local options, and a tradition passed through generations. This strong dependence stems from limited alternative employment and the relatively easy entry into this form of mining (Funoh, 2014).

2.4 Alluvial gold

Gold has been a valuable and sought-after metal for centuries. Alluvial gold refers to gold deposits formed by the erosional processes of rivers and streams, transporting and concentrating gold in riverbeds, floodplains, and deltas (Smith et al., 2020). These deposits have been an essential source of gold throughout history, supporting artisanal and large-scale mining activities (Johnson & Clark, 2019). Alluvial gold mining has played a crucial role in the economies of many gold-producing regions.

The process of alluvial gold formation is influenced by a combination of geological, hydrological, and environmental factors. Understanding these processes is essential for effective exploration and sustainable mining.

2.4.1 Geological processes of formation

Alluvial gold formation is primarily driven by the weathering and erosion of primary gold sources, such as quartz veins within hard rock deposits (Brown & Taylor, 2018). Over time, mechanical and chemical weathering release gold particles, which are transported by water and deposited based on size, shape, and weight (Williams, 2021). The movement of gold is influenced by factors such as river gradient, water velocity, and sediment load.

As gold-bearing rocks are exposed to weathering, gold particles are freed and carried by surface water to lower elevations. The process involves oxidation, dissolution, and mechanical breakdown, which lead to the separation of gold from its host minerals. Over extended periods, these particles accumulate in areas of reduced water flow, forming placer deposits (Harrison & Green, 2020).

2.4.2 Characteristics and occurrence

Alluvial gold is commonly found as flakes, nuggets, or dust, with its size and purity depending on the distance traveled from the primary source (Anderson, 2022). The physical properties of gold, such as its high density and malleability, influence its deposition in riverbeds and floodplains.

Deposits are classified based on their location and mode of formation sediments (Taylor et al., 2017). Common types include:

- **Eluvial Deposits:** Found close to the primary source, formed due to in-situ weathering.
- **Colluvial Deposits:** Occur on hill slopes, transported by gravity and short-distance runoff.
- **Alluvial Deposits:** Found in active river channels, terraces, and floodplains.
- **Paleo-Placer Deposits:** Ancient alluvial deposits buried under later

Alluvial gold deposits are widely distributed across different geographical regions. Major alluvial gold fields are found in Australia, Canada, Ghana, and Brazil, where extensive placer mining operations have been carried out for decades (Wilson, 2020). The presence of gold in these regions is closely linked to tectonic activities and past glacial movements.

2.4.3 Exploration techniques

The exploration of alluvial gold deposits requires a combination of geological, geophysical, and geochemical techniques to identify promising locations (Martinez & Lopez, 2018). Traditional methods include panning and trenching, while modern exploration utilizes remote sensing, geophysical surveys, and borehole sampling (Lewis & Scott, 2023).

Some of the commonly used exploration techniques include:

- **Panning:** A simple method used by prospectors to identify gold concentrations in river sediments.
- **Geophysical Surveys:** Methods such as ground-penetrating radar (GPR) and electrical resistivity help map subsurface deposits.
- **Sediment Sampling:** Collecting and analyzing stream sediments to detect gold anomalies.
- **Drilling and Bulk Sampling:** Used for resource estimation in larger mining operations (Patterson et al., 2021).

2.5 Alluvial gold mining

Alluvial gold mining, a practice dating back to ancient civilizations, remains a globally significant method for gold extraction (Mathioudakis et al., 2023). While employed worldwide, it is particularly prevalent in developing countries, where artisanal and small-scale gold mining serves as a crucial economic driver for local communities (NOVAFRICA, 2023). This reliance on artisanal small scale gold mining, however carries substantial environmental consequences. The often-informal nature of these mining operations contributes significantly to habitat destruction, water pollution and critically, widespread mercury contamination (Mathioudakis et al., 2023). The gold extracted through ASGM enters global markets, linking these local environmental challenges to international supply chains, thereby highlighting the need to sustainable practice and responsible practices and responsible resource management on a global scale (Funoh, 2014).

2.5.1 Alluvial gold mining in Africa

Gold mining in the African continent began as early as the 5th century, with Mali and Ghana being the main producers of the precious metal, known in Europe as the “Gold Coast”. Up until the 18th century, gold bars and coins were the primary exports of African states, supplying them to mediterranean countries where gold served as the main currency. Today, ASGM remains a crucial livelihood source for millions, particularly in countries like Ghana, Mali, DRC. These

operations, often informal, utilize basic techniques and equipment, contributing significantly to local economies.

However, this economic activity comes with severe environmental and social consequences. ASGM leads to appropriation of the land belonging to the local communities, impacts on health, alteration of social relationships, destruction of forms of community subsistence and life, social disintegration, radical and abrupt changes in regional cultures, displacement of other present and/or future local economic activities. All these have added to the hazardous and unhealthy working conditions of this type of activity.

The economic benefits of ASGM, while undeniable, must be balanced against its detrimental impacts. Sustainable practices are essential to mitigate these negative effects and ensure long term benefits. This requires international cooperation, responsible sourcing initiatives and the implementation of effective regulatory frameworks. Efforts to formalize ASGM, provide miners with safer technologies, and promote environmental awareness are crucial steps. Ultimately, a holistic approach that acknowledges the complex interplay of history, economics, and environment is necessary to address the challenges of alluvial gold mining in Africa and ensure a more sustainable future for the continent (Eloung et al.,2020).

2.5.2 Alluvial Gold concentration methods

The methods considered mainly involve the physical separation of gold from 'gangue' (which ranges from vein material in bed-rock deposits to sand and silt grade material in alluvial deposits) using gravity-based processing methods. Gold has a high specific gravity (19.3 g/cm³) in relation to most common gangue minerals (ranging from 2.65 to 3 g/cm³) and is therefore eminently suitable for gravity processing. Considering the minute quantity of gold normally present in even the most auriferous ores (down to 1 g/tonne in bed-rock and 0.25 g/tonne in alluvial deposits) gravity processing is virtually the only method effective at producing the concentration ratios required, especially with the high volume throughputs associated with alluvial mining.

It should be noted that recovery data are specific to particle-size, ore nature and processing operation. Certain gold grain characteristics influence the efficiency of gold recovery methods, particularly gravity separation. The influence of density upon the behaviour of a gold grain will lessen as the surface area to mass ratio increases. Gold is usually nonspherical, and it is typically flakier with decreasing grain size. This is mainly due to the malleability of gold, distorting rather than fracturing in response to loading and impact (during crushing and grinding of the ore, and

alluvial transport). This irregular shape leads to porosity; cavities and pores are often infilled with lower density material lowering the density of the composite particle (Wang & Poling, 1983).

The flaky shape, porosity and hydrophobic surface properties often cause gold to float. This is especially a problem for fine grained gold. Gold grain surfaces are often coated with an hydrophobic organic layer or iron oxide coatings and some are leached free of impurities (such as silver) leaving a rim of pure gold, all of these render the surface hydrophobic (Wang & Poling, 1983). The mineralogical character of the gold is often not considered when planning a processing plant, especially if the gold responds well to standard gravity and cyanidation processes. However, if the gold recovery is poor (430%) the ore is termed “refractory” and a detailed mineralogical investigation becomes necessary. This will involve the determination of the mode of occurrence of minute gold grains and the proportion of “invisible” gold. Gold usually occurs as “native gold”. A solid solution exists with many heavy metals including electrum (Au, Ag), argentian gold (Au, Ag), cuprian gold (Au, Cu), palladian gold (Au, Pd), mercurian gold (amalgam) (Au, Hg) and Au-Ag-Hg alloy. Other gold-bearing minerals occur only in very small amounts including gold tellurides, gold selenides, gold sulphides and intermetallic compounds such as amalgam (Au, Hg), aurostilbite (Au, Sb) and maldonite (Au, Si) (Petruk, 1989).

- **Panning**

Panning uses water to separate heavy gold particles from other lighter particles within a medium sized pan. In this process sediment or ore thought to contain gold is placed in a wide, curved pan along with water. The miner moves the pan in a series of motions designed to eject lighter sediments. The density of gold keeps it on the bottom of the pan as lighter material is ejected along with water. After a series of successful iterations have been completed, gold will be exposed on the bottom of the pan for the miner to recover.

Panning works best when gold is coarse and well liberated. Under right conditions, panning can produce high grade concentrates or even liberated gold. Then miners can employ gold recover methods such as direct smelting, although many panning operations lead to directly recoverable gold.

Panning offers miners a low cost method of gravity concentration but it requires time and skill to be effective. One of the major drawbacks to panning is that miners must pan small amounts

of concentrate. Therefore, panning is often done after other methods of gravity concentration such as sluicing have completed.



Figure 2.1: Panning Process

- **Sluicing**

Sluices use water to wash ore or alluvium down a series of angled platforms. As water washes sediment down a sluice, gold particles sink and are captured by material covering the bottom of the sluice, often carpets. Sluices are usually inclined at 5 to 15 degree angle. As moving water travels down a sluice, it generates greater force and keeps gold particles from sinking easily. For this reason most gold is captured at the beginning of the sluice. Carpets or other capturing devices on the bottom of sluices can be removed and washed in a bucket to remove the captured dense material. Sluice design can lead to higher gold recovery if the force of the water traveling through the sluice is decreased. A series of rifles can help break the flow to improve recovery. A zig zag sluice also achieves this by creating a drop between the first and second platform that disrupts the velocity of the water as it travels down the sluice (Martins et al, 1993).

A simpler alternative to the zig zag sluice is a combination of two sluice surfaces. The first is tilted at a steeper angle than the second, decreasing the velocity of the water as it hits the second sluice, increasing gold recovery. Sluices can be relatively expensive or affordable depending on the complexity of their design. Simple sluices can be a single angled platform a few feet in length and others can be very elaborate. Having an available and consistent water supply is necessary to have a functioning sluice operation. This can be done with piping, drums, buckets,

or natural flowing water bodies. A constant flow will be better than a bucket-driven flow. Sluices are good at concentrating large amounts of ore and sediment in a relatively short time but often do not yield concentrates with high amounts of gold. The resulting concentrate must usually undergo further methods of concentration, such as panning (Martins et al, 1993).



Figure 2.2: Sluicing Process

- **Shaking Table**

Shaking tables are elevated tables tilted to one side with raised ridges running horizontally down their length. Mineral feed (crushed ore or sediment) and water are released at one end of the table. The water washes the feed down the table. As the material is washed down the table, specialized grooves trap gold and direct it to collection points on the side of the table as lighter minerals are washed away. During this process, the table is continually shaken by a motor to agitate the material and aid in the separation of gold particles. Shaking tables are very effective and can concentrate sizeable amounts of ore at a time, providing high grade concentrates and liberated gold, but they are also relatively expensive and require some experience to operate.

The commonest form of shaking table used is the wet table (the 'dry' form is known as an air table, which uses air as the fluid separating medium). It consists of a flat table (or 'deck') with parallel riffles to trap the heavy minerals. The 'deck' is vibrated longitudinally and inclined laterally during operation. Perforated pipe feeds wash water from the upslope side. The slurries feed is introduced at the top upslope corner, minerals in the feed segregate. The heavy minerals sink to the deck, migrate along the riffles and are discharged over the end of the deck. The light minerals, entrained in the water, pass straight over the riffles and down to the bottom and so to

the tailings. Shaking tables are effective in the processing of Aerial in the size range 3 mm to 15 μ m. Shaking tables have been used to recover 88% of the gold present in a concentrate produced on a spiral (Eltham, 1984).

Wang & Poling (1983) record that up to 90% of gold coarser than 40 μ m can be recovered, whereas typically only 20% of 20 - 40 μ m gold can be recovered. The efficiency drops greatly below 40 μ m. The following table gives the size distribution of gold present in a shaking table middling product from a commercial mine in Malaysia i.e. material that had passed over the table and was stockpiled for possible later reprocessing. Estimated assay of around 10 tons is higher than the mined ore. There is considerable scope for increased yield with more effective processing. Particle-size distribution of gold in a middling product from a gold mine in Malaysia



Figure 2.3: Shaking table

- **Spiral Concentrators**

The spiral concentrator is described as a 'low feed rate, low feed density' flowing film gravity separators. It consists of a helical conduit of modified semi-circular cross-section, usually with between 3 and 5 complete 'turns' (Wills, 1992). Material is fed onto the top of the spiral as a slurry with typically 25 to 30% solids by weight. As the material flows spirally downwards the particles stratify due to factors such as centrifugal force, differential settling, hindered settling and reverse classification. There is usually a density gradation across the profile of the spiral with heavy minerals concentrating next to the axis and minerals of lower density being

swept to the outer edge. Concentrate, middling and tailing products are collected with the use of adjustable splitter plates

Spirals are effective in the processing of material in the size range 3 mm to 75 μm (although up to 5 % 'slimes' can be tolerated with sufficient wash water). Spiral performance is controlled by: the diameter and pitch of the spiral; the pulp density (i.e. the solids content of the slurry); the location of the splitters and take-off points; and, the volume and pressure of wash water. In one operation hydrocyclones are used to deslime (removing particles nominally finer than 30 μm in this case) the feed to spirals (only rejecting gold finer than 14 μm) and this leads to spiral recoveries of up to 65% (Eltham, 1984). At New Celebration gold mine in Western Australia a series of rougher (producing gold pre-concentrates) and cleaner (removing impurities from gold concentrates) spirals consistently achieve gold recoveries of 70 to 80% (Martins et al, 1993). Spirals are also known to be used for the recovery of fine flat free gold (recoveries up to 85%) and gold finer than 37 μm (recoveries up to 50%) (Feree, 1993).



Figure 2.4: Spiral concentrator

- **Bowl Concentrator**

A bowl concentrator consists of a rotating cylinder that segregates heavy minerals from light minerals by a combination of centrifugal force and wash water action. The Knelson bowl concentrator claimed to recover "gold particles ranging from 6 mm to less than one micron in a single pass" (sales brochure). Recovery is effective down to approximately 30 μm . Typically

Knelson concentrators have been retrofitted to process flotation tailings to recover gold coarser than 100 µm and also to replace mineral jigs as a means of recovering coarse gold ahead of flotation and cyanidation. A fully-automated Knelson concentrator was installed at the Dome Mine, South Porcupine, and Ontario in replacement for a jig circuit and exceeded jig gold recovery using only a tenth of the volume of jig feed (Brewis, 1995).

A similar concentrator was installed at the Golden Giant mine in north central Ontario which, accompanied by a single stage of tabling, accounted for up to 30% of the overall gold recovery. This was free-gold recovered directly from the grinding circuit prior to cyanidation (Brewis, 1995). Removal of coarser free gold ahead of cyanidation leads to savings from lowered carbon stripping (recovery of gold from solution) and a consequent reduction in the use of cyanide acid and other consumables. Also removal of free gold grains ahead of the grinding circuit will ultimately improve flotation efficiency as there is a reduction in gold 'smearing' onto other minerals and effecting flotation properties.



Figure 2.5: Bowl Concentrator

2.5.3. Alluvial gold recovery methods

- **Mercury Amalgamation**

Gold is commonly extracted from process concentrates using mercury which combines with gold to form an 'amalgam'. The gold is removed from the amalgam by evaporation of the mercury. Mercury is commonly added to sluice box riffles and also to grinding mills (Subasinghe & Maru, 1994). Also gold can be recovered from fine-grained tailings by washing them over a copper plate covered with mercury. Mercury amalgamation is effective for the recovery of gold from material in the size range 1.5 mm to 70 µm. Gold recovery efficiency

falls for grains finer than 70 µm and typically only 65% of free gold grains finer than 75 µm Guinea (Eltham, 1984).

Mercury is occasionally poured between the riffles on a sluice box in an attempt to capture fine-grained gold. However the contact time between the mercury and the gold is not sufficient to allow amalgamation to occur. Often fine gold remains suspended in the flow of material above the riffles and does not come into contact with the mercury. Up to 30% of the mercury used in sluices in Papua New Guinea finds its way directly into local rivers. Passing the tailings over ‘amalgamation units’ or through mercury filled columns has been recommended as a method of recovering this fine gold. However these are ultimately unsatisfactory as they still pose a threat to the environment (Subasinghe & Maru, 1994).

- **Cyanidation**

Cyanidation is the process whereby gold is recovered using a cyanide solution. Gold is dissolved using the cyanide solution and the resulting complex, Au (CN)₂ can be removed from solution by various methods (Deschenes, 1986):

- i) The “Merrill-Crowe” process, is used to remove the gold from the cyanide by cementation with powdered zinc.
- ii) Activated carbon absorption (otherwise known as C-I-P, carbon-in-pulp) is used for the processing of ores with a high slimes content which are difficult to treat by the Merrill-Crowe process. The absorption of gold is either performed by:
 - i) Carbon-in-column from solutions typically from heap leaching which are virtually free of suspended material
 - ii) Carbon-in-pulp (CIP) from leach pulps typically slimes, ground ores and calcines. An alternative to CIP is RIP (Resin-in-pulp) which is easier to use and less sensitive to the influence of naturally occurring carbon
 - iii) Carbon-in-leach (CIL) whilst leaching is still in progress. Typically, with ores containing carbonaceous material that could “rob” the gold from the “pregnant” (gold-bearing) solution. The carbon is reactivated by heating to 600 to 900°C in a reducing atmosphere.

2.6 Remote sensing

Remote sensing in a general sense refers to obtaining information about objects or areas by using electromagnetic radiation (light) without being in direct contact with the object or area. It occurs in the day-to-day business of people. Common activities such as reading the newspaper, watching cars, looking at a lecturer during classes, are all remote sensing activities of the human eye. The human eyes register the solar light reflected by these objects and the brain interprets the colors, the grey tones and intensity variations. These data are translated into useful information. The human eye however is limited to a small part of the electromagnetic spectrum. In remote sensing various kinds of tools and devices are used to make electromagnetic radiation outside this range visible to the human eye, especially the near infrared, middle infrared, thermal infrared and microwaves (De jong et al., 2004). Remote sensing, also called Earth Observation (OE), refers in a general sense to the instrumentation, techniques and methods used to observe, or sense, the surface of the earth, usually by the formation of an image in a position, stationary or mobile, at a certain distance remote from that surface. In a more precise way, remote sensing seeks to be able to have a total view of a large area at the same time in one view. In remote sensing, the electromagnetic radiation coming from an object, in case of earth observation this object is the earth's surface, is being measured and translated into information about the object or into processes related to the object. (De jong et al., 2004). Remote sensing techniques allow taking images of the earth surface in various wavelength region of the electromagnetic spectrum (EMS). One of the major characteristics of a remotely sensed image is the wavelength region it represents in the Electromagnetic Spectrum. Some of the images represent reflected solar radiation in the visible and the Near infrared regions of the electromagnetic spectrum, others are the measurements of the energy emitted by the earth surface itself that is in the thermal infrared wavelength region. Remote sensing imagery has many applications in mapping land-use and cover, agriculture, soils mapping, forestry, city planning, archaeological investigations, military observation, geomorphological surveying, water quality dynamics and urban growth (Agarwal.,2011)

2.6.1 Sensors in Remote Sensing

As stipulated by Boyd.,2005, sensors are instruments that have the capability of measuring electromagnetic radiation. The classification of sensors takes into considerations the following sensor characteristics, platforms and satellite orbits characteristics, and application domains

(Denègre., 2013). Boyd.,2005 further explains that they can be classified into two types as enlisted and described below:

- **Passive sensors**

Passive sensors do not have their own source of radiation. They are sensitive only to radiation from a natural origin, usually reflected sunlight or the energy emitted by an earthly object. The classical example of a passive imaging sensor is the camera, which records the distribution of radiation from an object on a photosensitive emulsion spread out on a film. Other examples are the multi-spectral scanner, the thermal scanner and the microwave radiometer. Both sensor and object are passive.

- **Active sensors**

Active sensors have a built-in source of radiation. The object is passive. Examples are RADAR (radio detection and ranging) and LIDAR (light detection and ranging). Radiation can be recorded in an analogue form, (the aerial photograph is a particular example,) or radiation can be stored in a digital arrangement, a set of signal values on a magnetic device CD-rom or DVD, as in most remote sensing records at present. Visualized images may be derived from digital data of imaging sensors.

2.6.2 The sources of the electromagnetic radiance

De Jong et al., (2004) explains that electromagnetic radiation is a characteristic of numerous physical processes where all materials with a temperature above 0 kelvin or +273 Celsius have the power to emit electromagnetic energy. Objects on or near the earth's surface are able to reflect or scatter incident electromagnetic radiation emitted by a source, which may be artificial, such as flash light, laser or microwave radiation, or natural, such as the sun. The visible, near-infrared (NIR) and middle-infrared (MIR) part of the electromagnetic spectrum, measures solar radiation reflected by objects at the earth's surface. The thermal-infrared (TIR) part, particularly in the atmospheric window at about 10 μm measures emitted radiation by objects at the earth's surface, be it that this radiation is originating from the sun. And the microwave part of the spectrum, both reflection of solar light and emission occur at very low energy rates. As a result, radiation mostly is transmitted to the earth's surface by an antenna on board the remote sensing system and, subsequently, the amount of radiation that is reflected is measure (backscattered) towards the same antenna.

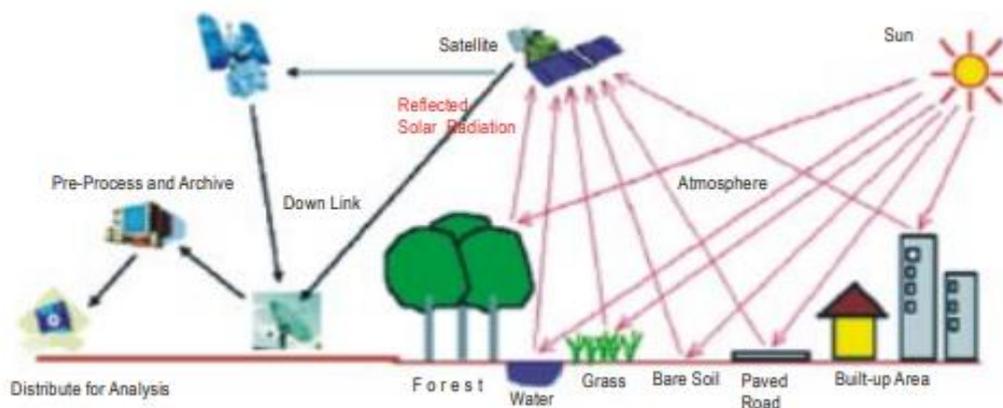


Figure 2.6: Illustration of remote sensing (Aggarwal, 2011)

Energy Spectrum Wavelengths used in Remote Sensing are;

- Ultraviolet – 0.3 to 0.4 μm
- Visible – 0.4 to 0.7 μm
- Near Infrared – 0.7 to 1.3 μm
- Middle Infrared – 1.3 to 2.8 μm
- Thermal Infrared – 2.4 to 14 μm
- Microwave – 1 mm to 1 m.

2.6.3 Stages in Remote Sensing

The following steps have been summarized by Aggarwal., (2011) as the stages involved in remote sensing (Figure 2.6):

- Emission of electromagnetic radiation, or EMR (sun/self- emission)
- Transmission of energy from the source to the surface of the earth, as well as absorption and scattering
- Interaction of EMR with the earth's surface: reflection and emission

Transmission, reception and (pre-) processing

The energy recorded by the sensor has to be transmitted, in electronic form, to a receiving and processing station where the data are processed into an image (digital and/or hardcopy). Generally, the provider of the image data will already apply some pre-processing. Pre-processing operations are intended to correct for sensor- and platform-specific radiometric and geometric distortions of data. Radiometric corrections may be necessary due to variations in scene illumination and viewing geometry, atmospheric conditions, and sensor noise and

response. Each of these will vary depending on the specific sensor and platform used to acquire the data and the conditions during data acquisition. Also, it may be desirable to convert and/or calibrate the data to known (absolute) radiation or reflectance units to facilitate comparison between data.

Image analysis and interpretation

The outstanding advantage of digital recordings is that numerous manipulations can be applied to the observational data according to the methods of digital image processing and pattern recognition. A much extended set of algorithms can be applied in an automatic way by using one of the various software packages for image analysis that are on the market. In principle, three categories of information can be derived from remote sensing:

- The assignment of class labels to the individual pixels or objects in an image, called classification creating, for example, a thematic land cover map;
- The estimation of object properties from remote sensing for example, assessing the amount of biomass of agricultural crops or forest types;

Observing, for example, the properties of vegetation, one has to pay attention to numerous variables. Examples of these are the irradiance, the direction of the radiation source, the condition of the atmosphere and its influence on the detected radiation, the presence of surrounding objects, the viewing angle of the sensor and, last but not least, the variations pertinent to the vegetation such as growing stage, moisture content, leaf area index, number of leaf layers and soil background. In summary, information about the earth's surface and its features may be obtained from images by detection on the basis of:

- Spectral characteristics (wavelength or frequency, reflective or emissive properties);
- Spatial characteristics (viewing angle of the sensor, shape and size of the object, position,
- Site, distribution, texture);
- Temporal characteristics (changes in time and position);
- Polarization characteristics (object effects in relation to the polarization conditions of the transmitter and receiver).

These information-extraction algorithms can generally only be applied to earth observation images when the images are radiometrically processed that is, converted from raw digital numbers into physical units such as radiance or reflectance. Such correction should account for

sensor characteristics, terrain topography and atmospheric conditions. Furthermore, images must be geometrically corrected for the effects of scanner distortions of the image, orbital geometry and figure of the earth.

The final product

The output from remote sensing can be in various forms and often is information that is used as input for further analysis, for example, in a geographical information system (GIS). On the one hand, information present in a GIS can help in the analysis and interpretation of remote sensing data. On the other hand, the results of a remote sensing analysis can be stored in a GIS. Subsequently, this information can be combined with other types of information for various types of studies or applications. As an example, a land cover map can be considered as an 'end product' of a remote sensing analysis. It can be used as input in a study towards groundwater pollution by combining it with various spatial and statistical data. (Jong et al., 2004)

2.6.4 Optical satellites used in remote sensing

LANDSAT

Landsat series is a joint USGS and NASA-led enterprise for Earth Observation that represents the world's longest running system of satellites for moderate-resolution optical remote sensing for land, coastal areas and shallow waters.

Landsat-1 to 3: Landsat-1 was launched in 1972, and was the first Earth observation satellite with the goal to monitor the world's land. Successful launches followed with Landsat-2 in 1975 and Landsat-3 in 1978.

Landsat-4 and 5: Landsat-4 was launched in 1982 and Landsat-5 in 1984. It carried the Multi Spectral Scanner and Thematic Mapper instruments

Landsat-6 satellite failed to achieve its orbit and the communication with satellite was never established. The series continues to this day, making Landsat the longest continuous Earth imaging programme in history

Landsat-7 was launched in 1999. It carries the Enhanced Thematic Mapper Plus 8-band whiskbroom scanning radiometer instrument. Landsat 7 is capable of generating 15 by 15 m resolution images

Table 2.1: Landsat 7 Bands, wavelength and resolution

Band No.	Wavelength (μm)	TM Band Information	Spatial resolution (m)
8	0.52 - 0.90	PAN	15
1	0.45 - 0.52	(VIS, blue)	30
2	0.53 - 0.61	(VIS, green)	30
3	0.63 - 0.69	(VIS, red)	30
4	0.77 - 0.90	NIR	30
5	1.55 - 1.75	SWIR	30
7	2.08 - 2.35	SWIR	30
6	10.4 - 12.5	TIR	60

Landsat-8 was launched in 2013. It carries the Operational Land Imager and Thermal Infrared Sensor Operators.

Table 2.2: Generalities of Landsat 8

Launched date	11 February 2013
Orbit Height	705 km
Orbit Type	Sun-synchronous near-polar
Orbit Period	99 minutes
Inclination	98.2
Repeat Cycle	16 days
Equatorial Crossing Time	10:00 a.m. +/- 15 minutes (United States Geological Survey)

The Landsat program comprises several generations of satellites, each improving spatial, spectral, and radiometric resolution. The most recent missions, Landsat 8 and Landsat 9, provide operational land imaging with enhanced sensors such as the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). These advancements enable accurate long-term environmental monitoring (Roy et al., 2021).

Applications of Landsat Imagery

- **Land Degradation Assessment**

Landsat imagery is widely used for assessing land degradation through spectral indices such as the Normalized Difference Vegetation Index (NDVI), Bare Soil Index (BSI), and Normalized Difference Moisture Index (NDMI). These indices help monitor vegetation loss, soil exposure, and moisture content in degraded landscapes (Huang et al., 2020).

- **Land Surface Temperature (LST) Analysis**

Landsat's thermal bands (TIRS) are used to estimate land surface temperature (LST), which is crucial for studying urban heat islands, deforestation, and climate change impacts. The split-window algorithm and radiative transfer models improve the accuracy of LST retrieval (Sobrino et al., 2022).

- **Land Use and Land Cover Change Detection**

With its long historical archive, Landsat data enables change detection analysis for deforestation, urban expansion, and agricultural transformation. Machine learning techniques, such as random forests and deep learning, are increasingly applied to classify land use patterns from Landsat images (Belward et al., 2021).

Case Studies Using Landsat Imagery

- **Desertification in the Sahara**

A study using Landsat NDVI and BSI indices to analyze desertification trends in the Sahara between 1985 and 2020 found a significant expansion of arid zones. Long-term analysis demonstrated a decline in vegetation due to climate change and overgrazing (Touati et al., 2021).

- **Deforestation in the Amazon**

Landsat imagery has been instrumental in tracking deforestation in the Amazon rainforest. A combination of NDVI and LST analysis between 2000 and 2022 showed extensive tree cover loss due to illegal logging and agricultural expansion (Souza et al., 2022).

Sentinel

Sentinel satellite imagery, developed by the European Space Agency (ESA) under the Copernicus Program, provides high-resolution, multi-temporal, and multi-spectral remote sensing data for various environmental applications. The Sentinel constellation consists of multiple satellites, including Sentinel-1 (SAR), Sentinel-2 (optical multispectral), Sentinel-3 (ocean and land monitoring), and others, which offer significant advancements in Earth observation for scientific research and policy-making (ESA, 2022).

. Advantages of Landsat Images

- Long-Term Data Availability: Landsat has been operational since 1972, providing a long-term dataset for historical analysis.
- Consistent Temporal Resolution: Landsat satellites provide data every 16 days, useful for monitoring long-term environmental changes.
- Thermal Imaging Capability: Landsat 8 and 9 include Thermal Infrared Sensor (TIRS), beneficial for land surface temperature and moisture studies.
- Higher Radiometric Resolution: Landsat 8 and 9 have 12-bit radiometric resolution, allowing better detection of subtle spectral variations.
- Global Coverage: Landsat provides systematic and continuous global coverage, making it suitable for large-scale environmental studies.

Sentinel Mission Overview

The Sentinel satellite program comprises several missions designed to monitor different aspects of the Earth's surface. The key Sentinel missions include:

Sentinel-1: Synthetic Aperture Radar (SAR) for all-weather, day-and-night land and ocean monitoring.

Sentinel-2: Optical and multispectral imaging for land monitoring, vegetation analysis, and land use classification.

Sentinel-3: Ocean and land surface monitoring, including sea surface temperature, vegetation, and atmospheric composition.

Sentinel-5P: Atmospheric monitoring for air pollution and greenhouse gas emissions.

Sentinel-6: High-precision sea-level monitoring.

Table 2.3: Sentinel 2 Bands, wavelength and resolution

Sentinel -2 bands	Characteristic	Sentinel-2A		Sentinel-2B		Spatial resolution (m)
		Central wavelength (nm)	Bandwidth (nm)	Central wavelength (nm)	Bandwidth (nm)	
1	Coastal aerosol	442.7	21	442.2	21	60
2	Blue	492.4	66	492.1	66	10
3	Green	559.8	36	559.0	36	10
4	Red	664.6	31	664.9	31	10
5	Vegetation red edge	704.1	15	703.8	16	20
6	Vegetation red edge	740.5	15	739.1	15	20
7	Vegetation red edge	782.8	20	779.7	20	20
8	NIR	832.8	106	832.9	106	10
8A	Narrow NIR	864.7	21	864.0	22	20
9	Water vapour	945.1	20	943.2	21	60
10	SWIR Cirrus	1373.5	31	1376.9	30	60
11	SWIR	1613.7	91	1610.4	94	20
12	SWIR	2202.4	175	2185.7	185	20

Sentinel-2: Multispectral Analysis for Environmental Monitoring

Sentinel-2, launched in 2015, is specifically designed for high-resolution multispectral imaging of land surfaces. It provides 13 spectral bands ranging from visible to shortwave infrared (SWIR), enabling applications such as vegetation monitoring, land use/land cover classification, and water quality assessment (Drusch et al., 2012). The mission offers a high spatial resolution (10m, 20m, and 60m) and a frequent revisit time (5 days), making it highly suitable for environmental change detection.

Applications of Sentinel Imagery

- **Land Degradation Assessment**

Sentinel imagery is widely used for monitoring land degradation processes such as deforestation, soil erosion, and desertification. Multispectral indices such as NDVI (Normalized Difference Vegetation Index), NDMI (Normalized Difference Moisture Index), and BSI (Bare Soil Index) derived from Sentinel-2 data have been instrumental in tracking vegetation loss and soil exposure (Zhu et al., 2020).

- **Water Quality Monitoring**

Sentinel-2 and Sentinel-3 provide essential data for monitoring water bodies by assessing parameters such as turbidity, chlorophyll-a concentration, and suspended sediments. The Normalized Difference Water Index (NDWI) is commonly used to evaluate surface water extent and water quality variations (Pahlevan et al., 2019).

- **Climate Change and Urban Expansion**

Sentinel data supports climate change studies by providing long-term land surface temperature (LST) trends, urban heat island analysis, and changes in vegetation phenology. The integration of Sentinel-1 SAR with Sentinel-2 optical data enhances urban expansion monitoring and infrastructure growth analysis (Pesaresi et al., 2021).

Case Studies Using Sentinel Imagery

- **Land Degradation in the Sahel**

A study in the Sahel region utilized Sentinel-2 NDVI and NDMI indices to assess vegetation degradation trends from 2016 to 2023. The results revealed a decline in vegetation health due to increased drought frequency and land-use changes (Dossa et al., 2023).

- **Monitoring Deforestation in the Amazon**

Sentinel-1 and Sentinel-2 data were used to map deforestation patterns in the Amazon rainforest. Time-series analysis demonstrated significant vegetation loss in mining-affected

areas, with Sentinel-1 SAR detecting deforestation under cloud cover conditions (Silva et al., 2022).

Advantages of Sentinel Images

Higher Spatial Resolution: Sentinel-2 provides up to 10m resolution in visible and near-infrared bands, compared to Landsat's 30m, offering finer details.

Frequent Revisit Time: Sentinel-2 satellites revisit the same location every 5 days, significantly improving temporal resolution compared to Landsat.

More Spectral Bands: Sentinel-2 has 13 spectral bands, including dedicated bands for vegetation and water monitoring, enhancing accuracy in index calculations.

Free and Open Access: Similar to Landsat, Sentinel-2 data is freely available, promoting extensive research and application.

Better Cloud Coverage Handling: Sentinel-2's short revisit time allows for better selection of cloud-free images.

Application-Based Comparison between Landsat and Sentinel

- **NDVI & Vegetation Monitoring:** Sentinel-2's higher spatial and temporal resolution offers more detailed vegetation analysis.
- **Water Quality and NDWI:** Sentinel-2's additional bands improve water body delineation and quality assessment.
- **LULC Classification:** Higher resolution Sentinel-2 data improves land cover classification accuracy.
- **Historical Change Detection:** Landsat's long-term archive makes it ideal for tracking environmental changes over decades.

2.7 Spatiotemporal Analysis

Spatiotemporal analysis is a method of examining data that considers both the spatial (location) and temporal (time) aspects, allowing researchers to study how phenomena change across different geographic areas over time, revealing patterns and trends that might not be apparent when looking at only one dimension (space and time) alone; essentially, it analyzes data collected across space and time to understand how things evolve geographically over time (Nushrat et al., 2022).

Spatiotemporal analysis is crucial in environmental monitoring because it allows for the simultaneous study of spatial patterns and their changes over time, providing a more

comprehensive understanding of environmental processes and enabling better management and prediction (Kokinou et al., 2023).

By analyzing data across different locations, researchers can pin point areas with high pollution levels, sensitive ecosystems, or areas particularly vulnerable to climate change (Sahragard et al.). Spatiotemporal analysis can help identify potential sources of pollution or environmental degradation by correlating spatial patterns with temporal changes in human activities or natural phenomena (Jiajia et al., 2024).

2.7.1 Methods and techniques used in spatiotemporal analysis

Spatiotemporal analysis encompasses a range of methods and techniques designed to understand phenomena that vary across both space and time. These methods are crucial for analyzing dynamic processes, such as environmental changes, urban development, and disease spread.

Time series analysis

Purposed: To identify patterns, trends, and relationships in data collected over time, and make forecasts and predictions about future values based on the observed historical data (Yen., 2023).

Techniques:

- **Trend analysis:** Examines changes in data over both time and location, revealing patterns and relationships that might be missed by analyzing space or time alone (Hernandez et al., 2025).
- **Seasonality Analysis:** Identifying and understanding recurring patterns within the data that occur at fixed time intervals, such as daily, weekly, or yearly cycles, to understand the influence of seasonal factors on spatial distributions and trends (Kenton., 2020).
- **Autocorrelation Analysis:** examines the correlation between data points at different time lags (Noble and Kavlakoglu, 2024).
- **Spectral Analysis:** Decomposes spatiotemporal data (data varying both in space and time) into spatial and temporal components, allowing for the analysis of frequencies and wave vectors in this dimension to reveal underlying dynamic patterns (Szymko et al., 2021).

2.7.2 Spatiotemporal Indices for environmental monitoring

- **Bare Soil Index (BSI)**

The Bare Soil Index (BSI) is a remote sensing-derived index used to identify and quantify bare soil surfaces. It utilizes spectral bands from satellite imagery to distinguish bare soil from

vegetation, water bodies, and built-up areas (Zhao et al., 2018). The importance of BSI has grown in environmental monitoring, particularly in land degradation studies, agricultural assessments, and urban expansion monitoring (Roy et al., 2020).

BSI Calculation and Methodology

BSI is calculated using the following formula:

$$\text{BSI} = \frac{[(\text{SWIR1} + \text{Red}) - (\text{NIR} + \text{Blue})]}{[(\text{SWIR1} + \text{Red}) + (\text{NIR} + \text{Blue})]}$$

For Landsat 8:

$$\text{BSI} = \frac{[(\text{Band 6} + \text{Band 4}) - (\text{Band 5} + \text{Band 2})]}{[(\text{Band 6} + \text{Band 4}) + (\text{Band 5} + \text{Band 2})]}$$

This equation enhances the contrast between bare soil and other land cover types, making it particularly useful for soil exposure monitoring (Mandal et al., 2019).

Applications of BSI

Land Degradation and Desertification: BSI has been widely used to detect land degradation and desertification. It helps track soil erosion, sand encroachment, and vegetation loss in arid and semi-arid regions (Zhang et al., 2021).

Agricultural Land Management: BSI is crucial in assessing soil conditions and evaluating land suitability for cultivation. Farmers and researchers use it to monitor soil degradation caused by overgrazing, deforestation, and unsustainable agricultural practices (Xie et al., 2018).

Urban Expansion and Land Use Change: BSI is instrumental in mapping urban sprawl and distinguishing built-up areas from bare soil. It is often combined with machine learning algorithms to enhance urban planning and land-use classification (Roy et al., 2020).

Comparison with Other Remote Sensing Indices

BSI is often compared with indices such as NDVI (Normalized Difference Vegetation Index), SAVI (Soil-Adjusted Vegetation Index), and NDBI (Normalized Difference Built-up Index). Unlike NDVI, which is vegetation-focused, BSI highlights soil exposure, making it a more accurate tool for analyzing land degradation and soil surface conditions (Zhao et al., 2018).

- **Normalized Difference Moisture Index (NDMI)**

The Normalized Difference Moisture Index (NDMI) is a remote sensing-derived index used to assess vegetation moisture content, which plays a critical role in monitoring drought, forest health, and land degradation (Gao, 1996). NDMI is particularly effective in analyzing land degradation processes such as deforestation, soil erosion, and desertification (Xue & Su, 2017). The availability of high-resolution satellite data from Sentinel-2 has significantly enhanced

NDMI-based studies by providing improved spectral and temporal coverage (Van Leeuwen et al., 2020).

NDMI Calculation and Methodology

NDMI is derived from near-infrared (NIR) and shortwave infrared (SWIR) bands, making it sensitive to vegetation water content and soil moisture. The equation for NDMI is given as:

$NDMI = (NIR - SWIR) / (NIR + SWIR)$ For Sentinel-2 imagery, the specific bands used in NDMI calculation are:

NIR (Band 8: 842 nm)

SWIR (Band 11: 1610 nm)

Role of NDMI in Land Degradation Assessment

NDMI is widely used to monitor land degradation, particularly in regions affected by deforestation, overgrazing, and unsustainable agricultural practices. Since soil moisture is a key indicator of land degradation, NDMI effectively maps changes in vegetation water content, which can indicate stress due to degradation (Chen et al., 2021).

Sentinel-2 for NDMI-Based Analysis

The Sentinel-2 satellite, with its 10-20m spatial resolution, provides high-quality NDMI data for land degradation studies. Its frequent revisit time (5 days) allows near-real-time monitoring of vegetation and soil moisture dynamics (Drusch et al., 2012).

Case Studies on NDMI and Land Degradation

A study in the Sahel region used Sentinel-2 NDMI to analyze land degradation trends from 2015 to 2022. The results showed a decline in NDMI values, indicating increasing soil dryness and vegetation stress (Dossa et al., 2023).

In the Amazon rainforest, NDMI analysis has been used to track deforestation-induced soil moisture loss. A study found that regions experiencing tree loss showed a 20-30% reduction in NDMI values over 10 years (Silva et al., 2021).

- **Normalized Difference Vegetation Index (NDVI)**

The Normalized Difference Vegetation Index (NDVI) is a widely used remote sensing index for monitoring vegetation health, productivity, and land cover changes. Introduced by Rouse et al. (1973), NDVI utilizes the contrast between the red and near-infrared (NIR) spectral bands to measure vegetation vigor. The index has become an essential tool in agricultural monitoring, ecological assessments, and climate change studies, as it provides a reliable indication of vegetation stress and biomass productivity.

Historical Background and Development

NDVI was first conceptualized in the early 1970s during the development of multispectral remote sensing techniques. Rouse et al. (1973) formulated NDVI to quantify vegetation cover using Landsat satellite imagery. Since then, the index has been extensively used in ecological and agricultural research. Technological advancements, such as the introduction of high-resolution sensors on platforms like MODIS, Sentinel-2, and Landsat 8, have significantly enhanced NDVI applications (Pettorelli et al., 2005).

NDVI Calculation and Variants

NDVI is computed using the following equation:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$$

For Landsat 8:

$$\text{NDVI} = (\text{Band 5} - \text{Band 4}) / (\text{Band 5} + \text{Band 4})$$

For Sentinel-2:

$$\text{NDVI} = (\text{Band 8} - \text{Band 4}) / (\text{Band 8} + \text{Band 4})$$

Several NDVI modifications exist, such as the Enhanced Vegetation Index (EVI), which improves sensitivity to high biomass areas by reducing atmospheric effects (Huete et al., 2002).

Applications of NDVI in Environmental and Agricultural Monitoring

Vegetation Health and Drought Monitoring: NDVI is extensively used to assess vegetation health and drought conditions. Research by Tucker et al. (1985) demonstrated NDVI's capability in detecting drought-induced vegetation stress. Modern applications include integrating NDVI with meteorological data to assess agricultural vulnerability to climate variability (Pettorelli et al., 2005).

Land Use and Land Cover Change Detection: NDVI has played a crucial role in monitoring deforestation, urbanization, and land degradation. Hansen et al. (2013) used NDVI time-series data to analyze global forest loss, highlighting its utility in long-term ecological assessments.

Agricultural Productivity and Crop Monitoring: NDVI-based remote sensing enables precision agriculture by monitoring crop health, estimating yield, and detecting pest infestations. Studies have demonstrated NDVI's effectiveness in optimizing irrigation schedules and fertilizer application (Lobell et al., 2015).

Comparison with Other Remote Sensing Indices

NDVI is often compared with alternative vegetation indices such as EVI, SAVI, and MSAVI. While NDVI is widely used for vegetation health monitoring, EVI provides better performance in dense vegetation areas by minimizing soil background effects (Huete et al., 2002).

Case Studies on NDVI Applications

Several studies have demonstrated NDVI's utility in vegetation monitoring. For example, Pettorelli et al. (2005) analyzed NDVI trends to assess the impact of climate change on vegetation dynamics in the Sahel region. Similarly, NASA's MODIS NDVI data has been extensively used to track global agricultural trends and ecosystem productivity.

- **Normalized Difference Water Index (NDWI)**

Water resources are vital for ecological balance, human consumption, and economic activities. Remote sensing has emerged as an essential tool in monitoring hydrological changes, enabling the detection of water bodies, seasonal variations, and the impact of anthropogenic activities (Gao, 1996). One of the most widely used indices for water body detection is the Normalized Difference Water Index (NDWI), first introduced by McFeeters (1996). The index enhances open water features in satellite imagery by leveraging spectral differences in water absorption and reflectance.

Historical Background and Development

NDWI was developed to distinguish water bodies from land using multispectral satellite imagery (McFeeters, 1996). It was originally designed for use with Landsat TM data, utilizing the Green and Near-Infrared (NIR) bands to enhance the water reflectance while minimizing vegetation influence. However, researchers soon identified limitations in NDWI's performance, particularly in urban environments where built-up areas often had similar spectral characteristics to water bodies (Xu, 2006). As a result, a modified version, the Modified Normalized Difference Water Index (MNDWI), was introduced by Xu (2006) to improve water detection in urban and turbid environments by replacing NIR with the Short-Wave Infrared (SWIR) band.

NDWI Calculation and Variants

NDWI is derived using the following equation:

$$\text{NDWI} = (\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$$

For Landsat 8:

$$\text{NDWI} = (\text{Band 3} - \text{Band 5}) / (\text{Band 3} + \text{Band 5})$$

For Sentinel-2:

$$\text{NDWI} = (\text{Band 3} - \text{Band 8}) / (\text{Band 3} + \text{Band 8})$$

MNDWI, a variation of NDWI, replaces the NIR band with SWIR to improve water body detection in highly reflective environments:

$$\text{MNDWI} = (\text{Green} - \text{SWIR}) / (\text{Green} + \text{SWIR})$$

For Landsat 8:

$$\text{MNDWI} = (\text{Band 3} - \text{Band 6}) / (\text{Band 3} + \text{Band 6})$$

Applications of NDWI in Environmental Monitoring

NDWI has been widely used for various hydrological and environmental studies. Key applications include:

Water Body Detection and Monitoring: NDWI is extensively used to delineate water bodies, such as lakes, rivers, and reservoirs, by enhancing the contrast between water and surrounding land features (Gao, 1996). Research has shown that NDWI effectively maps surface water changes over time, aiding in hydrological studies and water resource management (McFeeters, 2013).

Flood Monitoring and Disaster Assessment: Flood events significantly alter water coverage, and NDWI has proven effective in rapidly assessing flood extent. Pekel et al. (2016) used NDWI-based time-series analysis to detect flooding patterns across multiple regions. Studies utilizing Sentinel-1 and Sentinel-2 data have combined NDWI with synthetic aperture radar (SAR) to improve flood mapping accuracy (Huang et al., 2018).

Water Quality and Turbidity Analysis: Water quality assessment has become a critical application of NDWI, particularly when coupled with MNDWI and other spectral indices. Researchers have employed NDWI to monitor sedimentation in mining-affected rivers, where high turbidity impacts aquatic ecosystems (Chen et al., 2020). Further, integrating NDWI with the Chlorophyll-a Index has been useful for detecting algal blooms and assessing eutrophication levels in water bodies.

Comparison with Other Remote Sensing Indices

NDWI is often compared with other indices in remote sensing, including NDVI and BSI. NDVI primarily focuses on vegetation health, whereas NDWI enhances water detection (Ouma & Tateishi, 2006). In contrast, the Bare Soil Index (BSI) is used for identifying exposed soil, making it less effective in detecting water bodies.

Case Studies on NDWI Applications

Several studies demonstrate NDWI's effectiveness in water body detection. Pekel et al. (2016) mapped global surface water changes over 30 years using NDWI, revealing substantial shifts due to climate change and human activities. Additionally, NDWI has been applied in mining-affected regions to assess water pollution levels and land degradation (Kumar et al., 2019).

- **Turbidity Index**

Turbidity is a key parameter in water quality assessment, representing the cloudiness or haziness of water caused by suspended particles (Brown & Johnson, 2019). High turbidity levels can negatively impact aquatic ecosystems, drinking water quality, and industrial applications. Remote sensing has emerged as a powerful tool for monitoring turbidity over large spatial and temporal scales (Gao et al., 2020). Turbidity results from natural sources such as sediment transport, organic matter, and algal growth, as well as anthropogenic activities like deforestation, mining, and wastewater discharge (Smith et al., 2020). It affects light penetration in water bodies, impacting photosynthetic activity and aquatic habitats (Brown & Johnson, 2019). High turbidity can also harbor pathogens, posing health risks (EPA, 2021). Regulatory standards, such as those set by the U.S. Environmental Protection Agency (EPA), help establish acceptable turbidity levels for various water uses.

Concept and Development Turbidity Index (TI) is a mathematical representation of water clarity based on spectral reflectance characteristics (Lee et al., 2018). It is commonly derived using satellite data, which capture variations in water optical properties (Martinez et al., 2022).

Different TI models

Single-Band Methods: Utilizing specific spectral bands (e.g., red or near-infrared) to estimate turbidity levels

Multi-Band Indices: Combining multiple spectral bands to enhance accuracy and reduce atmospheric interference

Remote Sensing Methods for Turbidity Assessment

Remote sensing provides cost-effective and frequent monitoring of turbidity over large areas. Optical sensors on satellites such as Landsat, Sentinel-2, and MODIS have been widely used for turbidity assessment (Wang & Li, 2017). Key aspects include:

Spectral Reflectance Properties: Turbidity affects the absorption and scattering of light, influencing satellite-derived measurements (Zhang & Chen, 2023).

Empirical vs. Analytical Models: Empirical models use field-measured turbidity data for calibration, while analytical models derive turbidity from inherent optical properties (Clark et al., 2021).

Cloud and Atmospheric Correction Techniques: Addressing the impact of atmospheric conditions on satellite-based turbidity retrievals (Nguyen et al., 2019).

Comparative Analysis of Turbidity Indices

Different turbidity indices have been developed based on various sensors and analytical techniques. For example:

Landsat-Based Indices: Moderate spatial resolution (30m) suitable for large-scale monitoring but limited by temporal resolution (16-day revisit time) (NASA, 2022).

Sentinel-2-Based Indices: Higher spatial (10m) and temporal (5-day) resolution, improving turbidity detection in smaller water bodies (Clark et al., 2021).

MODIS-Based Indices: High temporal resolution (daily) but lower spatial resolution (250–500m), useful for large-scale ocean and river monitoring (Miller et al., 2021).

Applications of Turbidity Index in Environmental

Studies Turbidity indices are used in various environmental applications:

Water Quality Monitoring: Assessing pollution levels in lakes, rivers, and coastal zones (Jackson et al., 2020).

Impact of Land Use Changes: Understanding how deforestation and urbanization influence sediment transport and water clarity (Harris et al., 2018).

Climate Change Studies: Analyzing long-term trends in turbidity levels due to changes in precipitation and temperature patterns (Thompson & White, 2023).

- **Suspended Sediment Concentration (SSC)**

Suspended Sediment Concentration (SSC) is a crucial parameter in hydrology and environmental science, representing the concentration of fine-grained particles suspended in water bodies. These sediments originate from soil erosion, urban runoff, and industrial discharges, significantly impacting water quality, aquatic habitats, and reservoir capacities (Horowitz, 2008). Accurate monitoring of SSC is essential for effective water resource management and environmental protection. Traditional in-situ measurement methods, while accurate, are often labor-intensive and spatially limited. Remote sensing technologies have emerged as efficient alternatives, offering extensive spatial coverage and frequent temporal observations (Miller & McKee, 2004).

SSC refers to the mass of sediment particles suspended per unit volume of water, typically expressed in milligrams per liter (mg/L). These particles include clay, silt, and fine sand, which can originate from natural processes like soil erosion and anthropogenic activities such as deforestation and urbanization (Walling, 2006). Elevated SSC levels can reduce light penetration, affecting photosynthesis in aquatic plants and altering thermal stratification in water bodies (Bilotta & Brazier, 2008). Additionally, high sediment loads can transport nutrients and contaminants, leading to eutrophication and degradation of water quality (Brakenridge et al., 2020).

Traditional Measurement Techniques

Conventional methods for measuring SSC involve collecting water samples and analyzing them in laboratories to determine sediment concentrations. Techniques such as filtration, gravimetric analysis, and optical turbidity measurements have been widely used (Gray et al., 2000). While these methods provide accurate point measurements, they are limited by their spatial and temporal coverage. Deploying field campaigns to collect samples across large or remote areas can be resource-intensive and may not capture the dynamic variability of SSC, especially during episodic events like storms or floods (Liu et al., 2018).

Remote Sensing Approaches for SSC Estimation

Remote sensing offers a powerful tool for monitoring SSC over extensive areas with high temporal frequency. Satellite sensors detect reflected solar radiation from water surfaces, capturing variations in spectral signatures influenced by suspended sediments. As sediment levels increase, water reflectance typically rises in the red and near-infrared bands due to scattering effects (Binding et al., 2010).

Satellite Sensors Utilized in SSC Monitoring

Several satellite sensors have been employed to estimate SSC:

Landsat Series: The Landsat program has provided multispectral imagery since the 1970s, with sensors like the Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI). These sensors offer moderate spatial resolution (30 meters) and a 16-day revisit cycle, making them suitable for monitoring large water bodies and detecting long-term sediment trends (Gao, 2020).

Sentinel-2: Launched by the European Space Agency, Sentinel-2 satellites provide high-resolution multispectral imagery with a 10 to 20-meter spatial resolution and a 5-day revisit

period. The increased temporal frequency and finer spatial resolution enhance the capability to monitor SSC in smaller or dynamic water bodies (Vanhellemont & Ruddick, 2015).

MODIS (Moderate Resolution Imaging Spectroradiometer): MODIS sensors aboard NASA's Terra and Aqua satellites provide daily global coverage with moderate spatial resolution (250 to 500 meters). Despite the coarser resolution, MODIS data are valuable for monitoring large-scale sediment dynamics and capturing transient events like floods or storms (Mertes et al., 1993).

Empirical and Analytical Models for SSC Retrieval

Retrieving SSC from remote sensing data involves developing models that relate spectral reflectance to sediment concentrations. Empirical models establish statistical relationships between in-situ SSC measurements and corresponding satellite-derived reflectance values (Nechad et al., 2010). Analytical or semi-analytical models incorporate the inherent optical properties of water and sediments to simulate the interaction of light with suspended particles (Chen et al., 2014). Advancements in machine learning techniques have further enhanced SSC retrieval by enabling the development of algorithms that can capture nonlinear relationships and improve prediction accuracy (Huang et al., 2021).

Applications of SSC Monitoring

Accurate SSC monitoring has diverse applications in environmental management and research:

Water Quality Assessment: High sediment concentrations can degrade water quality, affecting drinking water supplies and aquatic habitats (Zhang et al., 2019).

Erosion and Sediment Transport Studies: Understanding sediment dynamics is crucial for managing soil erosion and sediment deposition in rivers and reservoirs (Vercruyssen et al., 2017).

Coastal and Marine Studies: SSC monitoring supports the study of coastal erosion, estuarine sediment dynamics, and the impact of human activities on marine ecosystems (Wu et al., 2020).

- **Land Use/Land Cover (LULC) Evaluation**

With the availability of remote sensing products, it is possible to study the changes on land with changing times. Several studies have been carried out using different methods, and satellites to evaluate land changes around the world.

Aguro, 1996 used remote sensing and GIS to evaluate Land Degradation and Land Management in Ghana where he demonstrates how these technologies have been successfully used in Ghana to assess degraded lands within the Nation's Forest Reserves. In his research, Landsat TM bands 453 (Red, Green, Blue) were combined with digital maps to separate forest from non-forest.

Degraded portions of the forest were then delineated and their areas digitally computed. These areas were then successfully validated through ground checks to provide data for reforestation program.

Lobo et al., 2018 in their research in Mapping Mining Areas in the Brazilian Amazon Using MSI/Sentinel-2 Imagery noticed that mining plays an important role for the economy of the Amazon, yet little is known about its attributes such as area, type, scale, and current status as well as socio/environmental impacts. Therefore, they propose a low time-consuming and high detection accuracy method for mapping the mining areas. This method involved the. Detection of the mining areas conducted in five main steps which are; MSI (Multispectral Instrument)/Sentinel-2A image selection; definition of land-use classes and training samples; supervised classification, vector editing for quality control; and validation with high-resolution Rapid Eye images. The results of using this method gave the total areas occupied by mining areas. A look at the recent events of mining impacts in this area, the large extension of mining areas detected raised a concern regarding its socio-environmental impacts for the Amazonian ecosystems and for local communities.

Kiran et al., 2018 in their research on Land Use/Land Cover Dynamics During 2001 And 2021 Using Google Earth Engine and GIS in Ramagundam Coal Mining Area, A Part of Pranhita Godavari Valley, Southern India, used Landsat 5 and Landsat 8 multispectral satellite data from 2001 to 2021 with <5% cloud cover was used to classify LULC classes. Using. Google Earth Engine through supervised classification And Regression Tree (CART) classifier. Their research showed that mining area had increased to 298% (from 15.20 km²to 60.50 km²) from 2001 to 2021 and significantly reduces other classes. And as such concluded that these results could be useful to the coal industry/company in carefully monitoring the effects of mining. The studied further recommended the use of such data as an aid in policy making and environmental analysis in understanding the nature of change in LULC features in the area.

Pei et al., 2017 used Object-based image analysis to map land use in the Panxie coal mining area, East China, where long-term underground coal mines have been exploited since the 1980s. A rule-based classification approach was developed for a Pleiades image to identify the desired land use classes, and the same rule-based classification strategies, the threshold values were modified slightly, and applied to the Landsat series images. They succeeded to produce an overall accuracy of between 80 and 94%. The results of this study provided a valuable basis for sustainable land management and environmental planning in the Panxie coal mining area.

Singh et al, research on the use of Landsat satellite images (MSS, TM, and ETM+) carryout Land use/land cover change detection analysis of Dhanbad district, in India. The study evaluated the LU/LC changes due to exploitation of coal in Dhanbad district of India during the period of 1987 to 2017 by means of supervised classification. The LU/LC change indicated that; for 30 years the percentage share of dense forest, open scrub, agricultural fallow, river, water body and mining was at a decrease. Land use changes were due to harvesting of forest for fuel, shelter and agriculture, construction of residential houses in fallow land, urbanization and sand removal for construction material. An increase in low dense forest, agricultural land, barren land, sand and built-up area were due to shift of land use from forest to open scrub, agricultural fields and barren lands, new settlement by utilizing sands from river banks making the river stretch wider, open mine pits converted into water bodies in the district. This research further confirms to the fact that man and his activity in most communities is the major cause of land degradation. With these findings, they concluded that there is a need of enhancement of forest area due to dwindling of life support system (vegetation) for biological organisms, a need for the mine managers and local inhabitants to pay attention to forest protection and to reduce the air and water pollution in the coal capital of India.

Nodem et al., 2018 carried out a study aimed at assessing the impacts of mining on the environment using a combination of spatial analysis, questionnaire administration and Leopold's grid of impact assessment. The impacts of mining on physical environment included air pollution by emission of dusts and fumes from engines, soil and subsoil degradation by earthworks and release of wastewater containing chemicals from companies. Destruction of habitats; decrease in quantity of forested area since the arrival of mining companies were observed. Aquatic fauna was seen to be threatened by high turbidity and death of fishes. The research recommended that Government bodies must ensure permanent monitoring and environmental audit to check the compliance of mining companies and their activities with regulations. That the Protection of environment and people in the area required some management strategies which included: control and monitoring of deforestation and its evolution; a review of the law or current mining code should be performed. The operator must develop and submit an EIA and an Environmental and Social Management Plan to ensure the protection of the environment during and after the gold mining. For the excavations, holes, land degraded, and sites affected by the activities; proper measures are needed for their maintenance and restoration. Mining activities in the area require the supervision of an interdisciplinary team

where the role and actions of different stakeholders are clearly stated. The state must ensure permanent monitoring, compliance and control of mining by a regular environmental audit of each mining company. Such a study shows the correlation between questionnaires, and remote sensing for effective results. In the study of land use and land cover analysis

Gadal et al, 2021.research on a new soil degradation method analysis by Sentinel 2 images combining spectral indices and statistics analysis: application to the Cameroonian shores of Lake Chad and its hinterland paper where it aimed at modeling the soil degradation risk along the Cameroonian shores of Lake Chad. The processing was based on a statistical analysis of spectral indices of sentinel 2A satellite images. A total of four vegetation indices such as the Greenness Index and Disease water stress index and nine soil indices such as moisture, brightness, or organic matter content are computed and combined to characterize vegetation cover and bare soil state, respectively. All these indices are aggregated to produce one image (independent variable) and then regressed by individual indices (dependent variable) to retrieve correlation and determination coefficients. Principal Component Analysis and factorial analysis are applied to all spectral indices to summarize information, obtain factorial coordinates, and detect positive/negative correlation. The first factor contains soil information, whereas the second factor focuses on vegetation information. The final equation of the model is obtained by weighting each index with both its coefficient of determination and factorials coordinates. This result generated figures cartography of five classes of soils potentially exposed to the risk of soil degradation.

Temgoua et al., 2018 in their study carried out in Ajei upland watershed community forest in the North West Region of Cameroon analyzed the spatial and temporal dynamics of land cover and land use from 1988 to 2018 where they identified and characterized the agents, drivers and pressures of change. The study involved the use of Landsat satellite images, field survey, interview and a focus on group discussion methods to identify the activities carried out by the local population and to determine agents, drivers and pressures of land use and land cover change. By using landsat images they were able to discover the four main land cover of the Ajei community forest; dense vegetation, sparse or degraded vegetation, savanna and bare soil. From the field surveys, and group discussion methods, the lost in vegetation resulted from the actions of farmers, cattle grazers and wood extractors who through farming, grazing and lumbering activities pressurize and converted the dense forest cover. Economic motives notably the need to increase household income from a frequent demand for farm and wood products in nearby

markets represent the drivers of forest cover change. At the end of this research, the research recommended that, controlling grazing activities notably in the dry season to check out the use of fires, community sensitization especially among cattle headmen on the importance of the community forest, reforestation activities through natural regeneration or tree planting are needed in the forest.

Kamga et al., 2017 carried out research in the eastern region of Cameroon with the aim of monitoring Land Use and Land Cover (LULC) changes between 1987 and 2017 within Bétaré-Oya, Ngoura and Batouri Districts which are witnessing extensive gold mining activities, assessing the dynamics between LULC types and understanding the anthropogenic impact of gold mining activities during this period. A series of Landsat images acquired in 1987, 2000, and 2016/2017 were used to examine LULC change trajectories at per-pixel scale with the post-classification change detection techniques based on the matrix of changes. A supervised classification by the maximum likelihood algorithm composed of five classes – Bare land, Settlements, Water bodies, Vegetation and Mine activities, was designed for this study, in order to classify Landsat images into thematic maps. This research revealed spatio-temporal change patterns, various composition and rates among the three study areas. Also, it shows the strong appearance and emergence of mining activities between 2000 and 2017 are coupled with increase in settlement surfaces and major changes in environment in the study areas. The LULC change analysis over time for the study areas have provide the current change trends. This study stresses the usefulness of Landsat TM/ETM+ and Landsat Data Continuity Mission (LDCM) data and highlights the data processing methods for long-term monitoring of artisanal mining activities impacts on the environment. The findings gathered from this research should be used to influence policy, legislation and decision-making in the mining and environmental sector.

2.8 Rehabilitation

This refers to the process restoring degraded or damaged ecosystems to functional state, emphasizing the recovery of ecosystem processes and services, rather than necessarily restoring the original species composition.

2.8.1 Principles of rehabilitation

Acknowledge the importance of ecosystem integrity:

Ecological rehabilitation seeks to restore the structure, function and processes of ecosystems, aiming to enhance biodiversity and resilience. The focus is not necessarily on recreating an

exact replica of the original ecosystem, but rather on facilitating its recovery and ensuring its capacity to provide ecological services (Gann et al., 2019).

Tailor restoration to local contexts:

Restoration efforts should be tailored to specific environmental conditions, including the unique characteristics of the degraded ecosystem and its surrounding landscape. This means considering factors such as climate, soil types, hydrology and native species to ensure the success of restoration efforts (Gann et al., 2019).

Prioritize ecological goals:

Restoring activities should be guided by ecological goals, with a focus on restoring natural processes and functions, such as water flow, nutrient cycling and habitat provision (Gann et al., 2019). This may include for example, promoting the recovery of native plant and animal communities, reducing pollution and restoring soil wealth (Maanavilja et al., 2014).

Engage stakeholders and promote participation:

Successful ecological rehabilitation requires the participation of local communities, land managers, scientists, and policy makers (Gann et al., 2019). Engaging stakeholders in planning and implementation can ensure that restoration efforts are relevant, sustainable and culturally appropriate (eden-plus.org).

Emphasize long term sustainability:

Restoration projects should be design to be sustainable in the long term, with a focus on self-sustaining ecosystems that can withstand environmental changes. This may involve reducing human impact on the ecosystem, promoting biodiversity, and ensuring that restoration activities are managed effectively (Maanavilja et al., 2014).

Monitor and assess restoration outcomes:

Regular monitoring and assessment are essential to track the progress of restoration projects and make adjustments as needed. This can involve measuring changes in biodiversity, ecosystem structure and function and water quality (Trinidad et al., 2023).

2.8.2 Ecosystem Services

Ecosystem services are the direct and indirect contributions of ecosystems to human well-being. They are the benefits that people obtain from nature. Ecosystem services are typically categorized into four main types:

- **Provision services:** These are the tangible goods that humans obtain from ecosystems, such as food, water, timber and raw materials.

- **Regulatory services:** These are the benefits derived from the natural processes that regulate ecosystem functions, such as climate regulation, flood control and disease regulation.
- **Supporting services:** These are the fundamental processes that sustain other ecosystem services, such as nutrient cycling, soil formation and pollination.
- **Cultural services:** These are the non-material benefits that ecosystems provide to human societies, such as recreation, tourism, aesthetic appreciation, and spiritual or cultural activities.

Restoration of ecosystem services

Ecological rehabilitation efforts often focus on restoring degraded ecosystems to enhance their capacity to provide ecosystem services. Key strategies include:

- **Revegetation and reforestation:** Restoring vegetation cover helps to improve soil stability, regulate water flow and sequester carbon. It also provides habitat for wildlife and enhances aesthetic values (Massoukou et al., 2023).
- **Wetland Restoration:** Restoring wetlands improve water purification, flood control and habitat provision. Wetlands are highly productive ecosystems that provide numerous services.
- **Soil remediation:** Restoring soil health enhances nutrient cycling, water infiltration and plant growth. This is particularly important in mining-affected areas with contaminated soils.
- **Habitat creation:** Creating and restoring habitats for specific species or communities enhances biodiversity and ecosystem resilience. This can include creating artificial reefs, building wildlife corridors, and restoring degraded forests.
- **Restoring natural hydrology:** Restoring the natural water flow of an area, greatly increases the ability of the local ecosystem to heal itself.

2.8.3 Remote sensing applications in mining Rehabilitation

Remote sensing plays a crucial role in both characterizing mining sites before rehabilitation and monitoring the progress of restoration efforts. By providing a synoptic view and enabling repeated observations, it offers valuable insights for effective rehabilitation planning and execution.

1. Baseline site characterization

Land cover mapping: Remote sensing allows for the creation of detailed land cover maps, which are essential for understanding the pre-mining and post mining landscape. This involves identifying areas of bare ground, vegetation, water bodies and infrastructure. High resolution imagery can be used to map detailed features, while moderate-resolution imagery can cover larger area (McKenna et al.,2020).

Topographic analysis: Digital Elevation Models (DEMs) derived from remote sensing data (LiDAR, satellite stereo imagery) are used to analyze topography, identify erosion-prone areas, and plan landform construction. DEMs are also used to monitor changes in landform stability during rehabilitation (Sodnomdarjaa et al.,2023).

Soil Characterization: Hyperspectral remote sensing can be used to assess soil properties, such as organic matter content, moisture, and heavy metal contamination. This information is crucial for planning soil remediation and revegetation strategies (Lau et al.,2008).

2. Monitoring rehabilitation progress:

Vegetation recovery monitoring: Vegetation indices (NDVI, EVI) are used to track the progress of revegetation efforts, assess vegetation health, and identify areas where recovery is lagging. Time series analysis of satellite imagery allows for the monitoring of long-term trends in vegetation recovery (McKenna, 2021).

Water quality Monitoring: Remote sensing is used to monitor changes in water quality during rehabilitation, ensuring that remediation efforts are effective (Moliere et al., 2012).

Landform stability monitoring: Repeated DEMs are used to monitor changes in landform stability, detect erosion, and assess the effectiveness of erosion control measures (Zhao et al., 2016).

GIS-Based multi-criteria evaluation for land suitability assessment of post mining areas in the Antaibao open-pit coal mine” was explored by Bagdanaviciute and Valiunas., (2012) to assess and map land suitability for ecological restoration in a post-mining area using a GIS based multi-criteria evaluation (MCA) approach, and to provide spatial guidance for rehabilitation planning. The researchers collected spatial data on topography (DEM), soil properties, and land cover (Landsat); performed a weighted overlay analysis in GIS to come out with map zones of high, moderate and low. This resulted in the generation of a land suitability map showing spatial variations in revegetation potential and provided recommendations for rehabilitation strategies based on suitability maps.

Hyperspectral remote sensing for vegetation monitoring and species identification in mine rehabilitation” by Plaza et al., (2016) to review and demonstrate the applications of hyperspectral remote sensing for vegetation monitoring and specie identification in mine rehabilitation, and to show this technology can improve rehabilitation. They reviewed and discussed the use of hyperspectral imaging to capture detailed spectral signatures of vegetation and soils. Their results showed how to map the spatial distribution of different plant species in a rehabilitated mining area.

2.8.4 Case studies of successful mining-affected rehabilitation projects

Successful rehabilitation of mining-affected areas requires a multifaceted approach, as demonstrated by several global case studies. The Sudbury Regreening Program in Canada exemplifies the importance of sustained, long-term commitment and community involvement in ecological restoration. After decades of severe environmental damage from nickel and copper mining, Sudbury achieved significant vegetation recovery through liming acidic soils, planting native species, and reducing industrial emissions. This highlights the necessity of a scientific, adaptive management strategy in rehabilitation (Monet and McCaffrey2025).

Conversely, the Zollverein Coal Mine Industrial Complex in Germany showcases successful repurposing and revitalization. Transforming a former coal mine into a UNESCO World Heritage site, cultural hub, and recreational space demonstrates that rehabilitation can yield significant social and economic benefits while preserving industrial heritage. This case underscores the potential for innovative land-use strategies post-mining.

The Beenup Titanium Mine in Australia further emphasizes the importance of ecological restoration and community engagement. By focusing on creating permanent wetlands with native vegetation and fostering collaboration with scientific experts, the Beenup project achieved successful ecological rehabilitation. This exemplifies the importance of tailored rehabilitation strategies that focus on restoring specific ecosystem functions (Norrish et al., 2019).

Across these cases, several common factors emerge as critical for successful rehabilitation: early integration of rehabilitation planning into mining operations, active community participation, rigorous scientific monitoring and adaptive management, and a long-term commitment to ecological restoration. Furthermore, the use of remote sensing and GIS systems can provide valuable tools for monitoring and planning rehabilitation efforts, ensuring that restoration goals are met effectively. These case studies provide valuable insights for the

rehabilitation of alluvial gold mining-affected areas in Betaré-Oya, emphasizing the need for a comprehensive and adaptive approach."

Doumo et al., (2022) conducted a study assessing metallic contamination in soils and sediments with Betare-Oya gold artisanal mine district. Their analysis revealed significant levels of metallic contamination, indicating substantial environmental impact from mining activities. This study highlights the direct correlation between artisanal mining and increased heavy metal pollution in the region

Research carried out on mine waste and heavy metal pollution in Betare-Oya mining area (Eastern Cameroon) demonstrates the severe environmental consequences of mining activities. This research focuses on the levels of heavy metal pollution that are directly linked to mine waste that is produced by the artisanal gold mining.

A study focusing on the assessment of surface water quality in Betare-Oya gold mining area provides valuable insights into the hydrological impacts of mining. The research shows the degradation of surface water quality due to the mining operations.

Studies utilizing remote sensing techniques have documented significant land cover changes in Betare-Oya region, primarily driven by artisanal gold mining. Analysis of satellite imagery shows a marked increase.

2.9 Research gap

This literature review has highlighted the significant environmental and socio-economic impacts of alluvial gold mining in the Betaré-Oya region, and the potential of remote sensing for spatiotemporal analysis and rehabilitation. However, one significant gap lies in the assessment of rehabilitation effectiveness. While many studies document the environmental impact of alluvial gold mining, a lack of comprehensive research exists on the ecological and socio-economic sustainability of rehabilitation practices. This study focuses on monitoring and evaluation to understand the true impact of rehabilitation efforts, while proposing rehabilitation measures for enhancing sustainable mining practices in Betaré-Oya mining district.

CHAPTER 3

MATERIALS AND METHOD

3.1 Materials

This section outlines the materials used in conducting the research

3.1.1 Field Observation Materials

Field observations involved capturing images of active and abandoned mine sites, mapping affected areas using GPS, and conducting interviews with local communities.

Table 3.1: Field observation Materials

Material	Function
Garmin GPSMAP 64s	Used for mapping active and abandoned mine sites.
Smartphone	Captured images of land degradation, active mining zones, and abandoned sites.
Field Notebook	Recorded observations, GPS coordinates, and interview responses.
Semi-structured Interviews	Collected qualitative data on mining activities, environmental impacts, and community perspectives.

3.1.2 Remote Sensing Data

Satellite imagery was used to analyze land use changes, vegetation health, land degradation, and water quality caused by mining activities.

Table 3.2: Remote sensing Data

Satellite Data	Function
Sentinel-2 (10m resolution, MSI sensor)	Used for NDVI (vegetation health), NDWI (water body assessment), BSI (bare soil analysis), NDMI (moisture index), TI (Turbidity index), SSC (Suspended Sediment Concentration) and LULC classification.

3.1.3. Software Used for Data Processing

The following software tools were used for remote sensing analysis, geospatial mapping, and classification.

Table 3.3: Software used for Image Processing and Statistical analysis (Appendix A)

Software	Function
SNAP Tool (Sentinel Application Platform)	Pre-processing of Sentinel-2 images, including radiometric and atmospheric corrections.
Google Earth Pro	Used for high-resolution image validation and manual inspection of mine site changes.
ArcGIS	Used for spatial analysis, map creation, GPS data integration, and land use classification.
ENVI	Used for cloud-based processing of satellite imagery, time-series analysis, and spectral index computation.
MS Excel	Used for quantitative data analysis after performing spatial analysis

3.1.4 Safety and Ethical Consideration Materials

The research adhered to ethical and safety guidelines to ensure responsible environmental monitoring and data collection.

Table 3.4: Safety Materials

Material	Function
Safety boat	Protected the researcher while navigating rough terrain.
Face Mask	Minimized exposure to dust and contaminants in mining-affected areas.
First Aid Kit	Ensured quick response to potential injuries during fieldwork.



Figure 3.1: Garmin GPSMAP 64s

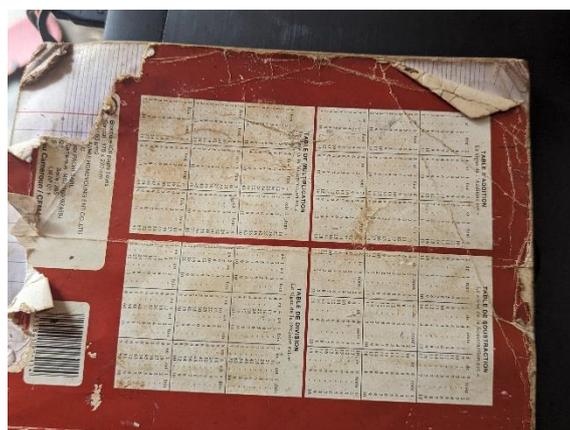


Figure 3.2: Field Notebook



Figure 3.3: Google Pixel 6 smartphone with high resolution camera



Figure 3.4: Safety boot

3.2 Methods

This study adopts a mixed-method approach combining remote sensing, GIS analysis, and field-based assessments to analyze spatiotemporal environmental changes in Betare-Oya's alluvial gold mining-affected areas. The study integrates quantitative methods (satellite image analysis, spectral indices computation, and water quality assessment) and qualitative methods (field basic assessment and expert consultations).

3.2.1 Field-based preliminary evaluation and satellite imagery for assessing land degradation

1. Field-based and Google Earth Pro Evaluation

A field visit was conducted between January and March 2025 to assess the extent of environmental degradation caused by alluvial gold mining. The assessment focused on active mining areas, abandoned mine sites, and general land degradation patterns. During the field visit, active and abandoned mine sites were identified and documented. Key observations included:

- Identification of active artisanal and semi-mechanized mining operations.
- Assessment of land degradation, deforestation, and soil erosion in affected areas.
- Visual examination of water bodies for signs of sedimentation and pollution.
- Inspection of abandoned mine sites to determine the extent of environmental impact.

A Garmin GPSMAP 64s was used to record the geographic coordinates of mining sites. GPS data collection was essential for spatial mapping and integration with satellite imagery. The collected data included:

- Locations of active mining pits and excavated areas.

- Coordinates of abandoned mine sites.
- Mapping of areas with visible land degradation and deforestation.

A Google pixel 6 smartphone with high resolution camera was used to capture photographic evidence of mining activities, abandoned sites, and environmental degradation. These images were used for validation of remote sensing analysis.

Semi-structured interviews were conducted with local residents, miners, and community leaders to gather qualitative information on mining activities and their environmental impacts. The discussions covered:

- Changes in land use and environmental conditions over time.
- Perceptions of the impact of mining on water quality and vegetation.
- Community perspectives on abandoned mine sites and possible rehabilitation strategies.

To supplement field observations, Google Earth Pro was used to observed high-resolution satellite images of selected mining-affected areas for the year 2023. The imagery provided a detailed view of abandoned mine sites and land degradation. The selection of 2023 was to evaluate rehabilitation efforts with recent field observation.

2. Remote Sensing Satellite Imagery Evaluation

A. Bare Soil Index

This study employs remote sensing techniques, specifically the Bare Soil Index (BSI), to analyze the spatiotemporal changes in bare soil extent within alluvial gold mining-affected areas in the Betaré-Oya region of Cameroon. Sentinel-2 satellite imagery from 2021, 2023, and 2024 were processed to quantify and map bare soil areas, providing insights into degree of land degradation. The workflow involves image acquisition, preprocessing using SNAP (Sentinel Application Platform), BSI calculation, and spatial analysis using ArcGIS 10.8.

Data Acquisition

Sentinel-2 Level-2 (surface reflectance) imagery were acquired for the Betaré-Oya region for the years 2021, 2023, and 2024. The selection of imagery prioritize dates within the dry season (November- March) to minimize cloud cover and vegetation influence on the BSI calculation. The images were downloaded from the Copernicus Open Dataspace System (formerly Sentinels Scientific Data Hub).

Image Selection Criteria:

- Images with less than 10% cloud cover over the study area were preferred.

- The Level-2 product provides atmospherically corrected surface reflectance values, reducing the need for additional atmospheric correction procedures.
- The imagery must cover the entire Betaré-Oya study area.

Table 3.5: Characteristics of downloaded Sentinel images

Year	Satellite	Date of image	Time	Phonological cycle
2021	Sentinel-2 Level 2	09/12/2021	09:22:59	Dry Season
2023	Sentinel-2 Level 2	14/12/2023	09:24:01	Dry Season
2024	Sentinel-2 Level 2	23/12/2024	09:23:19	Dry Season

Preprocessing using SNAP

SNAP (Sentinel Application Platform), developed by the European Space Agency (ESA) was used for preprocessing the Sentinel-2 imagery. SNAP provides a comprehensive environment for processing Sentinel data. The following preprocessing steps were performed within SNAP:

- The downloaded Sentinel-2 Level-2A granules were imported into SNAP.
- A subset operation was performed to extract the area of interest (Betaré-Oya) in order to reduce processing time and storage requirements.
- While Level-2A data is typically already coregistered, band resampling to a common spatial resolution was performed using the nearest neighbor method.
- Although the Level-2A data is atmospherically corrected, it may still contain clouds or cloud shadows. The quality information associated with the data will be used to generate a cloud mask to remove these areas from the analysis. The Sen2Cor algorithm embedded in SNAP was utilized for this purpose. Pixels identified as cloud or cloud shadow were masked out by setting their values to "NoData."
- Although Level-2A data is geometrically corrected, a visual inspection was performed to ensure accurate georeferencing.
- The preprocessed imagery, with cloud masking and resampling applied, were exported from SNAP in a format compatible with ArcGIS 10.8 (GeoTIFF).

Bare Soil Index (BSI) Calculation

The BSI is calculated using the following formula, which utilizes the red, blue, shortwave infrared (SWIR1), and near-infrared (NIR) bands of the Sentinel-2 imagery:

$$\text{BSI} = ((\text{SWIR1} + \text{Red}) - (\text{NIR} + \text{Blue})) / ((\text{SWIR1} + \text{Red}) + (\text{NIR} + \text{Blue}))$$

Where:

SWIR1: Shortwave Infrared 1 (Sentinel-2 Band 11)

Red band (Sentinel-2 Band 4)

NIR: Near-Infrared band (Sentinel-2 Band 8)

Blue: Blue band (Sentinel-2 Band 2)

The BSI was calculated using the Raster Calculator tool in ArcGIS 10.8. The band designations were carefully matched to the corresponding Sentinel-2 bands in the preprocessed imagery. BSI values range from -1 to +1. Higher BSI values typically indicate a greater proportion of bare soil.

Spatial Analysis and Mapping in ArcGIS 10.8:

The BSI values were classified into different categories of bare soil using a supervised (maximum likelihood classification) techniques. Ground truth data (collected through field surveys and/or high-resolution imagery interpretation) were used to train the supervised classification algorithm and validate the accuracy of the classification approach. The categories included:

- Bare Soil (actively mined areas or abandoned mine site)
- Dry grass (disturbed areas, partially revegetated areas)
- Sparse Vegetation (naturally bare areas, areas with minimal mining impact)
- Dense Vegetation

The accuracy of the classification was assessed using Kappa coefficient. Ground truth data were used as reference for accuracy assessment.

B. Normalized Difference Moisture Index

The Normalized Difference Moisture Index (NDMI) will be utilized as a proxy for vegetation moisture, which is a crucial indicator of land degradation and ecosystem disturbance in areas impacted by mining activities. Sentinel-2 satellite imagery from the years 2021, 2023, and 2024 will be processed and analyzed using SNAP (Sentinel Application Platform) and ArcGIS 10.8 to quantify and map changes in vegetation moisture content. This information will be used to assess the degree of environmental impact of alluvial gold mining in the study area in a time series approach. The NDMI analysis will complement the Bare Soil Index (BSI) analysis to provide a comprehensive understanding of land cover changes in the study area.

Data Acquisition

Sentinel-2 Level-2A (surface reflectance) imagery were acquired for the Betaré-Oya region for the years 2021, 2023, and 2024 (images have same characteristics as on Table 3.5). These years are selected to capture a baseline condition, an intermediate period, and a later stage of potential environmental change. The Sentinel-2 mission provides high-resolution multispectral imagery with a revisit time that is suitable for monitoring land cover dynamics. The Level-2A product provides atmospherically corrected surface reflectance values, which are essential for accurate NDMI calculation.

Preprocessing using SNAP

The downloaded Sentinel-2 Level-2A granules were imported into SNAP using the dedicated data import tool.

A subset operation was performed to extract the area of interest (Betaré-Oya region) from the full Sentinel-2 scene.

Band resampling is necessary to align all bands to a common spatial resolution. The 10-meter bands (Blue, Green, Red, and NIR) was used as the reference resolution, and the 20-meter SWIR bands was resampled to 10 meters using the nearest neighbor resampling method. This method preserves the original pixel values and avoids introducing artificial data.

Although Level-2A data is atmospherically corrected, residual cloud cover or cloud shadows may still be present. The Sen2Cor algorithm integrated within SNAP was used to generate a cloud mask. This algorithm utilizes spectral and spatial characteristics to identify cloud and cloud shadow pixels. Pixels identified as clouds or cloud shadows will be flagged and subsequently excluded from the NDMI calculation.

A visual inspection of the preprocessed imagery was conducted to ensure accurate georeferencing.

The preprocessed imagery, with cloud masking and resampling applied, will be exported from SNAP in GeoTIFF format for further processing in ArcGIS 10.8.

Normalized Difference Moisture Index (NDMI) Calculation

NDMI is calculated using the formula: $NDMI = (NIR - SWIR1) / (NIR + SWIR1)$

Where:

NIR: Near-Infrared band (Sentinel-2 Band 8)

SWIR1: Shortwave Infrared 1 (Sentinel-2 Band 11)The NDMI utilizes the reflectance difference between the NIR and SWIR1 bands. The NIR band is highly sensitive to vegetation canopy structure, while the SWIR1 band is sensitive to water content in vegetation and soil. Therefore, the NDMI provides a measure of vegetation moisture, which is an indicator of vegetation health and stress.

Spatial Analysis and Mapping

ArcGIS 10.8 was used for spatial analysis, mapping, and visualization of the NDMI results. ArcGIS provides a comprehensive suite of tools for raster analysis, spatial statistics, and map creation.

The NDMI raster layers for 2021, 2023, and 2024 were imported into ArcGIS 10.8.

The NDMI values were classified into different categories of vegetation moisture content. The classification scheme was based on a combination of literature review and visual interpretation of the NDMI values in relation to land cover types in the study area. The categories include:

- High Vegetation Moisture (Dense, healthy vegetation)
- Moderate Vegetation Moisture (Moderately dense vegetation)
- Low Vegetation Moisture(Sparse vegetation, stressed vegetation)
- Moisture-deficient areas(Bare soil, non-vegetated areas)

High-quality maps were created to visualize the spatial distribution of vegetation moisture content.

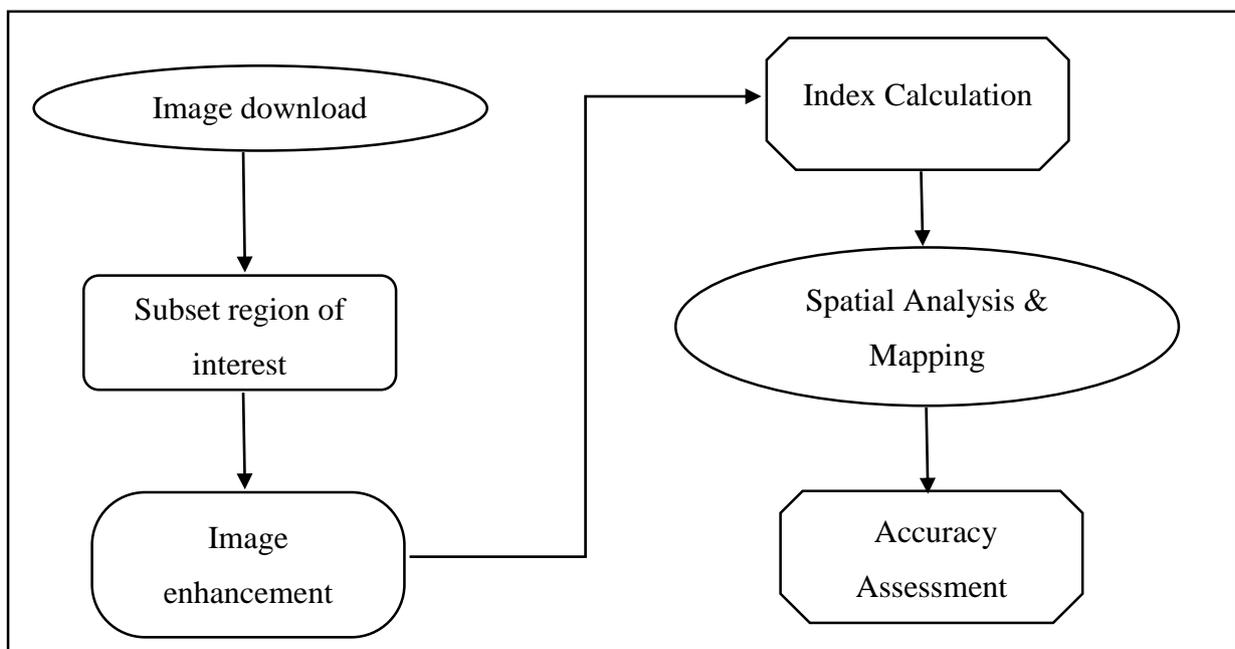


Figure 3.5: Flowchart for BSI, NDMI, NDVI, NDWI, TI and SSC

3.2.2 Vegetation Health Trend Assessment

Sentinel-2 satellite imagery from 2021, 2023, and 2024 were processed to quantify and map vegetation density, reflecting the impact of mining activities. The workflow encompasses image acquisition, preprocessing using SNAP (Sentinel Application Platform), NDVI calculation in ENVI and spatial analysis using ArcGIS Pro 10.8.

Data Acquisition

Sentinel-2 Level-2A (surface reflectance) imagery were acquired for the Betaré-Oya region for the years 2021, 2023, and 2024. The acquisition dates ideally for NVDI was to fall within the peak growing season (typically August-October) to maximize vegetation signal. But due to case persistent cloud cover during the peak growing season, imagery from adjacent months (December) was considered.

Table 3.6: Characteristics of downloaded Sentinel images used for NDVI

Year	Satellite	Date of image	Time	Phonological cycle
2021	Sentinel-2 Level 2	09/12/2021	09:22:59	Dry Season
2023	Sentinel-2 Level 2	14/12/2023	09:24:01	Dry Season
2024	Sentinel-2 Level 2	23/12/2024	09:23:19	Dry Season

The acquired images were preprocessed as earlier described above under the BSI preprocessing method using SNAP software.

NDVI Calculation

$$\text{NDVI is calculated as: } \text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$$

Where:

NIR = Near-Infrared band (Sentinel-2 Band 8)

Red = Red band (Sentinel-2 Band 4)

Spatial Analysis and Mapping in ENVI/ArcGIS 10.8

ArcGIS 10.8 and ENVI was used for spatial analysis and mapping. The Geotiff preprocessed raster images for 2021, 2023, and 2024 were imported into the software. Using the raster calculator, the NDVI values were obtained for each Year. The images were then classify into

meaningful categories (Dense Vegetation, Moderate Vegetation, Sparse Vegetation, Bare Soil and water).

Accuracy Assessment

The NDVI values and classifications were compared with satellite images from Google earth pro to assess the accuracy of the remote sensing analysis. Calculated metrics like Kappa coefficient, user's accuracy, and producer's accuracy were performed.

3.2.3 Water quality indices Assessment

A. Normalized Difference Water index

Alluvial gold mining frequently disrupts natural drainage patterns, alters water quality, and affects the extent and connectivity of water bodies. Sentinel-2 imagery from 2021, 2023, and 2024 were processed to quantify and map water bodies, allowing for the assessment of mining-related disturbances. The analysis involved image acquisition, preprocessing using SNAP (Sentinel Application Platform), NDWI calculation, and spatial analysis using ENVI and ArcGIS 10.8.

Data Acquisition

Sentinel-2 Level-2A (surface reflectance) imagery were acquired for the Betaré-Oya region for the years 2021, 2023, and 2024. The timing of image acquisition aimed for the end of the rainy season (October/November) or the beginning of the dry season (December), when water bodies are typically at their fullest extent, and cloud cover is less likely. Due to cloud cover, images from adjacent months (September/November or January/February) can be considered, with careful assessment of potential changes in water levels. The characteristics of the images used for this study are similar to that as shown on Table 3.6.

The acquired images were preprocessed as earlier described above under the BSI preprocessing method using SNAP software.

NDWI Calculation

$$\text{NDWI} = (\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$$

Where:

Green = Green band (Sentinel-2 Band 3)

NIR = Near-Infrared band (Sentinel-2 Band 8)

Spatial Analysis and Mapping Procedure

- Import NDWI raster layers for 2021, 2023, and 2025.

- Applied a threshold to the NDWI raster to extract water bodies. This is a critical step and requires careful consideration.
- Refined the threshold based on visual interpretation of the NDWI raster overlaid with high-resolution imagery from Google earth pro for accuracy assessment. Adjusted the threshold until the extracted water bodies accurately match the known water extents.
- Converted the threshold NDWI raster into a binary classification:
Water: NDWI values above the threshold (0.0)
Non-Water: NDWI values below the threshold (0.0).

B. Turbidity Index

Data Acquisition

To estimate the Turbidity Index (TI), Sentinel-2 Level-2A imagery was obtained from the Copernicus Open Space Datasystem. The selection of images was based on the following criteria:

- Minimal cloud cover (<10%) to reduce atmospheric interference.
- Availability of essential spectral bands for turbidity assessment
 - Band 2 (Blue, 490 nm)
 - Band 3 (Green, 560 nm)
 - Band 4 (Red, 665 nm)
 - Band 8 (NIR, 842 nm)

These bands were selected based on their spectral response to suspended particles and organic matter, which contribute to turbidity in water bodies.

Preprocessing in SNAP

The acquired Sentinel-2 Level-2A images were preprocessed using the Sentinel Application Platform (SNAP) to ensure radiometric and geometric consistency. The following steps were performed:

The Sentinel-2 Level-2A images in .SAFE format were loaded into SNAP, and the bands relevant for turbidity estimation were selected.

To optimize processing efficiency, the study area was clipped using the Subset Tool in SNAP. This step ensured that only relevant portions of the image were retained, eliminating unnecessary computational load.

Cloud-contaminated pixels were removed using the Scene Classification Layer (SCL) available in Sentinel-2 Level-2A products. Pixels corresponding to clouds, shadows, and land surfaces (SCL values: 3, 8, 9, and 10) were masked out to improve the accuracy of turbidity estimation. The final preprocessed image was exported as a GeoTIFF file with a 10-meter spatial resolution, making it compatible with GIS-based analysis in ArcGIS 10.8.

Processing in ArcGIS

The estimation of Turbidity Index (TI) was performed in ArcGIS 10.8 using empirical models that relate satellite reflectance values to in-situ turbidity measurements. The processing steps included:

The preprocessed GeoTIFF file was imported into ArcGIS using the Add Data tool. The spatial reference was verified to ensure proper georeferencing (UTM Zone 33N, WGS 84).

The Turbidity Index was calculated using a spectral band ratio approach that enhances the detection of suspended sediments and dissolved organic matter. The widely used formula is:

$$\mathbf{TI = (Red/Green)}$$

Where:

Red (Band 4, 665 nm) captures high turbidity levels due to its sensitivity to sediment-laden water.

Green (Band 3, 560 nm) serves as a reference to normalize the impact of background reflectance.

The Raster Calculator tool in ArcGIS was used to implement this equation by applying:

$$\mathbf{("B4" / "B3")}$$

Where B4 = Red band reflectance and B3 = Green band reflectance.

Classification of Turbidity Levels

The computed Turbidity Index (TI) values were classified into distinct turbidity levels using the Reclassify Tool in ArcGIS. The classification thresholds were adapted from previous studies (Dogliotti et al., 2015; Novoa et al., 2021):

- No Turbidity (<0)
- Low Turbidity (0 –0.1)
- High Turbidity (>0.1)

Visualization and Mapping

The final Turbidity Index (TI) map was styled using a color gradient to represent variations in water turbidity. The GeoTIFF and PNG files were exported for interpretation and reporting.

C. Suspended Sediment Concentration (SSC)

Data Acquisition

Sentinel-2 Level-2 imagery was utilized to estimate Suspended Sediment Concentration (SSC) in the study area. The images were acquired from the Copernicus Open space Datasystem website (Table 3.6). Level-2 data were selected as they provide atmospherically corrected Bottom of Atmosphere (BOA) reflectance, reducing the need for additional atmospheric correction.

The selection of images was based on the following criteria:

Cloud cover of less than 10% to ensure minimal atmospheric interference.

Availability of essential spectral bands for SSC estimation, including:

- Band 2 (Blue, 490 nm)
- Band 3 (Green, 560 nm)
- Band 4 (Red, 665 nm)
- Band 8 (NIR, 842 nm)

These spectral bands have been widely used in empirical models for SSC estimation due to their sensitivity to water reflectance and sediment load.

Preprocessing in ESA SNAP

The acquired Sentinel-2 images were preprocessed using the Sentinel Application Platform (SNAP) v11, developed by the European Space Agency (ESA). The following preprocessing steps were carried out:

The Sentinel-2 Level-2 images in .SAFE format were loaded into SNAP, and individual bands relevant for SSC estimation were extracted.

To optimize processing efficiency, the study area was extracted using the Subset Tool in SNAP. This step ensured that only relevant portions of the image were retained, minimizing unnecessary data processing.

Cloud-contaminated pixels were removed using the Scene Classification Layer (SCL) available in Sentinel-2 Level-2 products. Pixels corresponding to clouds, shadows, and non-water areas (SCL values: 3, 8, 9, and 10) were excluded to prevent errors in SSC estimation.

Exporting Preprocessed Data

The final preprocessed images were exported as GeoTIFF files with a spatial resolution of 10 meters, ensuring compatibility with GIS processing software such as ArcGIS.

Processing in ArcGIS

The estimation of SSC was performed using empirical models that relate satellite reflectance to in-situ sediment concentration measurements. The processing steps included:

The preprocessed GeoTIFF files were imported into ArcGIS 10.8 using the Add Data tool. Spatial reference was verified to ensure alignment with the study area's coordinate system (UTM Zone 33N, WGS 84).

SSC was estimated using an empirical algorithm based on the relationship between the Red (Band 4) and Blue (Band 2) spectral reflectance values. The applied model, widely used in remote sensing literature, is expressed as follows:

$$\text{SSC} = a \times (\text{Red}) / (\text{Blue}) + b$$

Where:

Red (665 nm, Band 4) is highly sensitive to suspended sediments due to its absorption properties.

Blue (490 nm, Band 2) is used to normalize the sediment influence.

a and b are calibration coefficients

The Raster Calculator tool in ArcGIS was used to implement this equation by inputting:

$$("B4" / "B2") * a + b$$

Where B4 = Red band reflectance and B2 = Blue band reflectance.

Reclassification of SSC Values

To facilitate interpretation, the derived SSC raster was reclassified into distinct sediment concentration levels using the Reclassify Tool in ArcGIS. The classification scheme followed thresholds adapted from (Novoa et al., 2021):

- Low Sediment Load (<10 mg/L)
- Moderate Sediment Load (10 - 50 mg/L)
- High Sediment Load (50 - 200mg/L)
- Very High Sediment (>200 mg/L)

Visualization and Mapping

The final SSC map was styled using a color gradient to represent sediment concentration levels.

The map was exported in GeoTIFF and PNG formats for visualization and reporting.

3.2.4 Land use land cover for monitoring rehabilitation success

Sentinel-2 images were downloaded from corpenicus websites within the same period of the year for 3 different years; 2021, 2023 and 2025 (see Table 3.5), the chosen period was between December to March. This choice was guided by the search for same birthday images, good quality images and same phenological cycle; dry season and also by the challenge of finding good images with no cloud cover.

Data pre-processing

Satellite image transformations involve manipulations of multiple band data in order to highlight particular properties or features of interest within the study area, in a better and more effective way than the original input images

Layer stacking

Layer Stacking was done for each of the sentinel-2 images using SNAP software. Layer stacking simply involves the process of combining multiple image layers into a single image. In order to do that the layers should have the same extent (number of rows and number of columns), which means other bands which have different spatial resolution will need to resample to the target resolution.

Geometric correction

Geometric corrections include correcting for geometric distortions due to sensor-Earth geometry variations, and conversion of the data to real world coordinates (for example, latitude and longitude) on the Earth's surface.

When a number images are to be used together, it is necessary that they be georeferenced, by georeferencing it is geometric correction, which is the process of correcting the distortions in an image and trans- forming it so that it has the properties of a map. Image-to-image registration method was conducted to match the images. So that the images could be as comparable as possible in terms of geometric and radiometric qualities. To ensure consistency between datasets during analysis, all data were projected to the Universal Transverse Mercator projection system (zone 32N) and the World Geodetic System 84 datum. Each image was demarcated and clipped to the extent of study.

Image Enhancement

Image enhancement was done to improve the appearance of the image to assist in visual interpretation and analysis. These enhancement functions included contrast, stretching to increase the tonal distinction between features, and spatial filtering to enhance or suppress

specific spatial patterns in the image. Also, different colour composites (4-3-2, 8-4-3 and 4-8-3, 5-4-3 bands, for RGB channels) were used to enhance the identification of features so as to select training set or classification signatures for use.

Selection of training set

To carry out supervised classification, specific sites on the image that represent homogeneous examples of the known land-cover types are first selected. And these are commonly referred to as training sets because the spectral characteristics of these known areas are used to train the classification algorithm. Training sets are statistical descriptions of the multispectral characteristics of thematic categories used to "programme" the classifier with the digital characteristics of categories. Training areas are sampled portions of the scene, randomly or purposely selected, used to derive training statistics, and as such must encompass the spectral variability in the multispectral scene. Training sets were selected for every image (2021, 2023 and 2025). Sample polygons were created based on visual interpretation on the image to recognize the Land Use/Land Cover feature classes. Every spectral analogous sub-area was demarcated with specified class name using a training set.

Image Classification

Image Classification is an abstract representation of features of the real-world using classes or terms derived through a mental process. In the case of spatial information, as for Land Cover, a classification describes the systematic framework, with the names of the classes, the criteria used to distinguish them, and the relationship between classes themselves. Classification thus requires the definition of class boundaries, which should be clear, precise, possibly quantitative, and based on objective criteria. Image classification operations are used to digitally identify and classify pixels in the data. It is usually performed on multi-channel data sets (A) and this process assigns each pixel in an image to a particular class or theme (B) based on statistical characteristics of the pixel brightness values.

After selecting the training sample/sets, they were satisfactorily reviewed, supervised classification was done using the maximum likelihood classification Classifier (MLC) which is the most common efficient statistical technique for evaluating the standard Land use/ land cover classifications. By the classification, 5 Land Use and Land cover (LULC) types were recognized, vegetation, bare land, water bodies, mining activities and settlement were recognized. Due to similarities in the reflectance of certain classes, the algorithm may experience a confusion while classify the land cover classes and as such may refer to one class

as another. This was adjusted by post-classification where mistaken classes were reclassified into the actual classes.

Accuracy Assessment

Pixels to be sampled were selected randomly and transferred to Google Earth Pro, by creating a kml file or by using Google Earth map in ArcGIS as a base map. Google Earth offers high resolution satellite imagery in different dates and times for many places.

Sample points are interpreted on Google Earth, the interpretation is compared to the classification results, and correctly classified pixels are tabulated.

The proportion of correctly assigned pixels is estimated by comparing the number of sampled pixels correctly classified to the total number of sample points.

The overall accuracy of the classified image compares how each of the pixels is classified versus the definite land cover conditions obtained from their corresponding ground truth data.

$$\text{Total (overall) accuracy} = \text{Number of correct plots} / \text{Total number of plots} \times 100$$

Producer's accuracy measures errors of omission, which is a measure of how well real-world land cover types can be classified.

$$\text{Producer Accuracy} = (\text{Number of Correctly Classified Pixels in each Category}) / (\text{Total Number of Reference Pixels in that Category}) \times 100$$

User's accuracy measures errors of commission, which represents the likelihood of a classified pixel matching the land cover type of its corresponding real-world location.

$$\text{Users Accuracy} = (\text{Number of Correctly Classified Pixels in each Category}) / (\text{Total number of Classified Pixels in that Category}) \times 100$$

$$\text{Kappa Coefficient (T)} = ((\text{TS} \times \text{TCS}) - \sum (\text{Column Total} * \text{Row Total})) / (\text{TS}^2 - \sum (\text{Column Total} \times \text{Row Total})) \times 100$$

The kappa coefficient has become a standard means of assessment of image classification accuracy.

Change detection of Land Cover/ Land Use

With the classification of images of the individual years, a post-classification approach of subtracting the classification maps, 2023 – 2021 and 2025 – 2023 was applied. Quantitative

area data of the overall land cover changes as well as the gains and losses in each category between 2021 and 2025 were compiled.

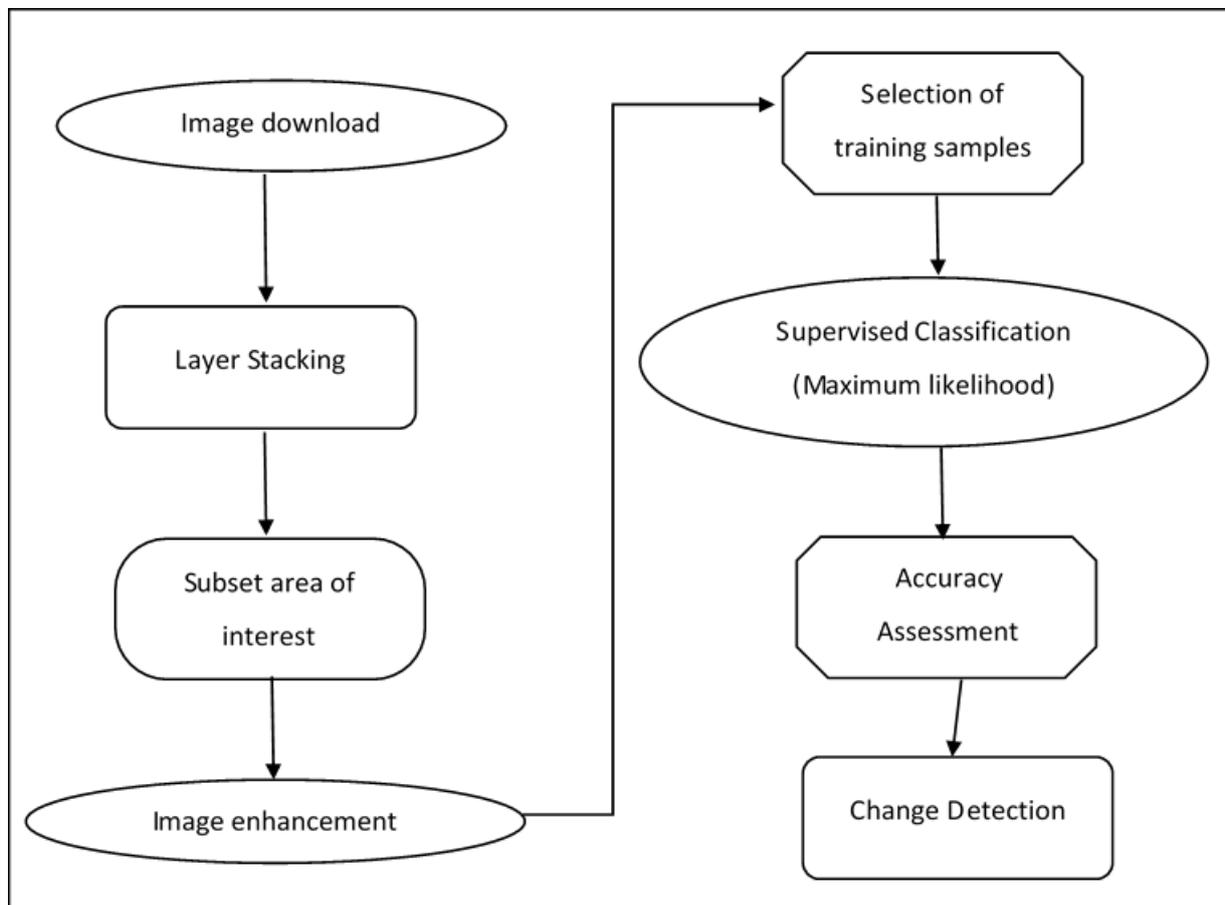


Figure 3.7: Flowchart for LULC

3.2.5 Proposed Mine Closure and Rehabilitation Strategy

This section outlines the methodology employed to develop a comprehensive and contextually relevant mine closure and rehabilitation strategy for alluvial gold mining-affected areas in the Betaré-Oya region of Cameroon. This strategy was based on scientific data collected through remote sensing analysis (NDVI, NDWI, BSI, LST), supplemented by field observations, and literature review. The strategy aims to provide a practical and sustainable pathway for restoring degraded landscapes, mitigating environmental impacts, and promoting long-term ecological recovery.

Literature Review

A comprehensive review of relevant scientific literature, regulatory frameworks, and industry best practices related to mine closure and rehabilitation were conducted. The review focused

on: Rehabilitation Techniques; Environmental Regulations; Best Practices and case Studies: Analyzing case studies of successful and unsuccessful mine closure projects.

Analysis of Remote Sensing Data and Field Observations

Specifically the data was used to: Identify priority areas for rehabilitation; Assess water Resources; Characterize vegetation loss and monitor efforts of successful post-mining rehabilitation.

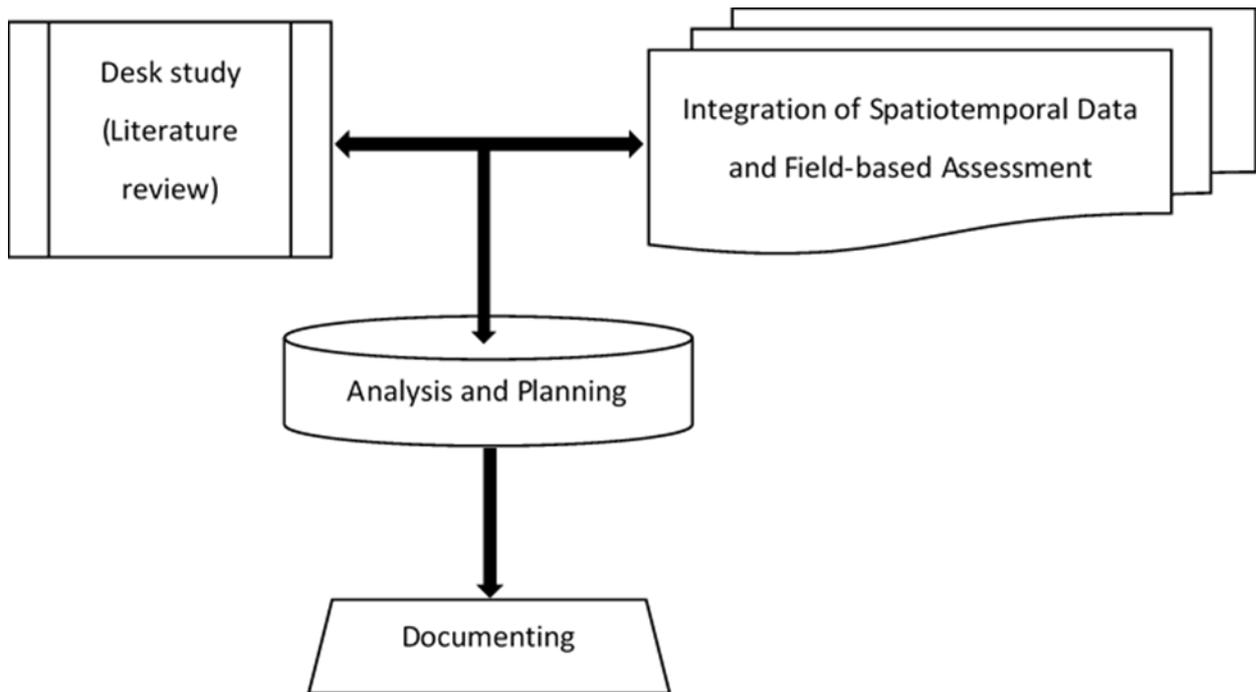


Figure 3.7: Flowchart for LULC

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Land Degradation Assessment

4.1.1 Field-based and Google Earth Pro preliminary evaluation

The field visit conducted between January and March 2025 provided valuable ground-truth data and preliminary insights into the extent and nature of land degradation within the Betaré-Oya alluvial gold mining district. Direct observations and photographic documentation from active and abandoned mine sites revealed a consistent pattern of extensive soil erosion and sedimentation impacting nearby water bodies, widespread deforestation and removal of topsoil, leaving barren landscapes, and the presence of large, unrehabilitated mining pits filled with stagnant water. These observations aligned with the findings of Tchindjang et al. (2018), who documented similar patterns of deforestation and soil erosion associated with gold mining in the Eastern Region of Cameroon. The field photographs captured during the visit vividly illustrate these impacts.



Figure 4.1: Abandoned Mining Pit with Turbid Water (Location: Kombo-koro)

Figure 4.1 shows a photograph taken at a former mining site at kombo-koro, depicting a large, abandoned mining pit filled with turbid, stagnant water. The water's opaque, brownish color suggests a high concentration of suspended sediments and potential chemical contamination, consistent with the findings of Babut et al. (2019), who reported elevated levels of mercury and other heavy metals in water samples from the Betaré-Oya region. The surrounding landscape is devoid of vegetation, with exposed soil and eroded banks clearly visible. This lack of vegetation cover exacerbates soil erosion and hinders natural regeneration, highlighting the long-term environmental consequences of unregulated mining practices, where excavated areas are left unrehabilitated, leading to the accumulation of contaminated water and the loss of biodiversity."



Figure 4.2: Active Mining Site with Heavy Machinery (Location: Timangaro)

Figure 4.2 shows an active mining site at Timangaro, with heavy machinery excavating soil and washing plant. The photograph reveals the scale of deforestation required to access alluvial gold deposits, with a significant area of previously forested land now cleared and disturbed. The presence of sediment plumes in nearby water bodies suggests ongoing soil erosion and sedimentation, further impacting water quality and aquatic habitats. This aligns with the

findings of Kanga et al. (2017), who used Landsat imagery to document the expansion of artisanal mining at the expense of vegetation cover in the Betaré-Oya region.



Figure 4.3: Altered River Course and Sediment Deposition (Location: Lom River)

Figure 4.3 depicts a section of the Lom River where the natural river course has been significantly altered due to mining activities. The photograph shows a large pile of excavated material deposited directly adjacent to the river, leading to increased sedimentation and turbidity. The altered river course can disrupt aquatic ecosystems and impact downstream water users, as noted by Lindahl (2014), who highlighted the excessive excavation of riverbanks leading to increased sedimentation and changes in river flow.

Figure 4.4 shows a barren landscape in an abandoned mining area, characterized by scattered debris, minimal vegetation cover, and compacted soil. The photograph suggests a complete loss of topsoil and a lack of conditions suitable for natural regeneration. This aligns with the findings of D'Souza (2020), who emphasized the severe environmental degradation, including land degradation, deforestation, and biodiversity loss, resulting from artisanal and small-scale mining in Africa."



Figure 4.4: Barren Landscape with Scattered Debris (Location: Nakayo)



Figure 4.5: Large Excavation Pit with Standing Water (Location: Mali village)

Figure 4.5 shows a large excavation pit filled with standing water, likely rainwater mixed with sediment and potential contaminants. The photograph highlights the scale of disturbance caused by mining activities and the lack of rehabilitation efforts to restore the landscape. The standing water can serve as a breeding ground for mosquitoes and other disease vectors, posing a risk to public health, as discussed by Esdaile & Chalker (2018), who highlighted the health risks associated with mercury and cyanide contamination in alluvial gold concentration.



Figure 4.6: Deforested Area with Mining Pits in the Distance (Location: Bouli)

Figure 4.6 shows a deforested area with mining pits visible in the distance, illustrating the encroachment of mining activities into previously forested regions. The photograph highlights the direct link between gold mining and deforestation, which can have significant impacts on biodiversity, carbon sequestration, and climate change, as noted by Sonwa et al. (2020), who documented extensive deforestation due to gold mining, agriculture, and logging in the Betaré-Oya region.

Figure 4.7 shows turbid water flowing through a stream near an active mining site. The photograph provides visual evidence of the direct impact of mining activities on water quality, with sediment runoff contributing to increased turbidity and potential contamination. This

aligns with the findings of Chica & Walker (2020), who reported increased turbidity and elevated concentrations of heavy metals in surface water samples from mining-affected rivers."



Figure 4.7: Turbid Water Flowing Through Mining-Affected Area (Location: Tributary of River Mari)

Figure 4.8, a photograph taken in an active mining area at Ngengue, provides a stark illustration of the severe soil erosion resulting from alluvial gold mining. The image reveals a deeply incised soil profile, exposing distinct soil horizons and highlighting the removal of the fertile topsoil layer. The vertical striations in the soil face indicate the presence of erosion gullies, formed by the concentrated flow of surface water. The presence of scattered rocks and debris further contributes to the instability of the landscape. This type of soil erosion can lead to the loss of valuable nutrients, reduced water infiltration, and increased sedimentation in nearby water bodies, as discussed by Mandal et al. (2019), who emphasized the use of remote sensing-derived indices to evaluate soil degradation and track soil erosion."

The limited vegetation cover in the upper portion of the image suggests that natural regeneration is hindered by the degraded soil conditions. The presence of a small amount of vegetation is not enough to prevent further erosion. The photograph highlights the long-term consequences of mining activities on soil health and the challenges associated with restoring degraded

landscapes, as emphasized by Smith & Watson (2017), who discussed the importance of soil remediation and sustainable land-use planning in effective reclamation and restoration strategies.



Figure 4.8: Exposed Soil Profile and Erosion Gullies (Location: Ngengue)

Interviews with local residents, miners, and community leaders further contextualized these physical observations. Residents consistently reported a decline in agricultural productivity due to soil degradation and water pollution. Miners acknowledged the environmental impacts of their activities but cited economic necessity as the primary driver. Community leaders expressed concerns about the long-term sustainability of mining and the need for effective rehabilitation strategies. One resident stated, 'Before the mining, we could grow anything here. Now, the soil is dead, and the water is poisoned.' This sentiment underscores the direct impact of mining activities on local livelihoods and the urgent need for sustainable mining practices and effective rehabilitation efforts.

To further contextualize the field observations and assess the spatial distribution and severity of land degradation across the study area, high-resolution Google Earth Pro imagery from 2023 was analyzed. The imagery confirmed the presence of numerous abandoned mine sites, often characterized by bare earth, altered drainage patterns, and a lack of vegetation cover. The

imagery also revealed the expansion of active mining areas into previously forested regions, highlighting the ongoing deforestation associated with the industry.



Figure 4.9: Google Earth Pro Image - Linear Mining Pattern (Location: N 5°33'43.2", E 14°03'15.84")

Figure 4.9 shows a Google Earth Pro image of a mining area characterized by a linear pattern of disturbance. The image reveals a series of interconnected mining pits and access roads extending through a previously forested area. The linear pattern suggests that mining activities are following a specific geological feature or river channel, as alluvial gold deposits are often concentrated along these features. The image also shows a clear contrast between the disturbed mining area and the surrounding intact forest, highlighting the impact of mining on the landscape. This pattern aligns with the findings of Kanga et al. (2017), who used Landsat imagery to document the expansion of artisanal mining at the expense of vegetation cover in the Betaré-Oya region.

Figure 4.10 shows a Google Earth Pro image of a mining area located directly adjacent to a water body. The image reveals extensive soil disturbance and sedimentation along the shoreline, indicating the direct impact of mining activities on water quality. The presence of bare earth and altered drainage patterns suggests that the natural hydrological processes have been disrupted. This proximity of mining activities to water bodies poses a significant threat to

aquatic ecosystems and downstream water users, as discussed by Babut et al. (2019), who reported elevated levels of mercury and other heavy metals in water samples from the Betaré-Oya region.

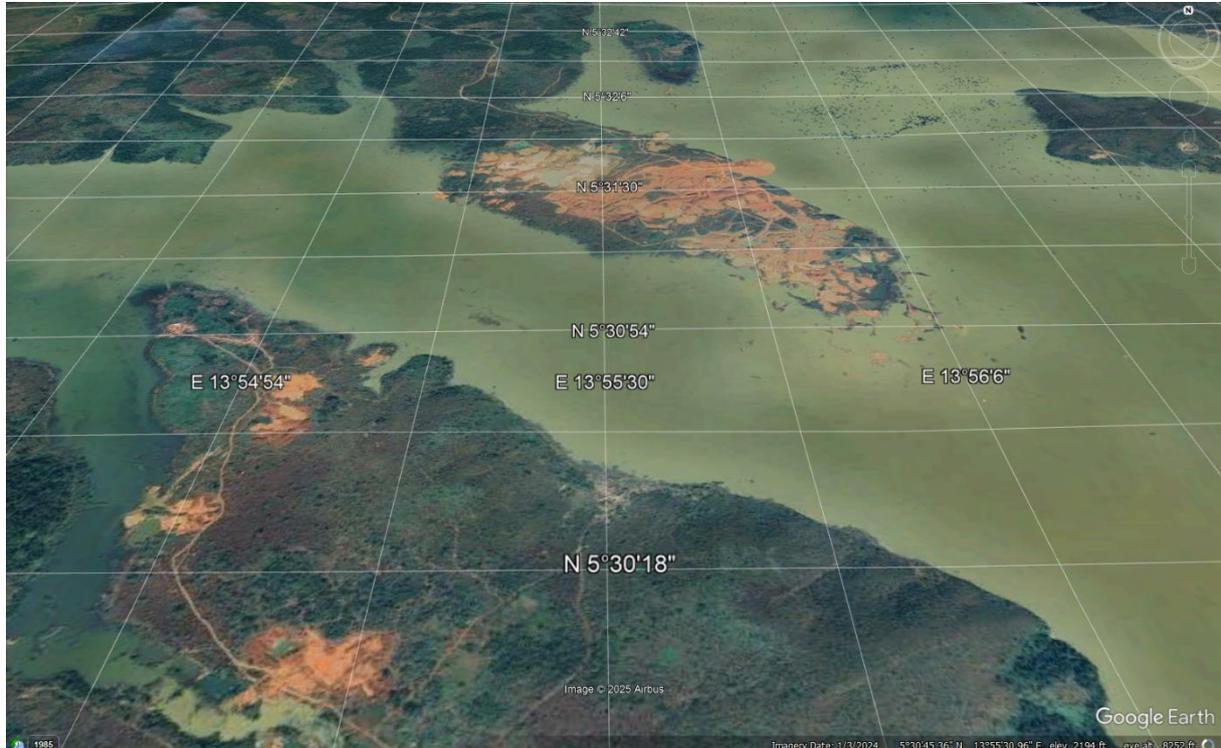


Figure 4.10: Google Earth Pro Image - Mining Area Adjacent to Water Body (Location: N 5°30'54", E 13°54'54")

Figure 4.11 shows a Google Earth Pro image of a large-scale mining operation, characterized by extensive deforestation, large excavation pits, and processing facilities. The image reveals the scale of disturbance caused by mechanized mining activities and the significant impact on the landscape. The presence of processing facilities suggests that the mining operation is extracting and processing large quantities of ore, potentially leading to increased environmental impacts. This aligns with the findings of D'Souza (2020), who emphasized the severe environmental degradation, including land degradation, deforestation, and biodiversity loss, resulting from artisanal and small-scale mining in Africa. Also, the image reveals a landscape dominated by bare earth, with limited vegetation cover and altered drainage patterns. The photograph highlights the direct link between gold mining and deforestation, which can have significant impacts on biodiversity, carbon sequestration, and climate change, as noted by Sonwa et al. (2020), who documented extensive deforestation due to gold mining, agriculture, and logging in the Betaré-Oya region.



Figure 4.11: Google Earth Pro Image - Large-Scale Mining Operation (Location: N 5°35'52.8", E 14°03'38.8")



Figure 4.12: Google Earth Pro Image - Flooded Mining Area (Location: N 5°38'2.4", E 14°16'45.92")

Figure 4.12 shows a Google Earth Pro image of a mining area that appears to be flooded. The image reveals a landscape dominated by water, with scattered patches of bare earth and limited vegetation cover. The flooding may be due to the disruption of natural drainage in the mining area and can lead to the mobilization of sediments and contaminants, further impacting water quality and aquatic ecosystems, as discussed by Chica & Walker (2020), who reported increased turbidity and elevated concentrations of heavy metals in surface water samples from mining-affected rivers.

A comparison of Google Earth Pro imagery with the field photographs revealed a strong correlation between areas identified as severely degraded in the field and areas exhibiting extensive bare earth and altered topography in the satellite imagery. Furthermore, the imagery allowed for a broader spatial assessment of land degradation patterns, identifying areas that were inaccessible during the field visit. For example, Google Earth Pro imagery revealed a network of interconnected mining pits and drainage channels that were not fully apparent from ground-level observations, highlighting the cumulative impact of mining activities on the landscape.

The use of Google Earth Pro also allowed for a preliminary assessment of rehabilitation efforts. While some areas showed signs of natural revegetation, particularly along riverbanks, the majority of abandoned mine sites remained largely unrehabilitated. This is evident in the field photograph shown in Figure 4.4, which depicts a barren landscape with scattered debris and minimal vegetation cover. This suggests a limited implementation of effective mine closure and rehabilitation strategies, consistent with the findings of Kouamé et al. (2022), who noted the lack of proper rehabilitation strategies in abandoned mining sites in the region.

4.1.2 Satellite Image Analysis

The extent of land degradation was analyzed using remote sensing techniques, including Bare Soil Index (BSI) and Normalized Difference Moisture Index (NDMI).

Bare Soil index (BSI)

The BSI maps (Figures 4.14, 4.15, and 4.16) illustrate the spatial distribution of bare soil across the Betaré-Oya region for the years 2021, 2023, and 2024. In 2021, the BSI map shows a relatively low proportion of bare soil, with most areas classified as dense vegetation, sparse vegetation, or dry grass. However, by 2023, a noticeable increase in bare soil is evident, particularly in areas near active and abandoned mining sites. This trend continues in 2024, with further expansion of bare soil areas and a corresponding decrease in vegetation cover. The

spatial patterns of BSI change appear to be strongly correlated with the locations of mining activities, suggesting a direct link between mining and land degradation.

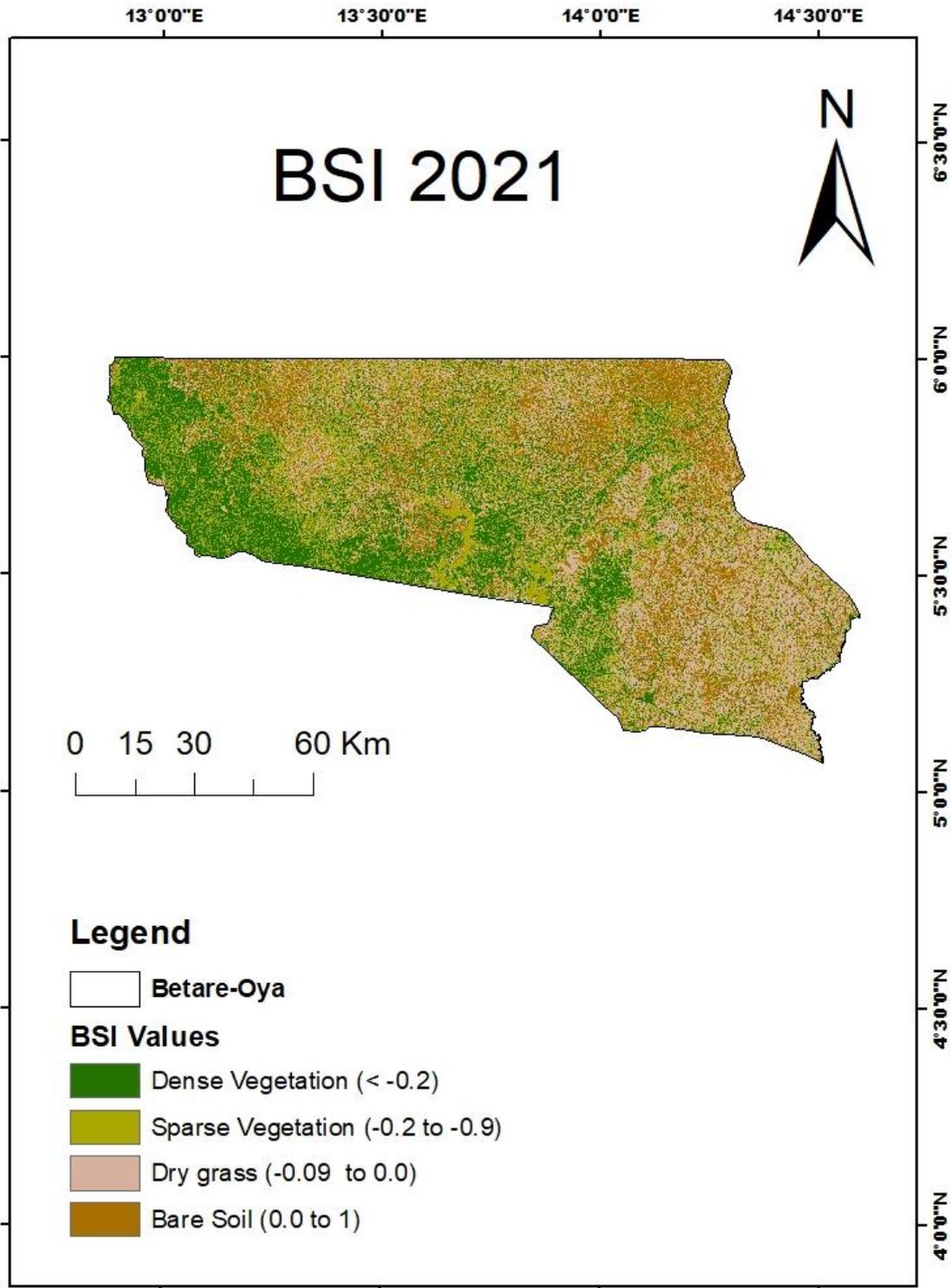


Figure 4.14: BSI for 2021

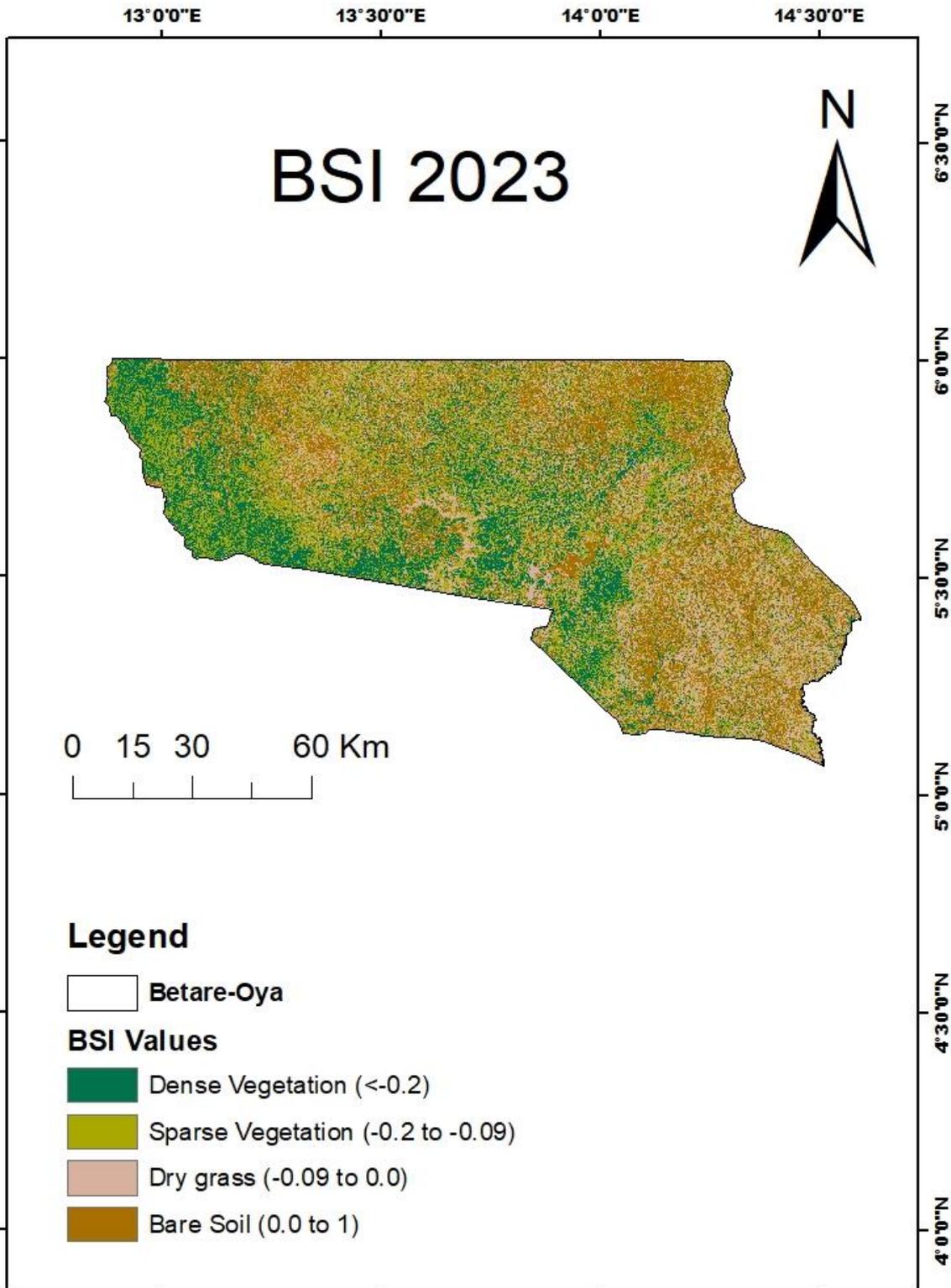


Figure 4.15: BSI for 2023

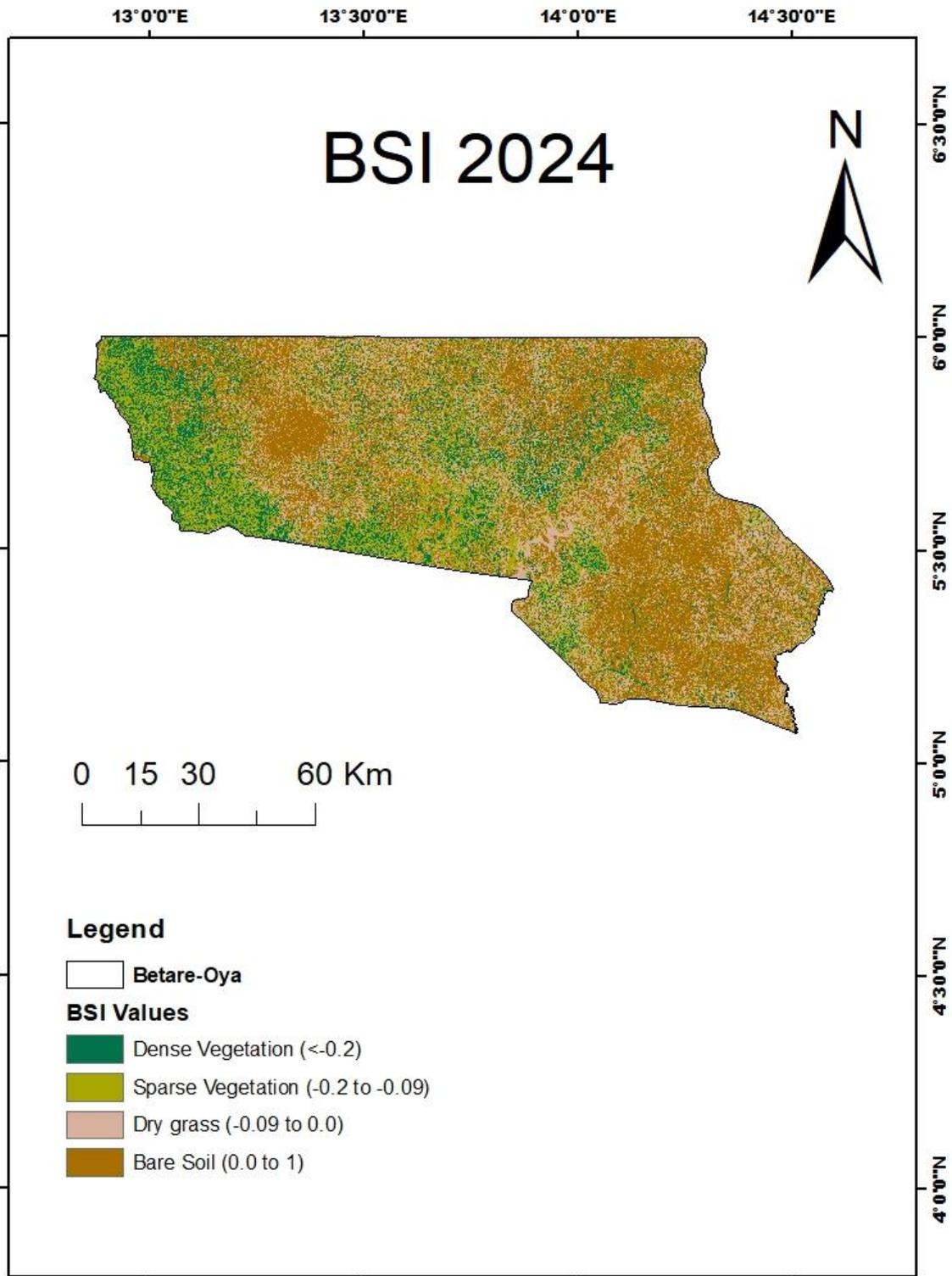


Figure 4.16: BSI for 2024

Table 4.1: Table Statistics for BSI

Index	Class Name	Area (hectares)	Percentage (%)
BSI 2021	Dense Vegetation	283285.26	25.21
	Sparse Vegetation	307170.9	27.34
	Dry grass	317425.64	28.25
	Bare Soil	215701.32	19.20
BSI 2023	Dense Vegetation	245231.05	21.83
	Sparse Vegetation	330714.56	29.43
	Dry grass	261889.88	23.31
	Bare Soil	285747.14	25.43
BSI 2024	Dense Vegetation	172727.72	15.37
	Sparse Vegetation	268090.67	23.86
	Dry grass	253227.35	22.54
	Bare Soil	429539.52	38.23

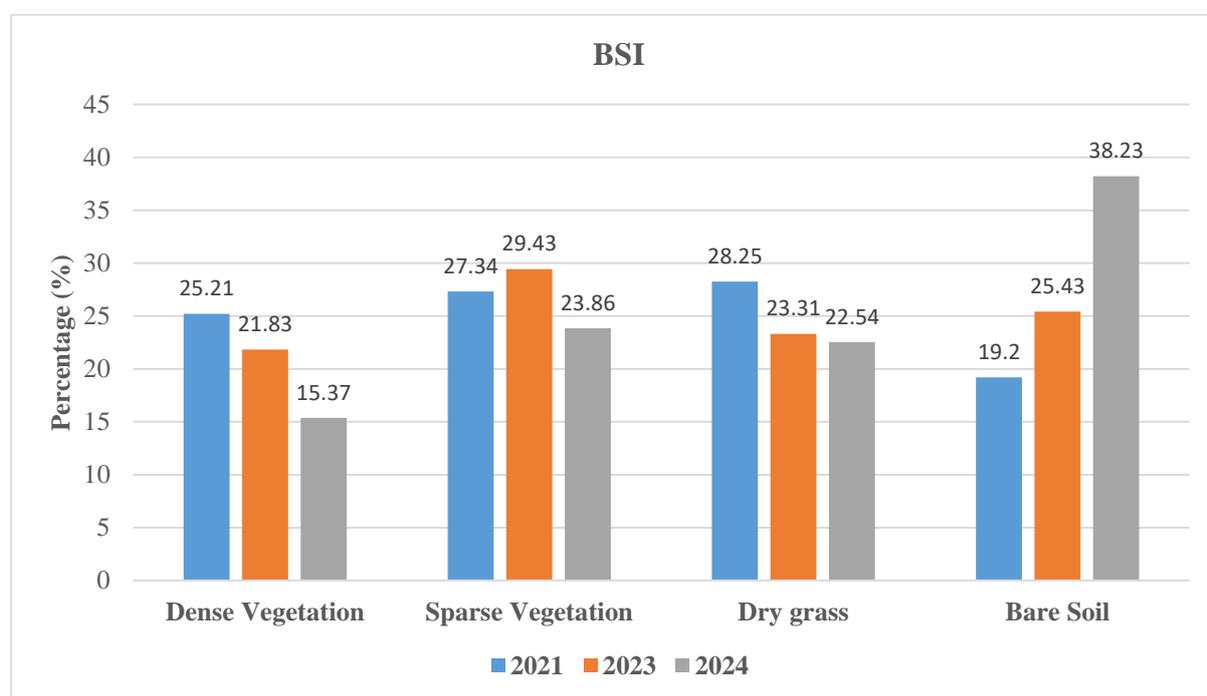


Figure 4.17: BSI trend from 2021 to 2024

The BSI statistics (Table 4.1) provide a quantitative assessment of bare soil changes. The area of bare soil increased from 19.20% in 2021 to 38.23% in 2024, representing a significant

increase in land degradation. Conversely, the area of dense vegetation decreased from 25.21% in 2021 to 15.37% in 2024, indicating a substantial loss of vegetation cover. The areas classified as sparse vegetation and dry grass also showed fluctuations, suggesting a dynamic response of vegetation to mining-related disturbances. The BSI trend from 2021 to 2024 (Figure 4.17) visually summarizes the changes in bare soil extent over time. The graph shows a consistent increase in the percentage of bare soil and a decrease in the percentage of dense vegetation. This trend suggests that mining activities are having a negative impact on land cover in the Betaré-Oya region.

- **Normalized Difference Moisture Index (NDMI)**

The NDMI maps (Figures 4.18, 4.19, and 4.20) illustrate the spatial distribution of vegetation moisture content across the Betaré-Oya region for the years 2021, 2023, and 2024. In 2021, the maps show a relatively high proportion of high vegetation moisture, particularly in the northern and western parts of the study area. However, by 2023, a noticeable increase in Moisture-deficient area/Bare soil is evident, with a corresponding increase in areas classified as low vegetation moisture and moderate vegetation moisture. This trend continues in 2024, with further shrinkage of low and moderate vegetation moisture areas and expansion of degraded areas (moisture deficient areas/bare soil). The NDMI statistics (Table 4.2) provide a quantitative assessment of vegetation moisture changes. Moisture-deficient areas (bare soil) remained nearly the same from 16.54% (2021) to 16.56% (2023). Low vegetation moisture decreased from 30.38% (2021) to 29.57% (2023). Moderate and high moisture vegetation increased slightly in 2023. The area of moisture-deficient /bare soil greatly increases from 16.56% in 2023 to 24.68% in 2024, indicating a substantial increase mining activities. Conversely there is an increased in high moisture from 25.34% in 2023 to 28.85% in 2024 but not as high as moisture deficient areas, this increase may be due to mining disturb soil structure reducing infiltration while promoting water logging, open pits and depressions created by abandoned mined sites that collect and retained water.

The NDMI trend from 2021 to 2024 (Figure 4.20) visually summarizes the changes in vegetation moisture content over time. The graph shows a consistent decline in the percentage of low and moderate vegetation moisture and an increase in the percentage of moisture-deficient areas/bare soil. This trend suggests that mining activities are having a negative impact on vegetation moisture in the Betaré-Oya region.

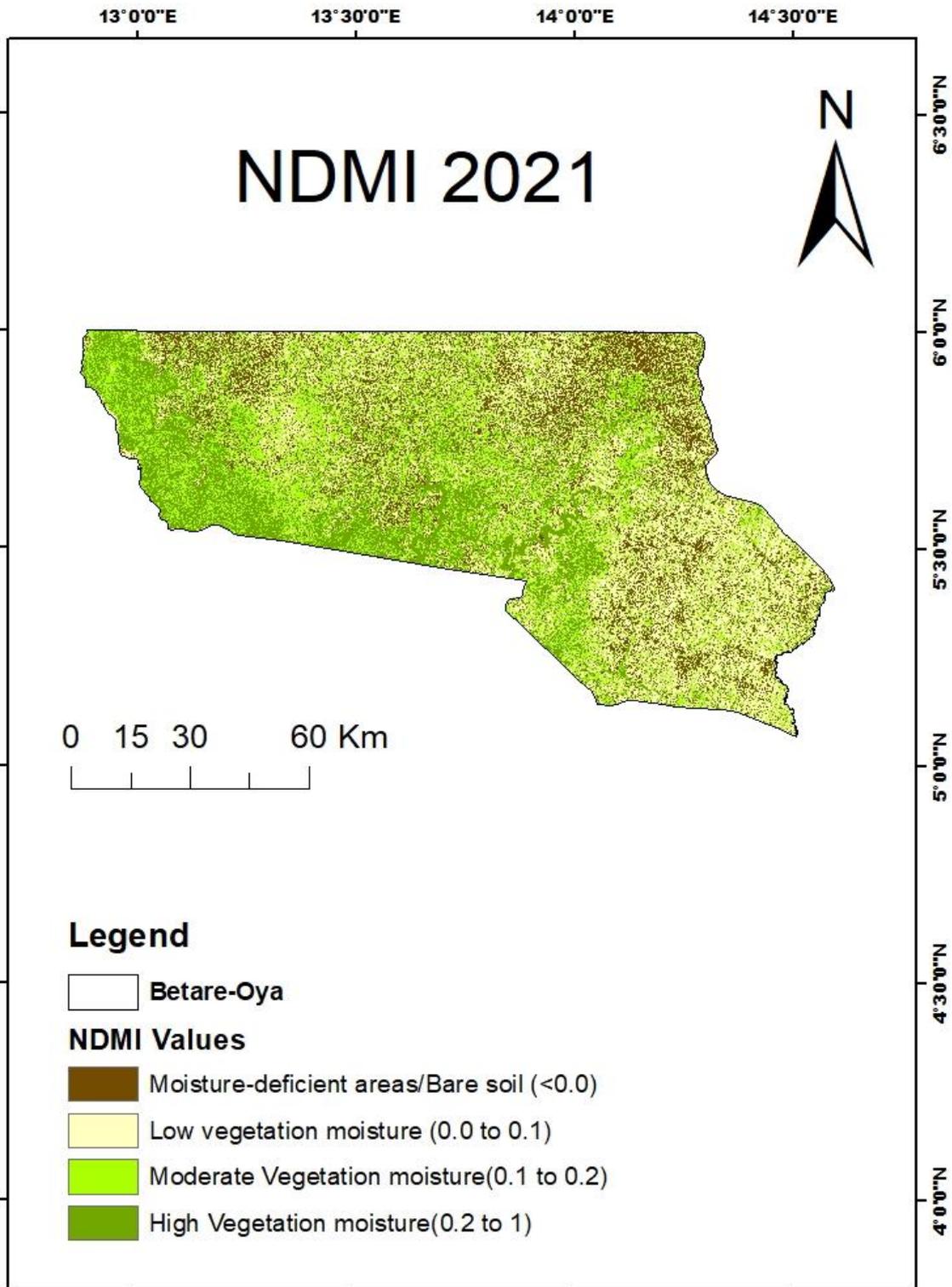


Figure 4.18: NDMI for 2021

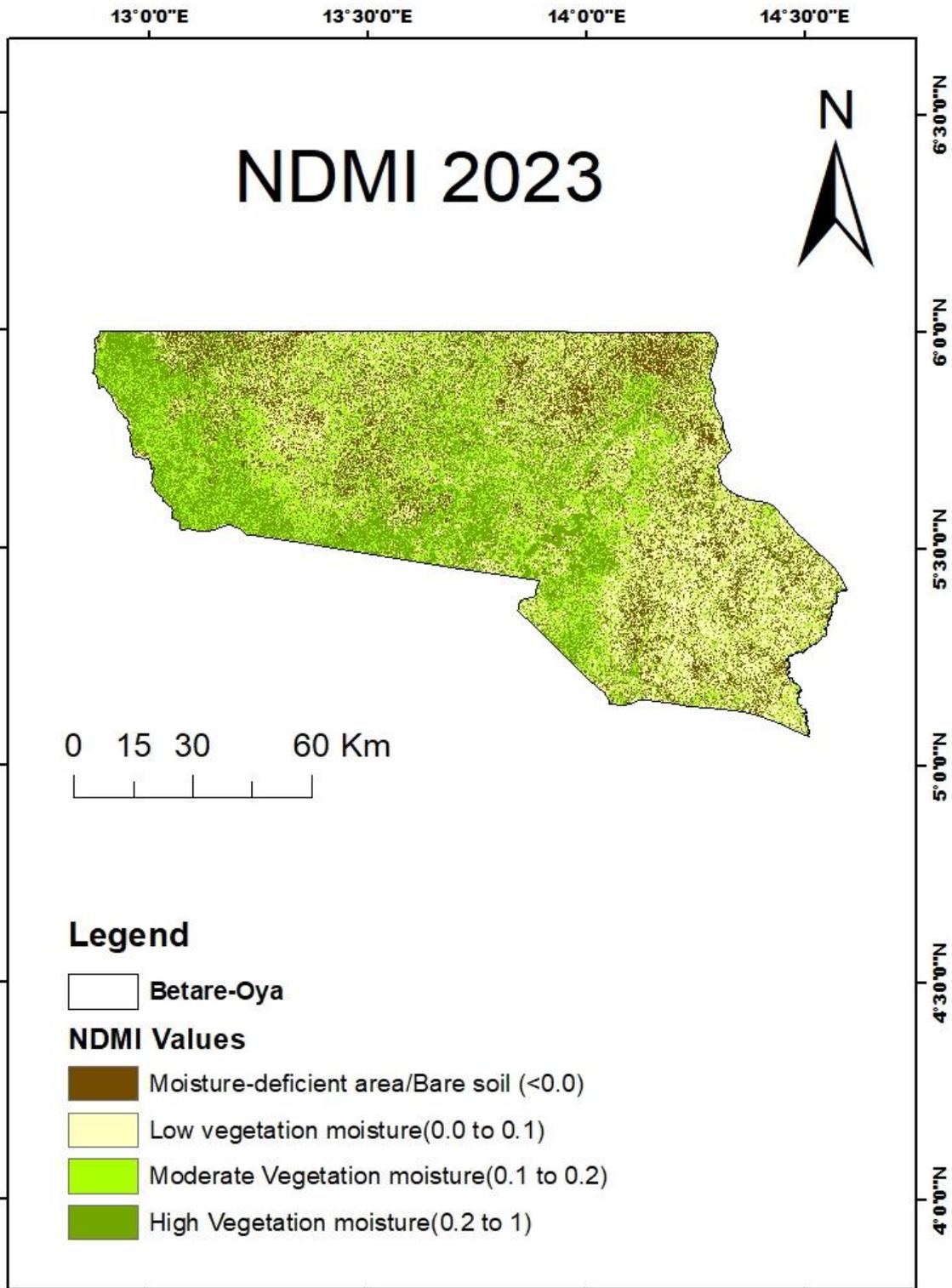


Figure 4.19: NDMI for 2023

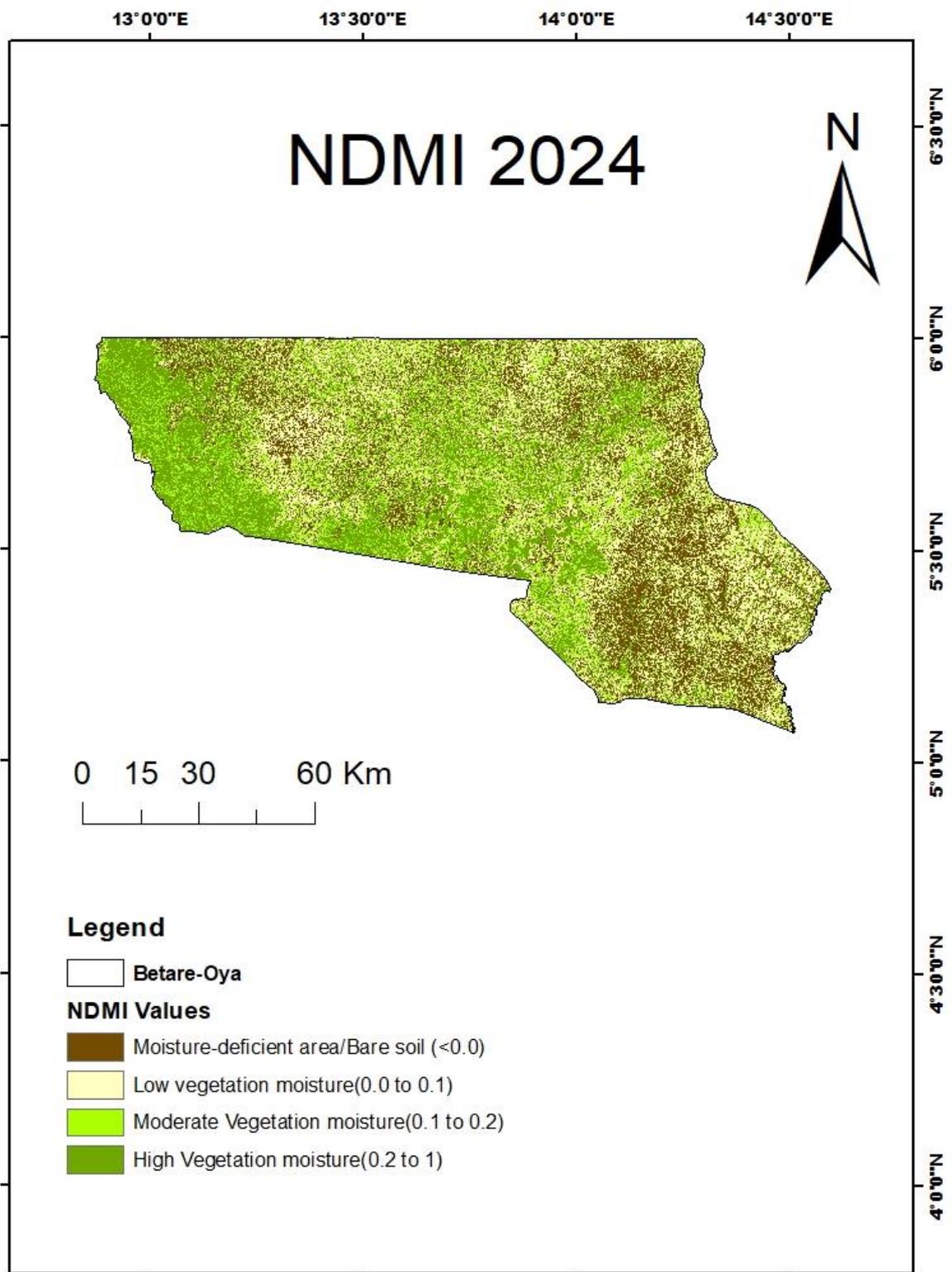


Figure 4.19: NDMI for 2024

Table 4.2: Table Statistics for NDMI

Index	Class Name	Area (hectares)	Percentage (%)
NDMI 2021	Moisture-deficient area/Bare soil	185862.18	16.54
	Low Vegetation Moisture	341330	30.38
	Moderate Vegetation Moisture	317577.88	28.26
	High Vegetation Moisture	278813.06	24.81
NDMI 2023	Moisture-deficient area/Bare soil	186046.40	16.56
	Low Vegetation Moisture	332242.87	29.57
	Moderate Vegetation Moisture	320538.28	28.53
	High Vegetation Moisture	284755.08	25.34
NDMI 2024	Moisture-deficient area/Bare soil	277331.19	24.68
	Low Vegetation Moisture	294139.89	26.18
	Moderate Vegetation Moisture	227989.99	20.29
	High Vegetation Moisture	324124.19	28.85

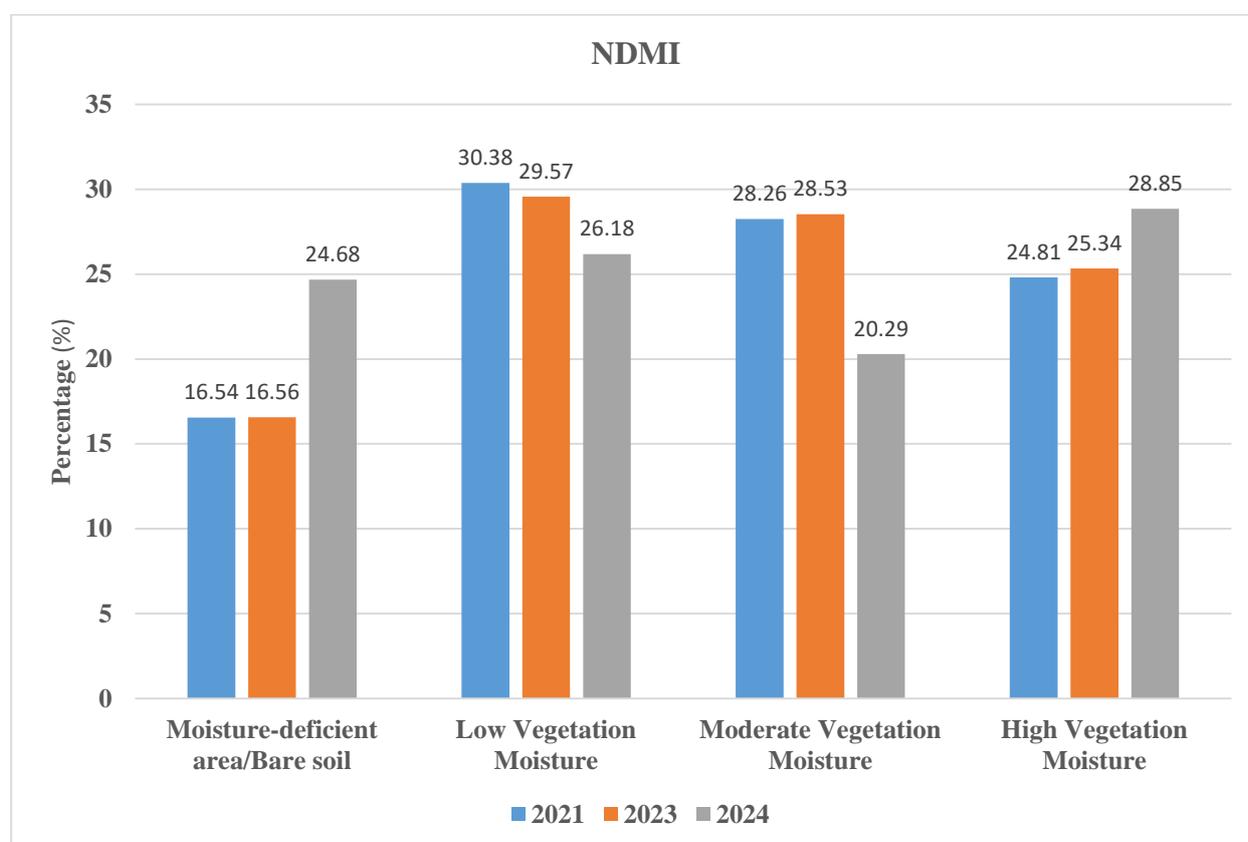


Figure 4.20: NDMI trend from 2021 to 2024

The BSI and NDMI maps and statistics reveal a clear trend of increasing bare soil extent and decreasing vegetation moisture content in the Betaré-Oya region from 2021 to 2024. The spatial patterns of BSI and NDMI change are strongly correlated with the locations of mining activities, suggesting a direct link between mining and land degradation.

The observed increase in bare soil extent and decrease in vegetation moisture content are likely due to a combination of factors associated with mining activities, including deforestation, topsoil removal, soil compaction, and soil contamination. Deforestation directly reduces vegetation cover, while topsoil removal and soil compaction hinder natural regeneration. Soil contamination from heavy metals and other pollutants can also inhibit plant growth and reduce vegetation moisture content.

BSI and NDMI are useful tools for assessing land degradation and vegetation moisture, but they have some limitations. BSI is sensitive to soil type and moisture content, which can affect the accuracy of the results. NDMI is sensitive to atmospheric conditions and vegetation type, which can also affect the accuracy of the results.

The findings are consistent with previous studies that have used BSI and NDMI to assess land degradation and vegetation moisture in mining-affected areas. For example, Chandrasekar et al. (2016) found that BSI values increased in areas affected by mining activities, indicating an increase in land degradation. Chen et al. (2021) found that NDMI values decreased in areas affected by mining activities, indicating a decrease in vegetation moisture.

4.2 Vegetation Health Assessment (Normalized Difference Vegetation Index)

The NDVI maps (Figures 4.21, 4.22, and 4.23) provide a visual representation of vegetation health across the Betaré-Oya region. In 2021, the maps show a relatively high proportion of dense vegetation, particularly in the northern and western parts of the study area. However, by 2023, a noticeable decline in dense vegetation is evident, with a corresponding increase in areas classified as sparse vegetation and bare soil. This trend continues in 2024, with further fragmentation of dense vegetation patches and expansion of degraded areas. The NDVI statistics (Table 4.3) provide a quantitative assessment of vegetation health changes. The area of dense vegetation decreased from 46.13% in 2021 to 42.34% in 2024, representing a significant loss of vegetation cover. Conversely, the area of bare soil increased from 1.82% in 2021 to 12.55% in 2024, indicating a substantial increase in land degradation. The areas classified as sparse vegetation and moderate vegetation also showed fluctuations, suggesting a dynamic response of vegetation to mining-related disturbances.

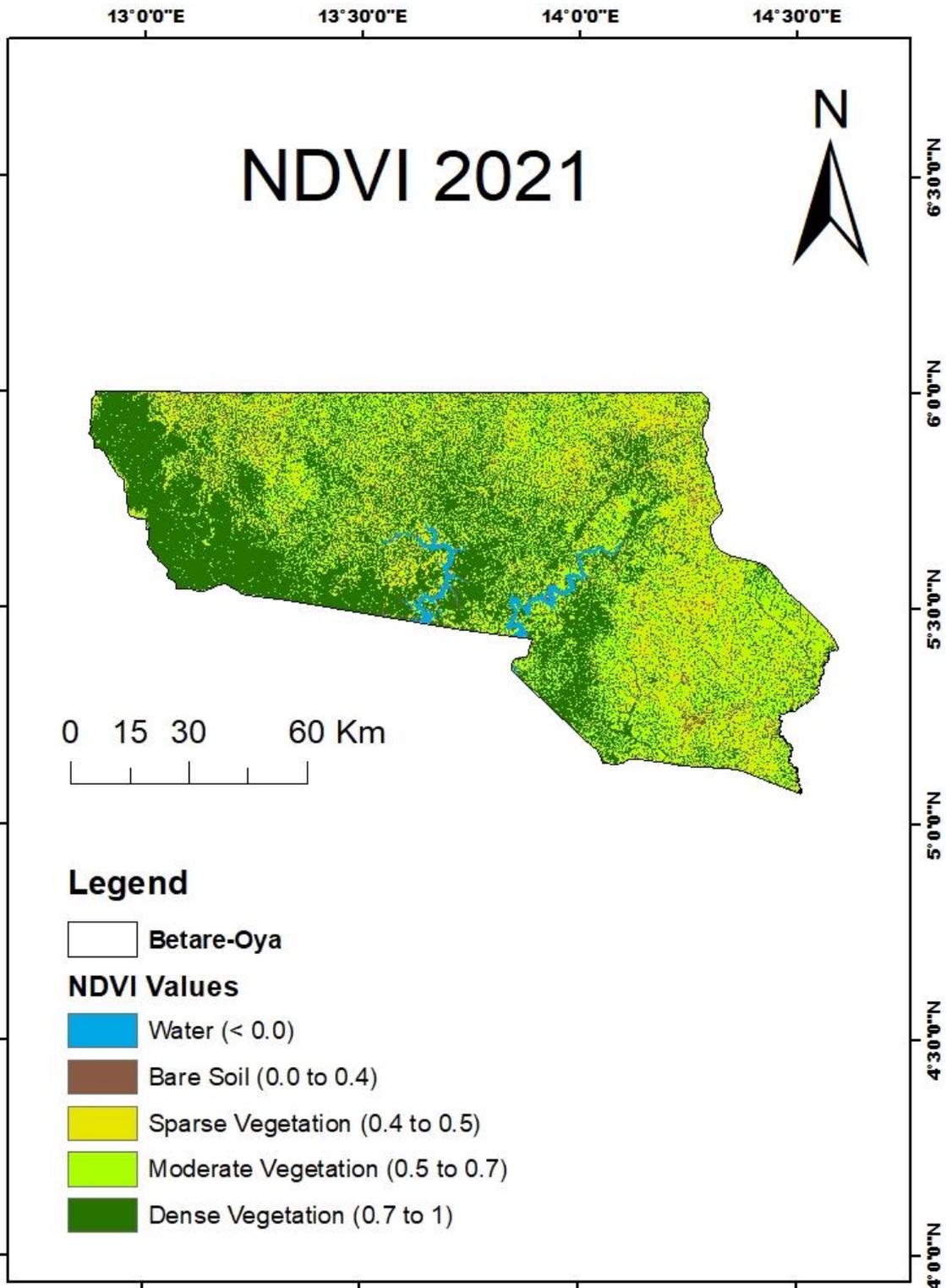


Figure 4.21: NDVI for 2021

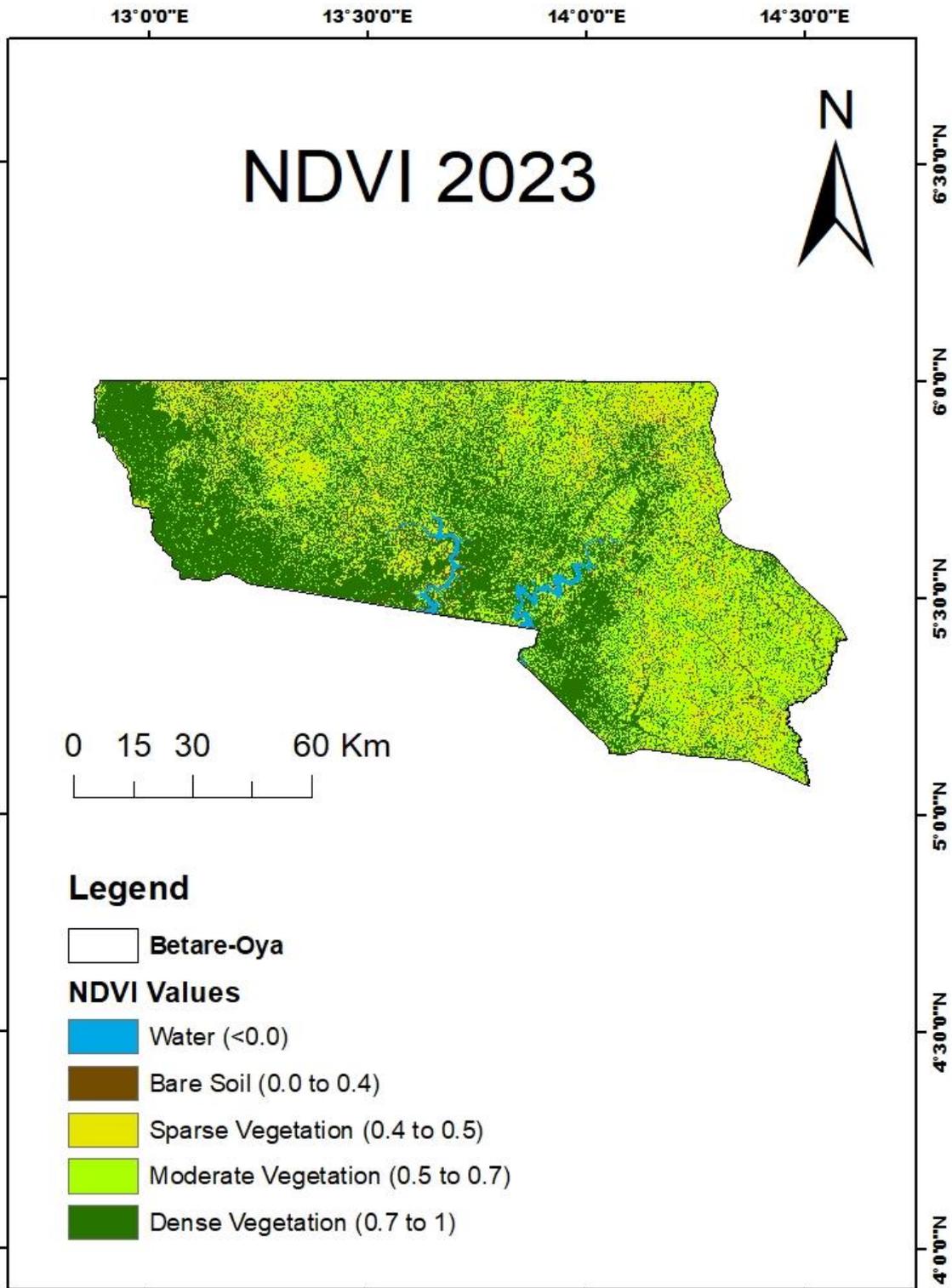


Figure 4.23: NDVI for 2023

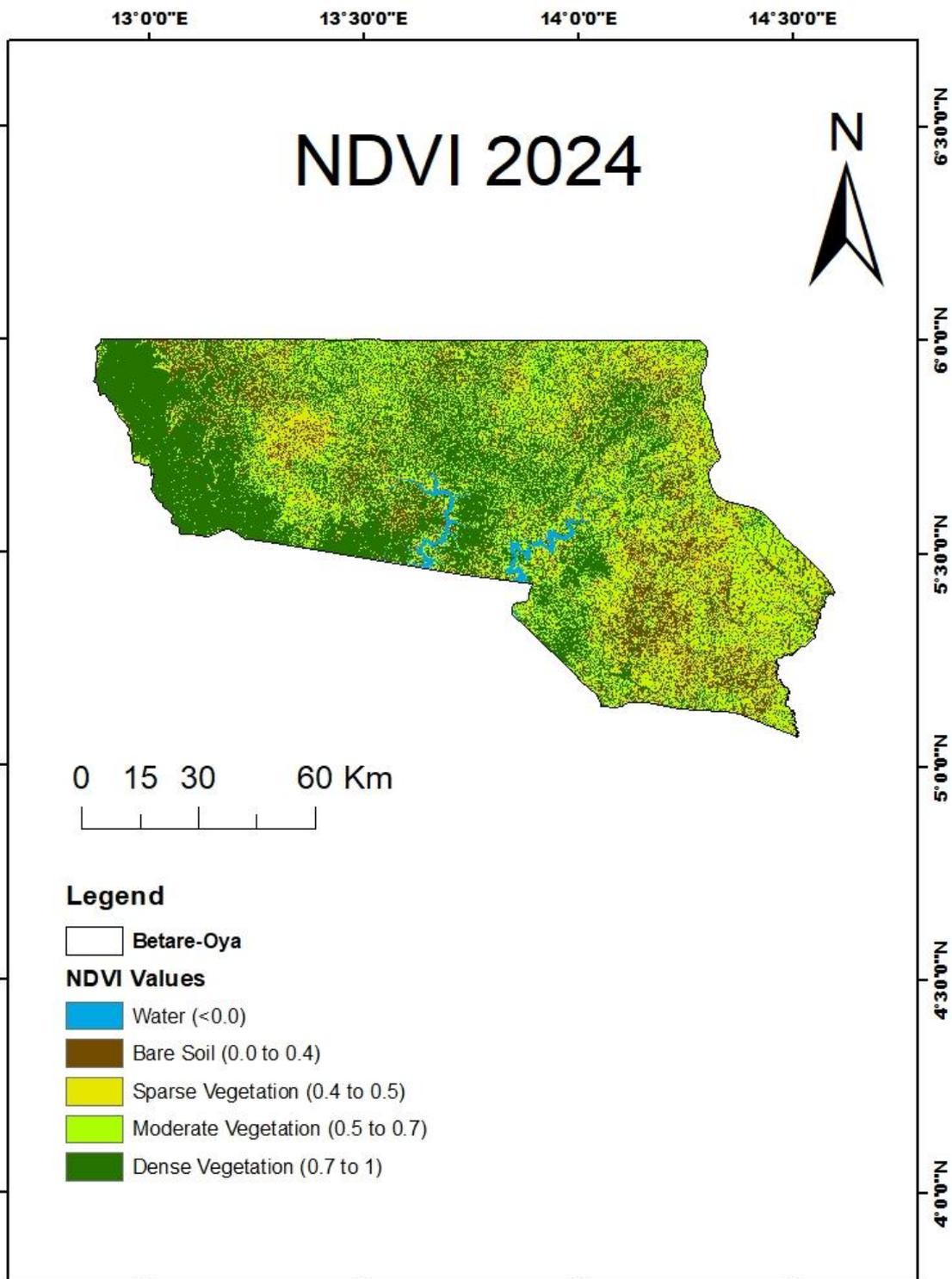


Figure 4.24: NDVI for 2024

Table 4.3: Table Statistics for NDVI

Index	Class Name	Area (hectares)	Percentage (%)
NDVI 2021	Water	18130.72	1.61
	Bare soil	20446.78	1.82
	Sparse vegetation	271631.71	24.18
	Moderate Vegetation	295101.27	26.26
	Dense Vegetation	518272.64	46.13
NDVI 2023	Water	17737.16	1.58
	Bare soil	76917.32	6.85
	Sparse vegetation	293233.83	26.10
	Moderate Vegetation	307388.95	27.36
	Dense Vegetation	428295.24	38.12
NDVI 2024	Water	16025.19	1.43
	Bare soil	140979.14	12.55
	Sparse vegetation	248247.3	22.09
	Moderate Vegetation	242560.41	21.59
	Dense Vegetation	475773.22	42.34

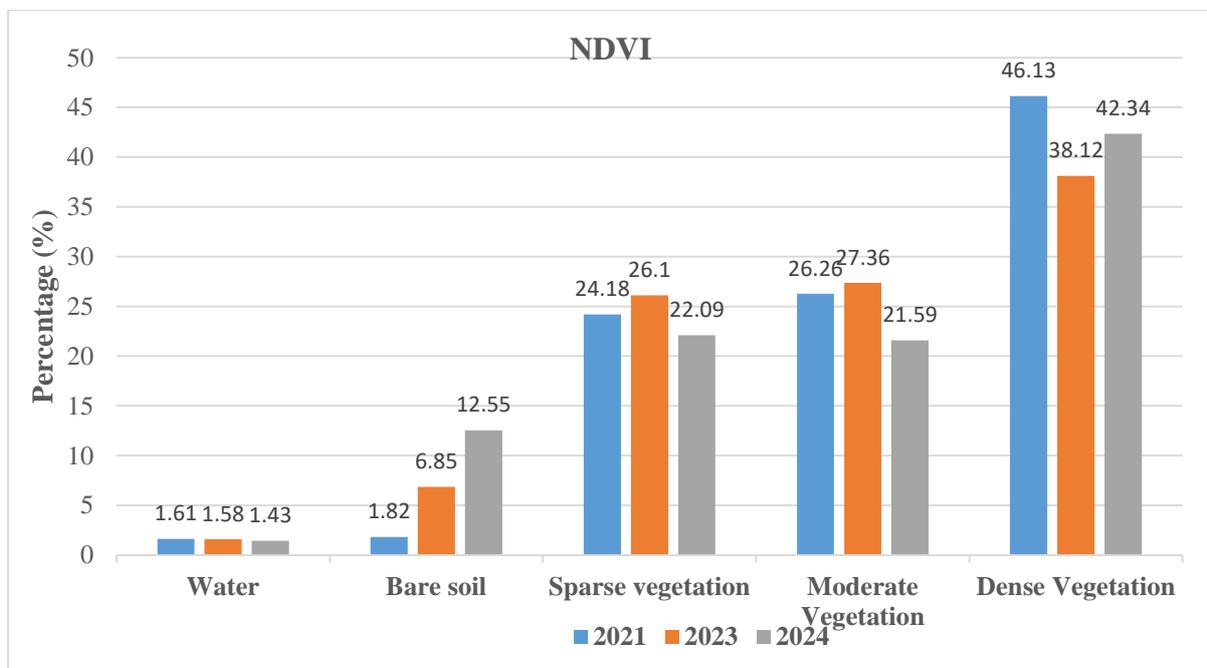


Figure 4.25: NDVI trend from 2021 to 2024

The NDVI trend from 2021 to 2024 (Figure 4.25) visually summarizes the changes in vegetation health over time. The graph shows a consistent increase in the percentage of bare soil.

The NDVI maps and statistics reveal a clear trend of declining vegetation health in the Betaré-Oya region from 2021 to 2024. The decrease in dense vegetation and the increase in bare soil indicate that mining activities are having a significant impact on vegetation cover. The fragmentation of dense vegetation patches suggests that mining activities are disrupting the connectivity of ecosystems and reducing the resilience of vegetation to disturbances. The observed decline in vegetation health is likely due to a combination of factors associated with mining activities, including deforestation, topsoil removal, soil compaction, and soil contamination. Deforestation directly reduces vegetation cover, while topsoil removal and soil compaction hinder natural regeneration. Soil contamination from heavy metals and other pollutants can also inhibit plant growth and survival. The findings are consistent with previous studies that have used NDVI to assess vegetation health in mining-affected areas. For example, Pettorelli et al. (2005) found that NDVI values decreased in areas affected by mining activities, indicating a decline in vegetation health. The study also supports the findings of Chen et al. (2021), who found that NDVI values were negatively correlated with soil degradation in mining areas.

4.3: Water Quality Assessment

- **Normalized Difference Water index**

The NDWI maps (Figures 4.26, 4.27, and 4.28) show the spatial distribution of water bodies and floodplains in the Betaré-Oya region. In 2021, the maps show a relatively high proportion of water bodies, particularly in the central and southern parts of the study area. However, by 2023, a noticeable decrease in water bodies is evident, with a corresponding increase in areas classified as floodplains/mine pit water. This trend continues in 2024, with further shrinkage of water bodies and expansion of floodplains/mine pit water.

The NDWI statistics (Table 4.4) provide a quantitative assessment of water body changes. The area of water bodies decreased from 1.71% in 2021 to 1.49% in 2024, representing a significant loss of water resources. Conversely, the area of floodplains/mine pit water increased from 1.41% in 2021 to 17.52% in 2024, indicating a substantial increase in areas affected by mining-related water disturbances.

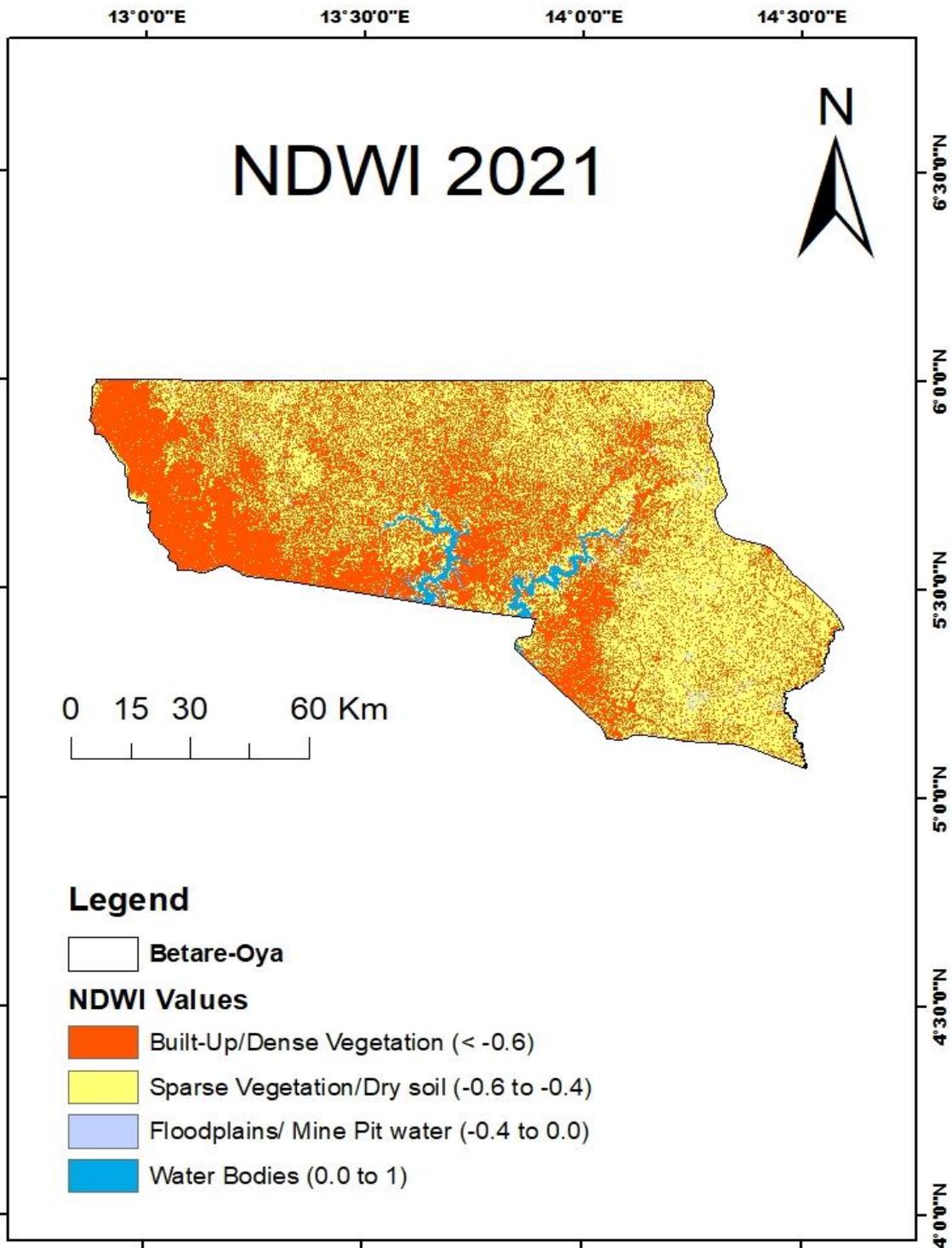


Figure 4.26: NDWI for 2021

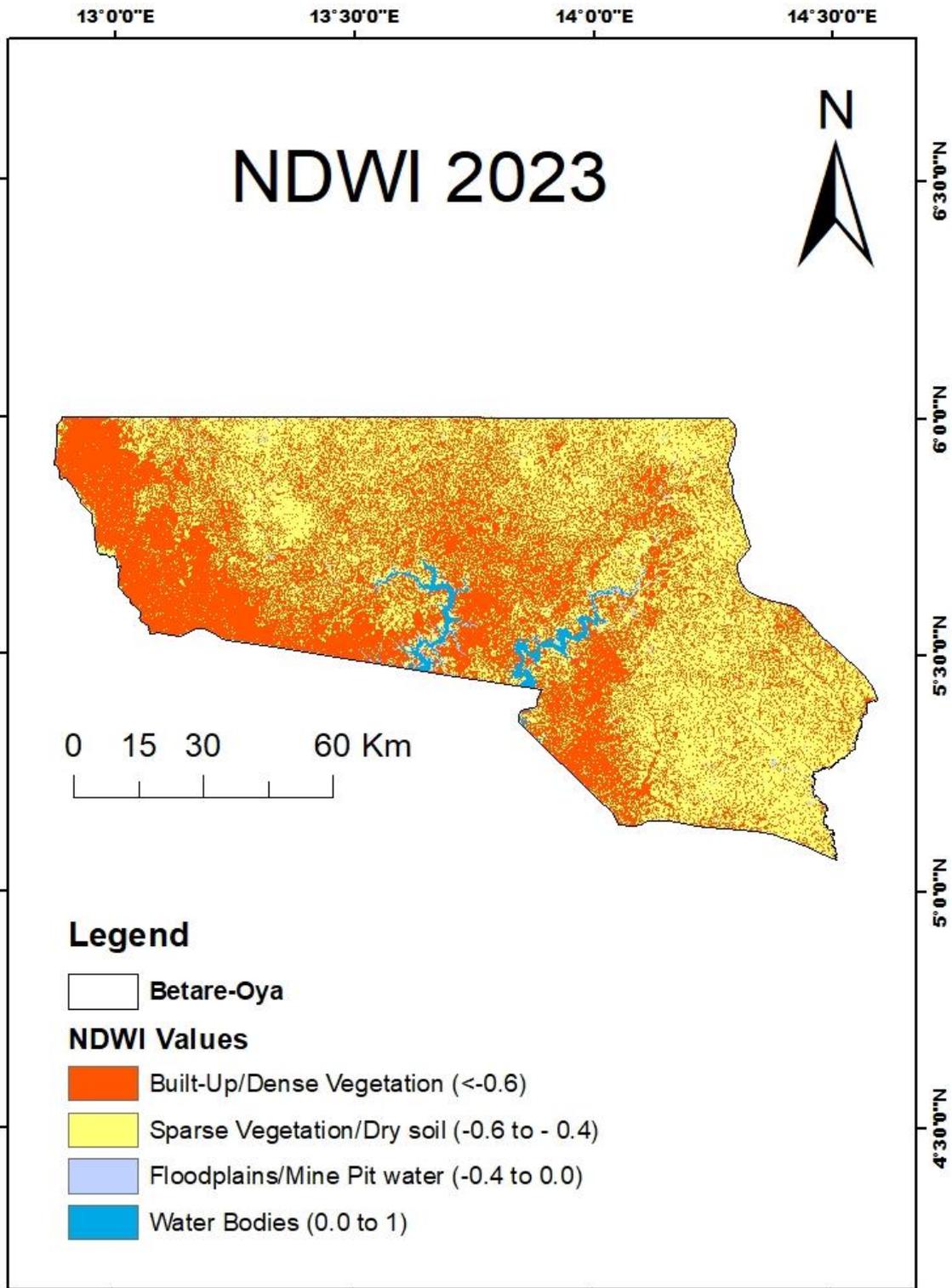


Figure 4.27: NDWI for 2023

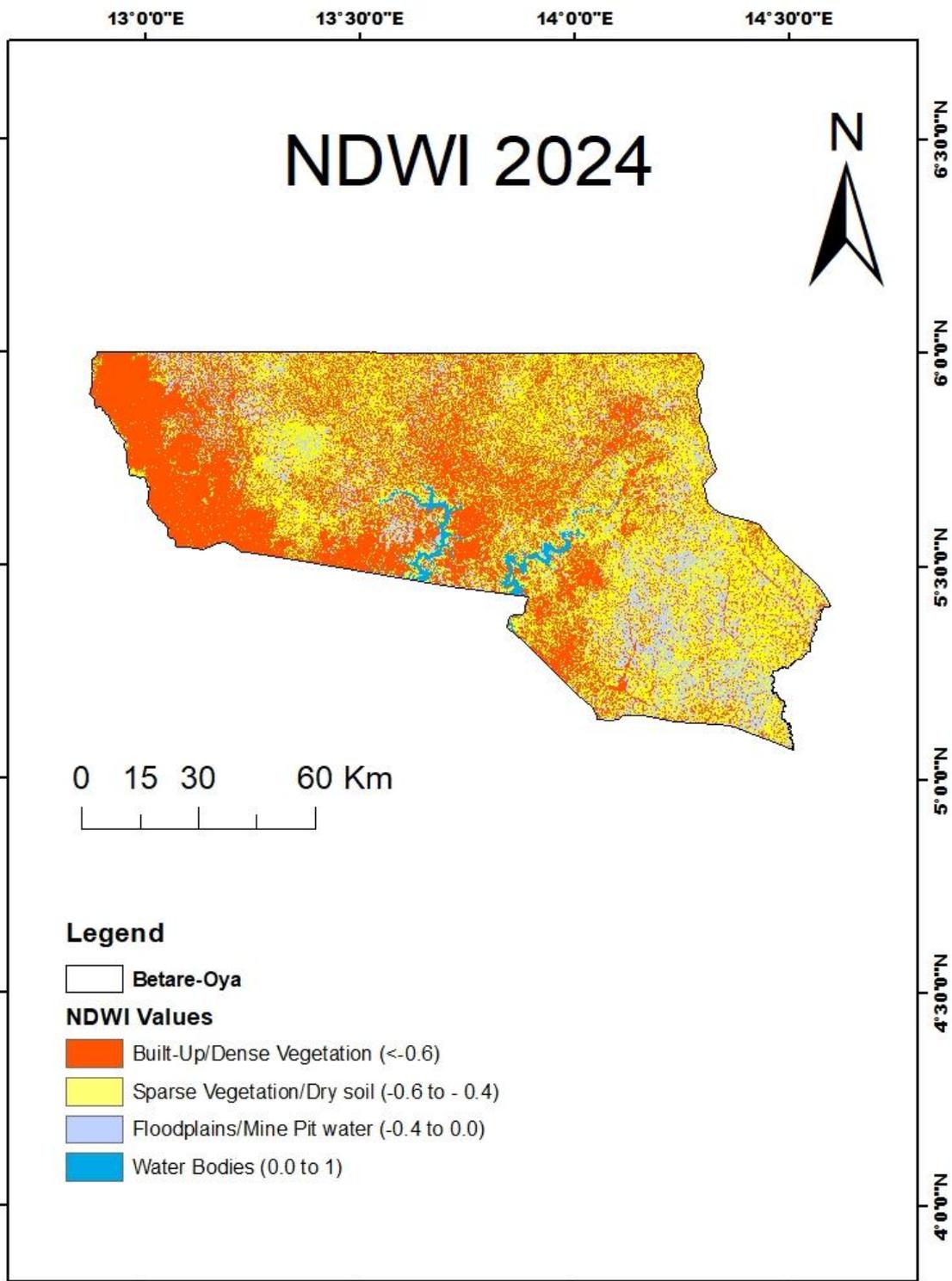


Figure 4.28: NDWI for 2024

Table 4.4: Table Statistics for NDWI

Index	Class Name	Area (hectares)	Percentage (%)
NDWI 2021	Built-Up/Dense Vegetation	547451.35	48.72
	Sparse vegetation/Dry Soil	541123.69	48.16
	Flood Plains/Mine Pit water	15831.29	1.41
	Water Bodies	19176.79	1.71
NDWI 2023	Built-Up/Dense Vegetation	538490.85	47.93
	Sparse vegetation/Dry Soil	550625.17	49.01
	Flood Plains/Mine Pit water	17026.17	1.52
	Water Bodies	17470.44	1.55
NDWI 2024	Built-Up/Dense Vegetation	492868.05	43.87
	Sparse vegetation/Dry Soil	417129.09	37.12
	Flood Plains/Mine Pit water	196795.78	17.52
	Water Bodies	16792.34	1.49

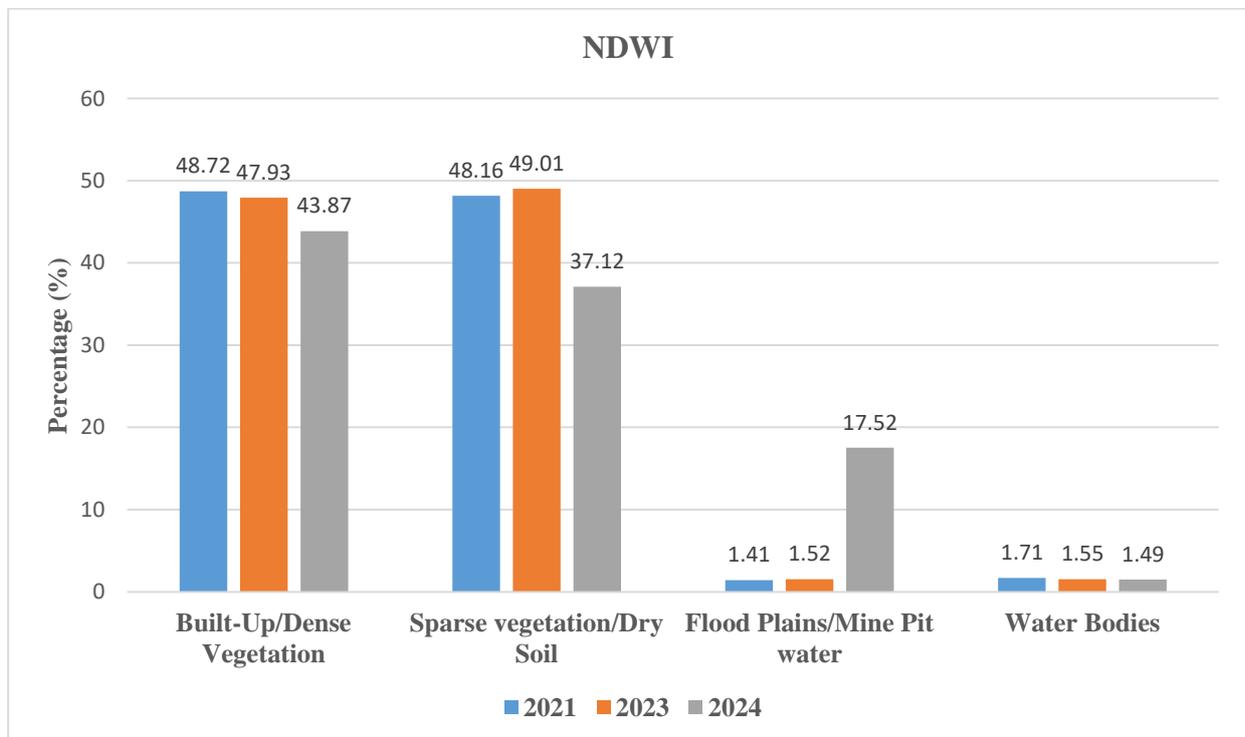


Figure 4.29: NDWI trend from 2021 to 2024

- **Turbidity Index (TI)**

The TI maps (Figures 4.30, 4.31, and 4.32) show the spatial distribution of turbidity in the Betaré-Oya region. In 2021, the maps show a relatively low proportion of high turbidity, with most areas classified as low turbidity. However, by 2023, a noticeable increase in low turbidity is evident (99.59%). However in 2024, there is slight decrease for low turbidity (88.09%).

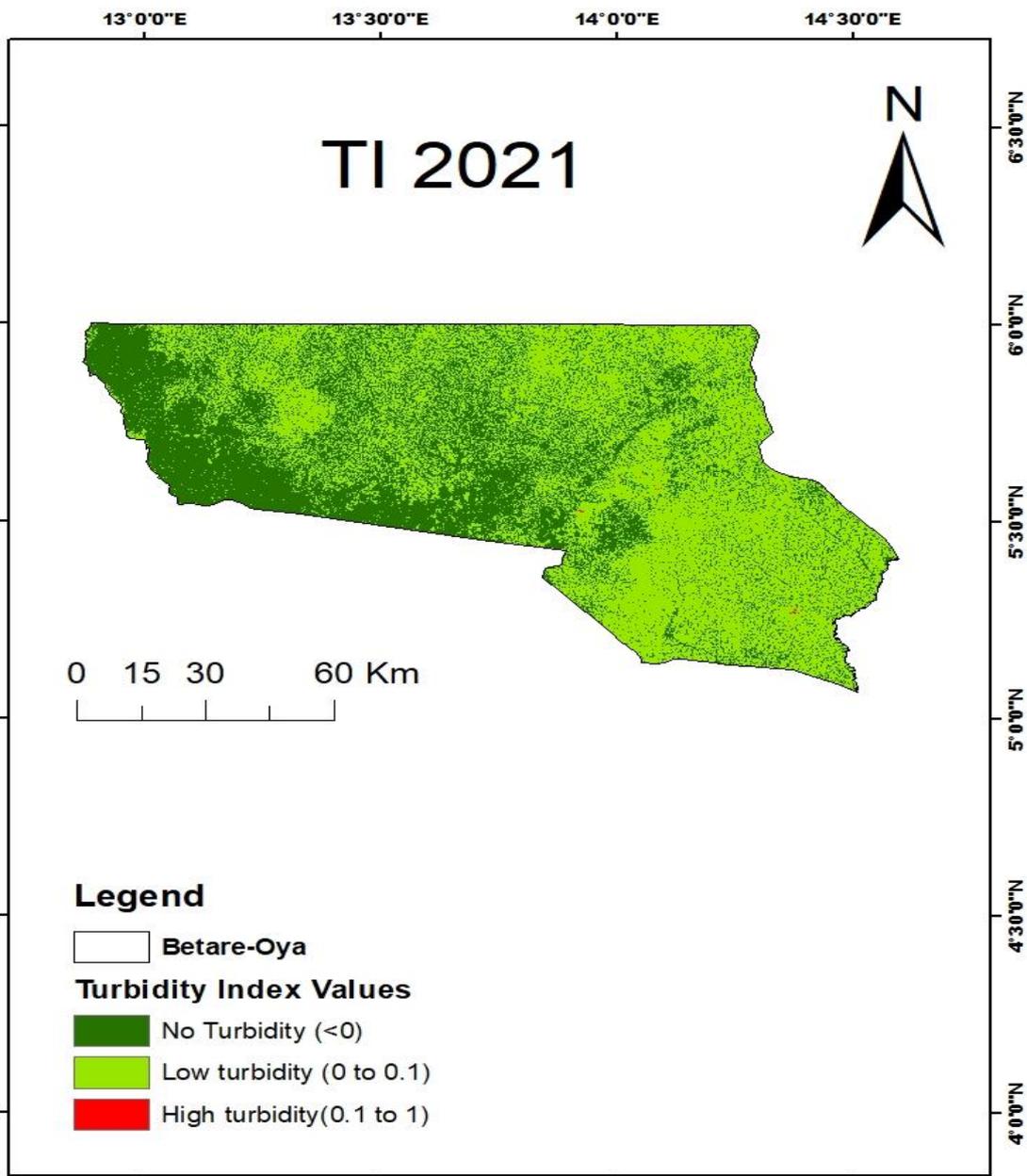


Figure 4.30: TI for 2021

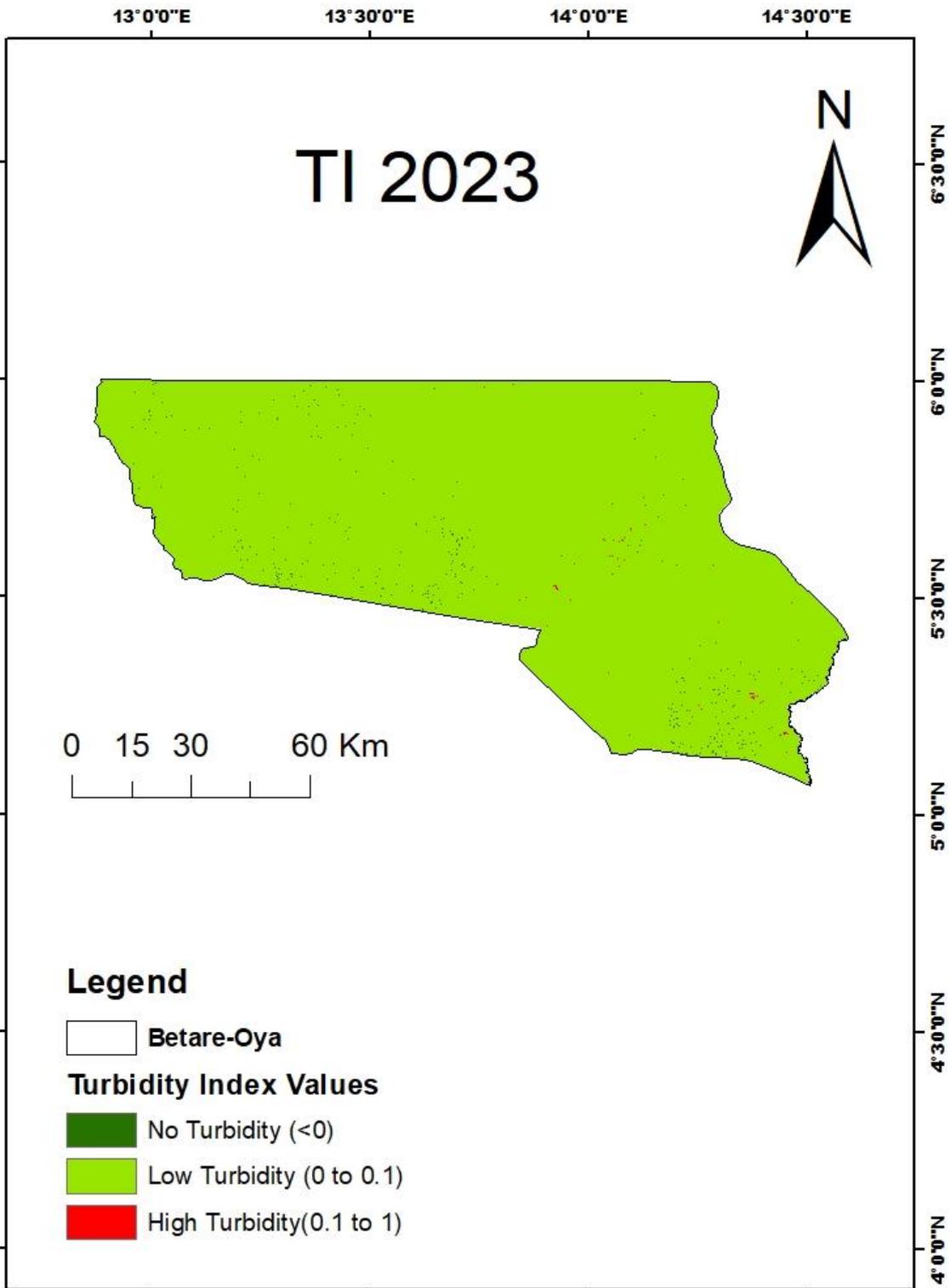


Figure 4.31: TI for 2023

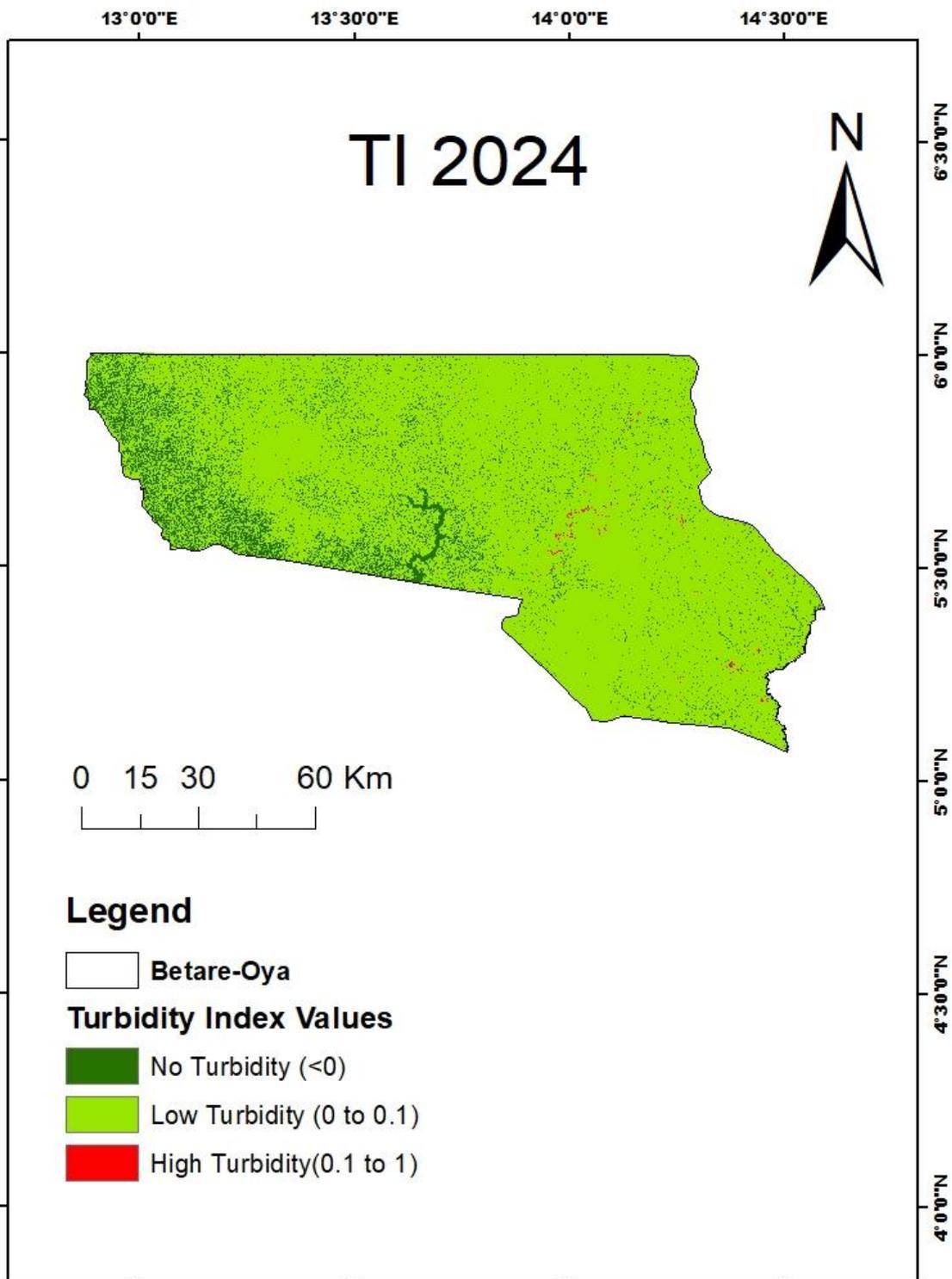


Figure 4.32: TI for 2024

Table 4.5: Table Statistics for TI

Index	Class Name	Area (hectares)	Percentage (%)
TI 2021	No Turbidity	475020	42.28
	Low Turbidity	648284.8	57.70
	High Turbidity	278.28	0.02
TI 2023	No Turbidity	3928.44	0.35
	Low Turbidity	1118957.88	99.59
	High Turbidity	696.31	0.06
TI 2024	No Turbidity	131318.88	11.69
	Low Turbidity	989816.77	88.09
	High Turbidity	2449.61	0.22

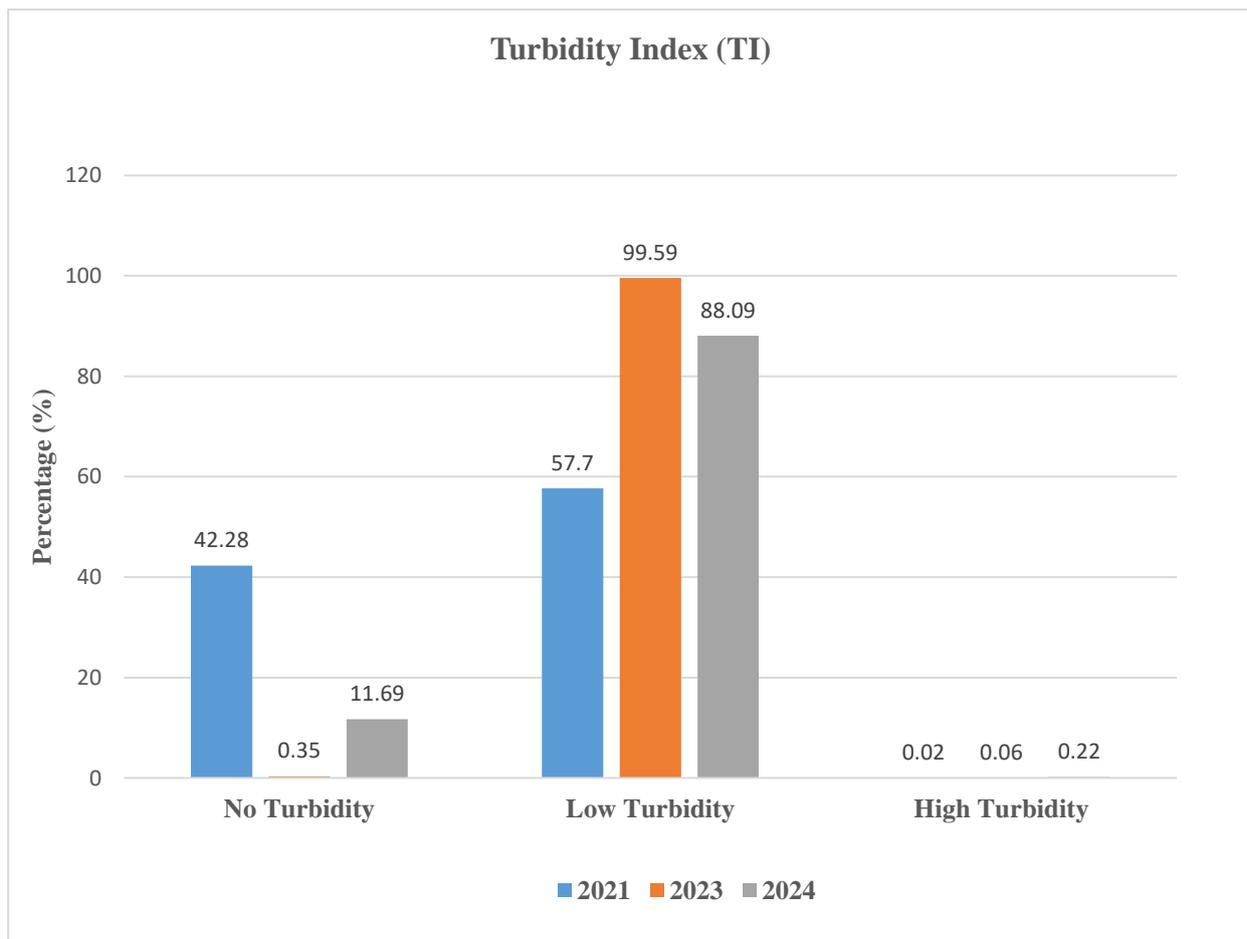


Figure 4.33: TI from 2021 to 2024

- **Suspended Sediment Concentration (SSC)**

The SSC maps (Figures 4.34, 4.35, and 4.36) show the spatial distribution of suspended sediment concentration in the Betaré-Oya region. In 2021, the maps show a relatively low proportion of very high sediment (1.81%), with most areas classified as moderate sediment load. However, by 2023, there was no change for very high sediment load (1.81%). This trend continues in 2024, with further expansion of very high sediment load (20.50%).

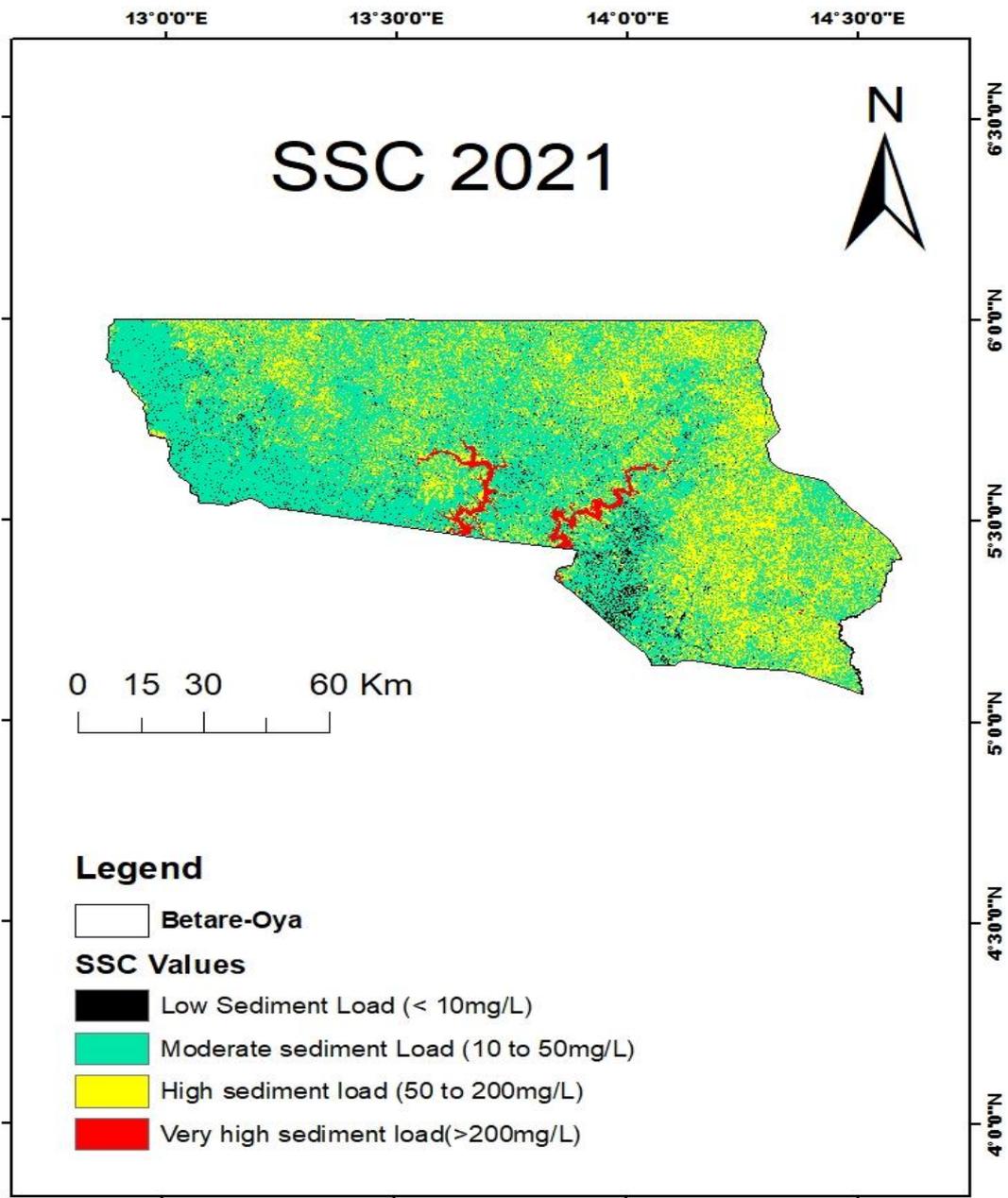


Figure 4.34: SSC for 2021

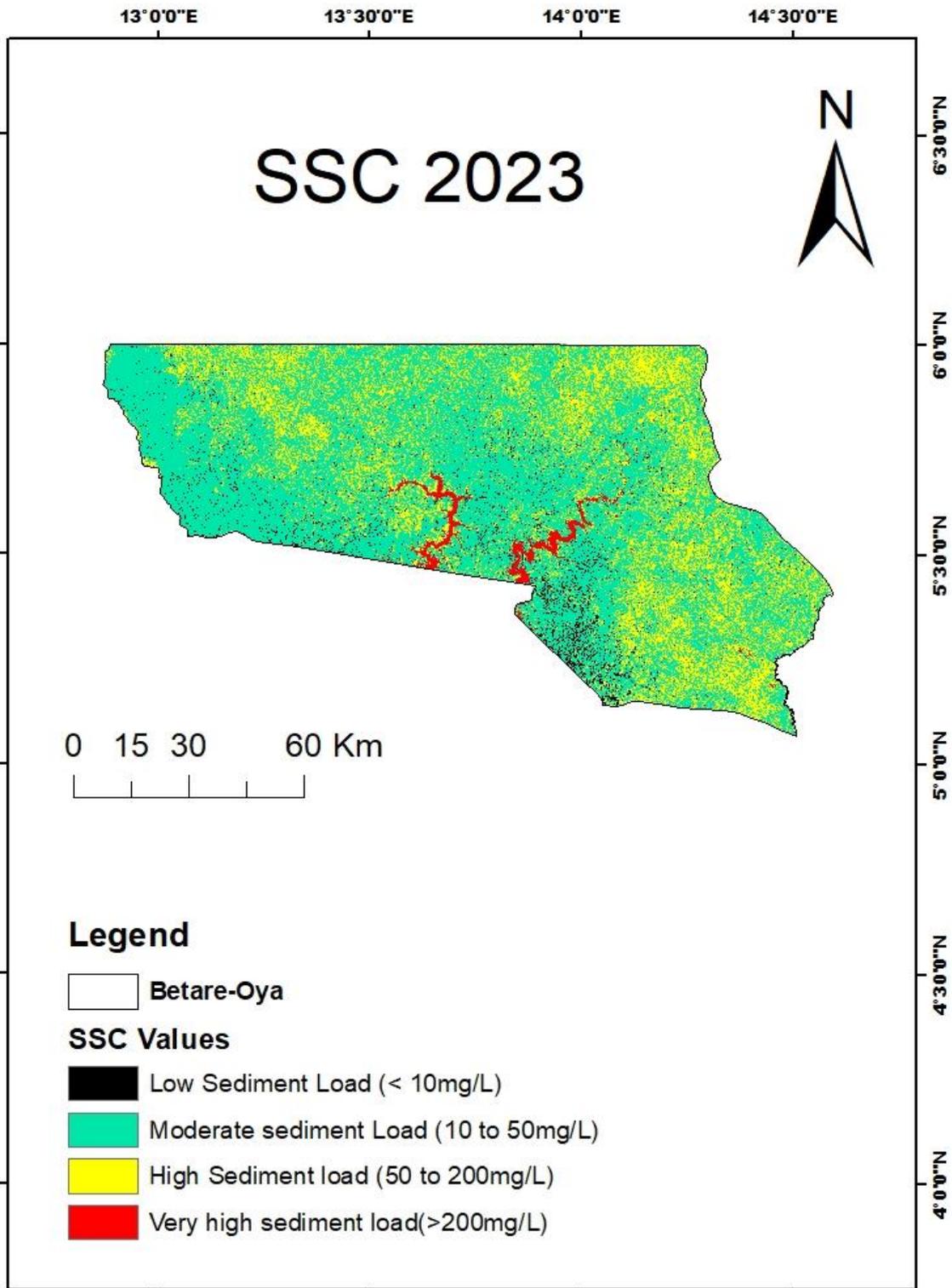


Figure 4.35: SSC for 2023

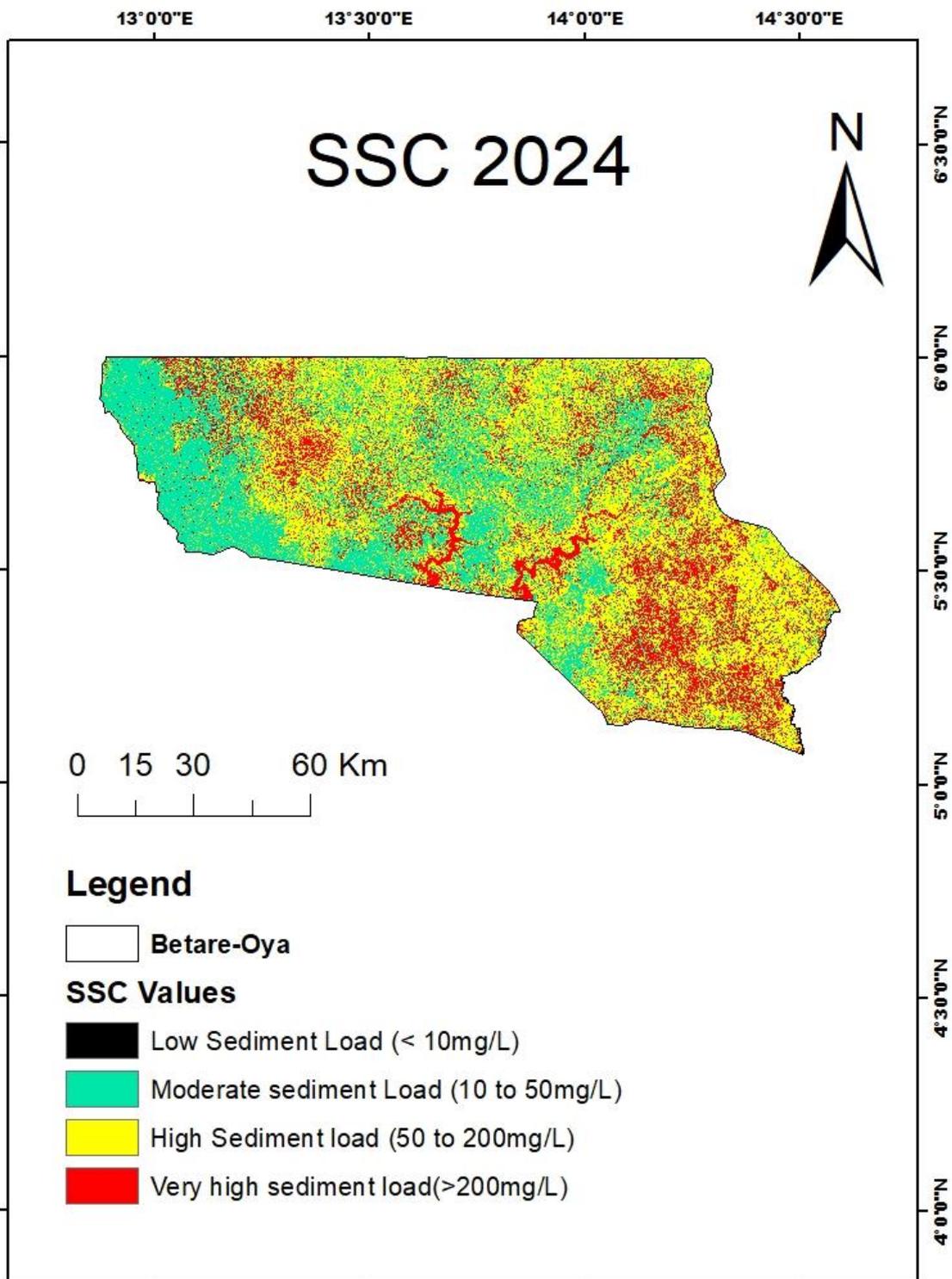


Figure 4.36: SSC for 2024

Table 4.6: Table Statistics for SSC

Index	Class Name	Area (hectares)	Percentage (%)
SSC 2021	Low sediment load	38443.33	3.42
	Moderate sediment load	680699.3	60.58
	High Sediment load	384064.11	34.18
	Very high sediment load	20376.38	1.81
SSC 2023	Low sediment load	14447.12	1.29
	Moderate sediment load	692314.65	61.62
	High Sediment load	396471.67	35.29
	Very high sediment load	20379.19	1.81
SSC 2024	Low sediment load	3982.22	0.35
	Moderate sediment load	373361.53	33.23
	High Sediment load	515956.15	45.92
	Very high sediment load	230285.36	20.50

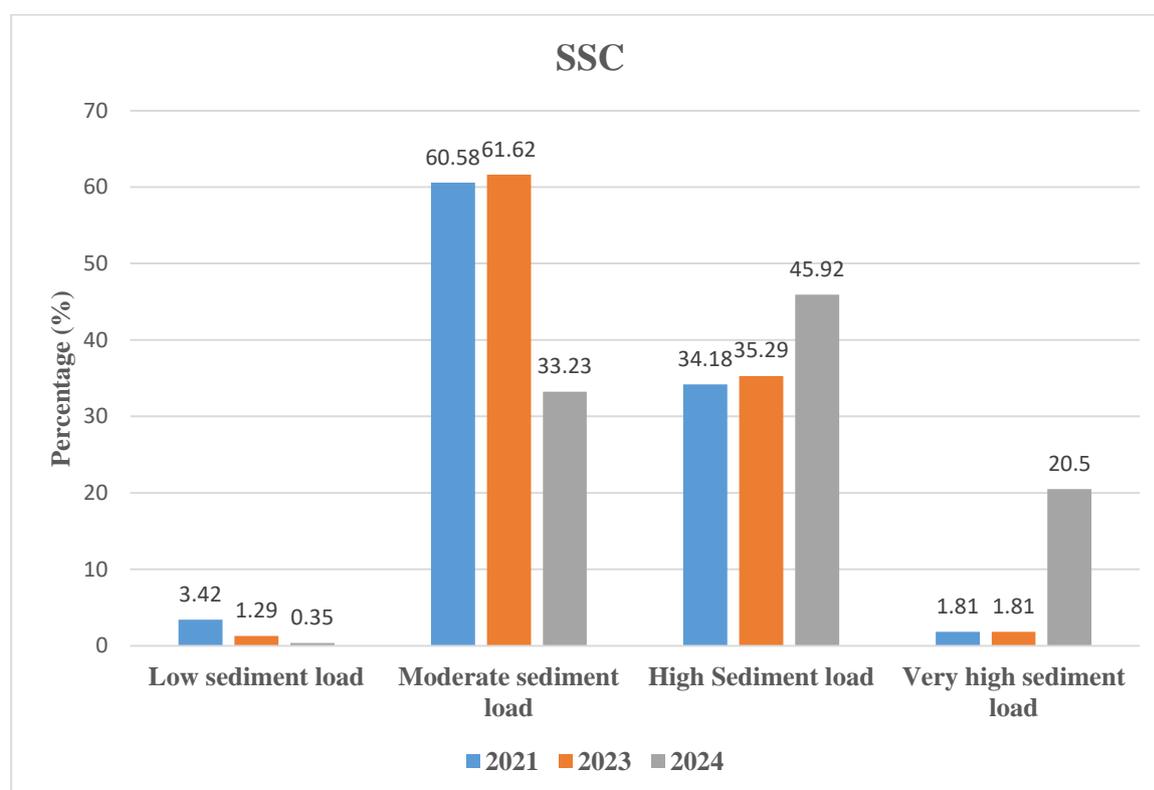


Figure 4.37: SSC from 2021 to 2024

The trends in NDWI, TI, and SSC values from 2021 to 2024 (Figures 4.29, 4.33, and 4.37) visually summarize the changes in water quality over time. The graphs show a decrease in water bodies and an increase in floodplains/mine pit water, low turbidity, and very high sediment load, indicating that mining activities are having a negative impact on water quality in the Betaré-Oya region.

NDWI, TI, and SSC maps and statistics reveal a clear trend of declining water quality in the Betaré-Oya region from 2021 to 2024. The decrease in water bodies and the increase in floodplains/mine pit water, turbidity, and sediment load indicate that mining activities are having a significant impact on water resources.

The observed decline in water quality is likely due to a combination of factors associated with mining activities, including sediment runoff, chemical contamination, and altered drainage patterns. The excavation of soil and the use of mercury and cyanide in gold extraction contribute to the contamination of water resources.

The findings are consistent with previous studies that have used NDWI, TI, and SSC to assess water quality in mining-affected areas. Chen et al. (2020) found that NDWI values decreased and TI and SSC values increased in areas affected by mining activities, indicating a decline in water quality. The study also supports the findings of Kumar et al. (2019), who found that mining activities were associated with increased levels of heavy metals in water resources.

4.4. Land Used/Land Cover Monitoring and Evaluation (LULC)

LULC maps (Figures 4.38, 4.39, and 4.40) provide a visual representation of land use and land cover across the Betaré-Oya region. In 2021, the maps show a relatively high proportion of dense vegetation, particularly in the northern and western parts of the study area. However, by 2023, a noticeable decrease in dense vegetation is evident, with a corresponding increase in areas classified as bare land and mine site. This trend continues in 2024, with further fragmentation of dense vegetation patches and expansion of degraded areas.

The LULC statistics (Table 4.7) provide a quantitative assessment of LULC changes. The area of dense vegetation decreased from 38.27% in 2021 to 30.69% in 2024, representing a significant loss of vegetation cover. Conversely, the area of bare land increased from 32.22% in 2021 to 45.48% in 2024, indicating a substantial increase in land degradation. The area of mine site also increased from 2.69% in 2021 to 4.76% in 2024, further confirming the expansion of mining activities.

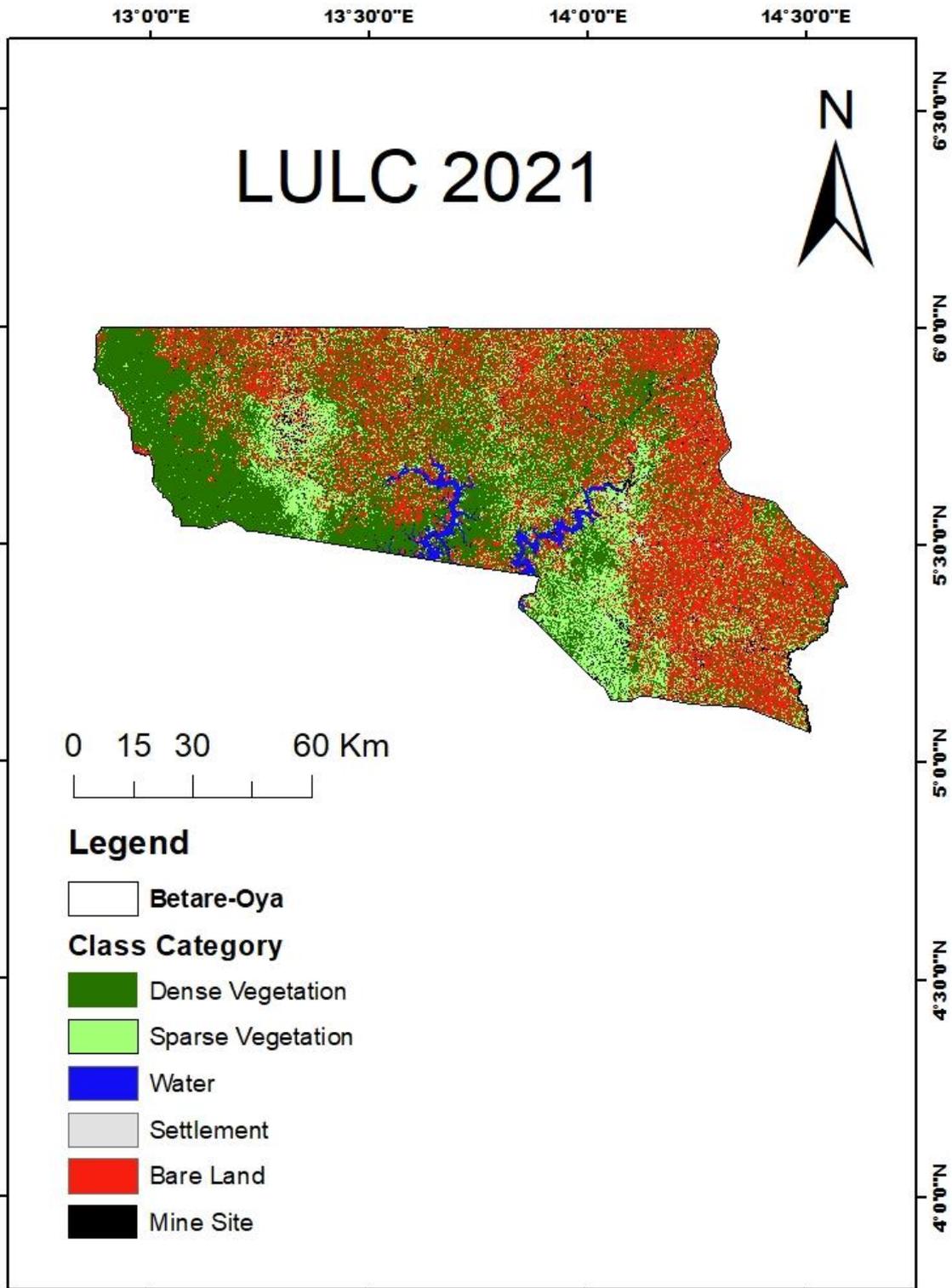


Figure 4.38: LULC for 2021

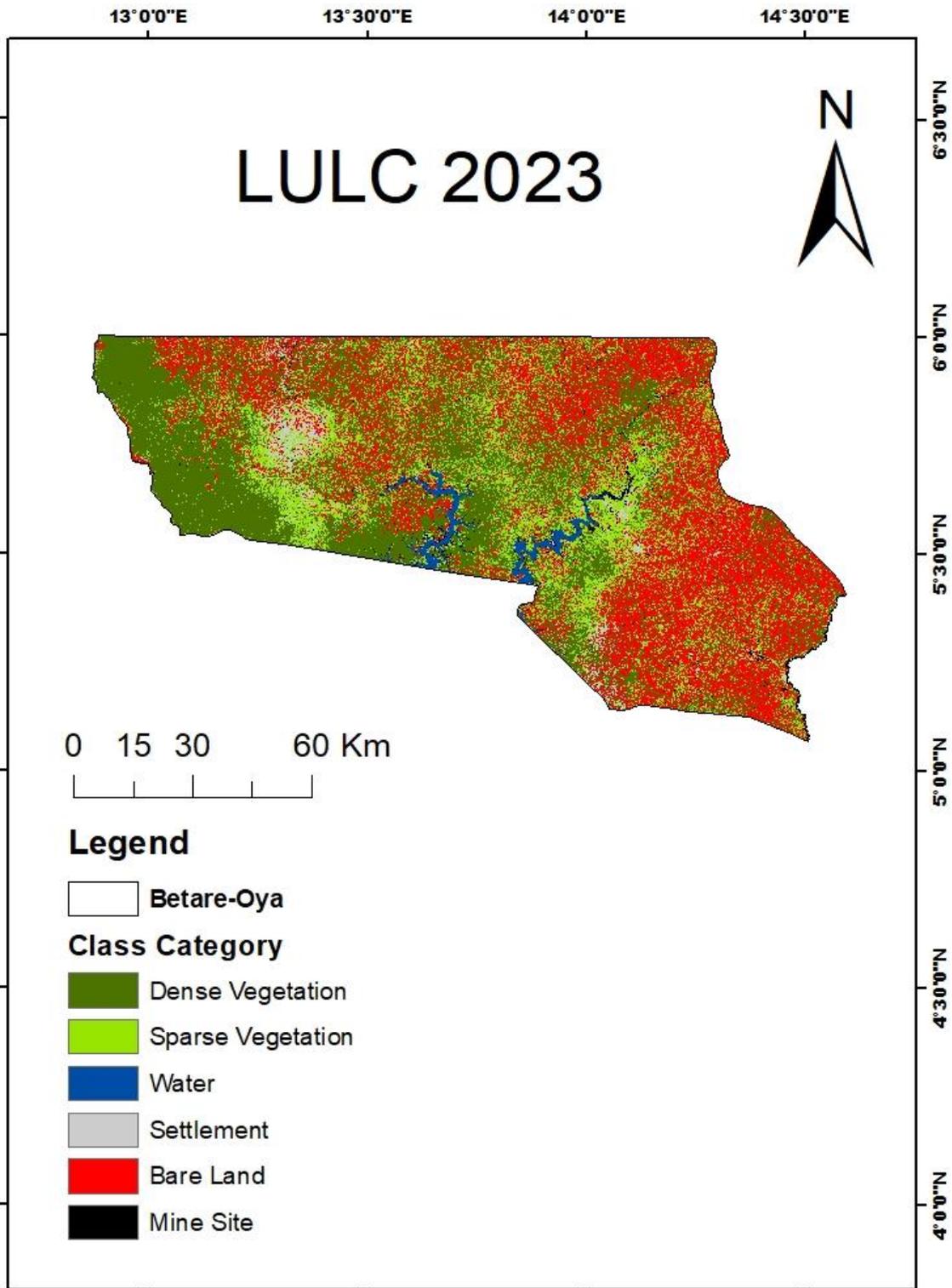


Figure 4.39: LULC for 2023

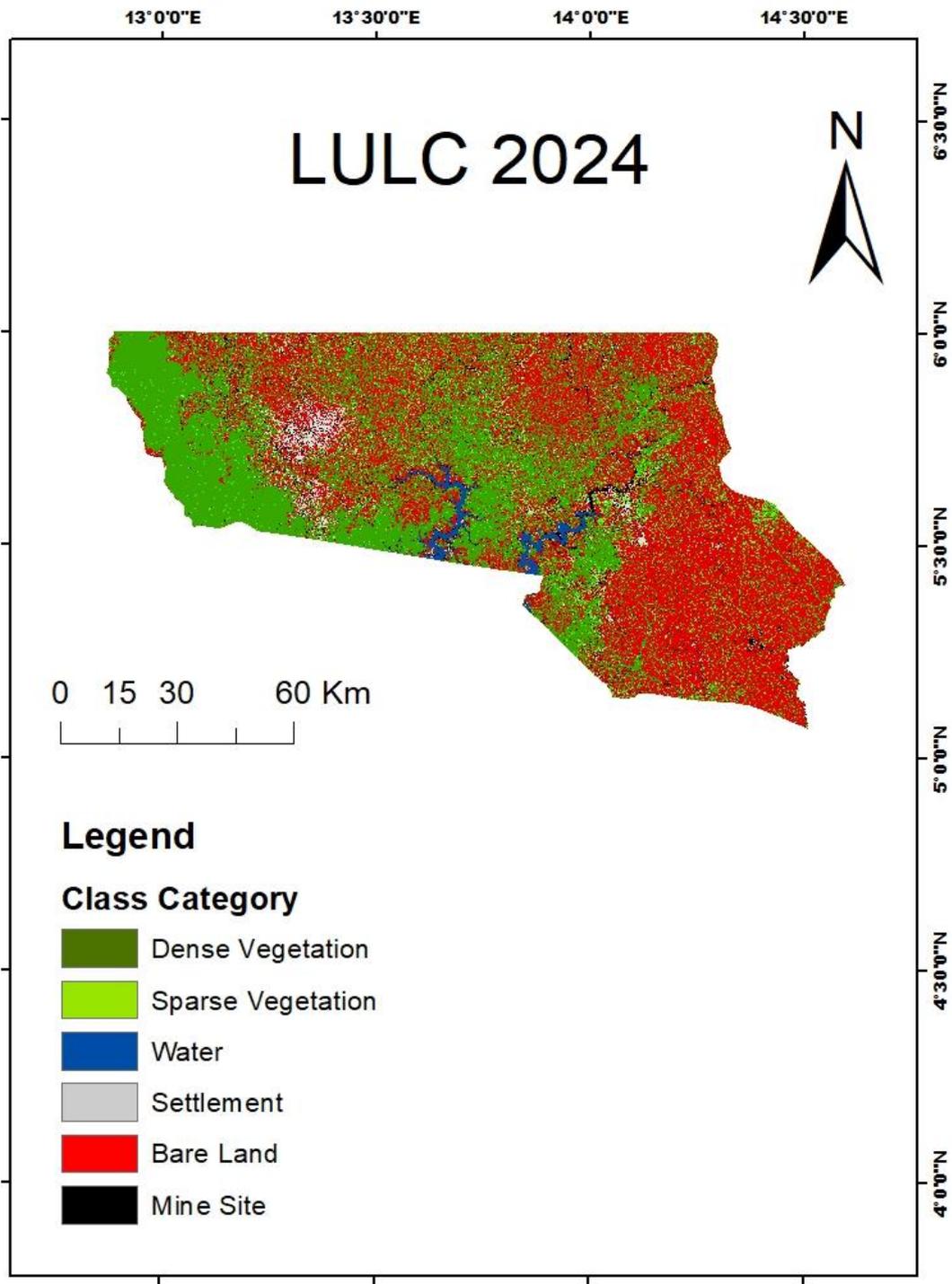


Figure 4.40: LULC for 2024

Table 4.7: Table Statistics for LULC

Index	Class Name	Area (hectares)	Percentage (%)
	Dense Vegetation	430001.36	38.27

LULC 2021	Sparse Vegetation	240000.67	21.36
	Water	20019.3	1.78
	Settlement	41378.37	3.68
	Bare Land	362011.39	32.22
	Mine Site	30202.77	2.69
LULC 2023	Dense Vegetation	410022.55	36.49
	Sparse Vegetation	220067.55	19.59
	Water	23871.62	2.12
	Settlement	45058.37	4.01
	Bare Land	389065.83	34.63
	Mine Site	35545.71	3.16
LULC 2024	Dense Vegetation	344844.74	30.69
	Sparse Vegetation	151026.71	13.44
	Water	15046.81	1.34
	Settlement	48103.41	4.28
	Bare Land	511034.88	45.48
	Mine Site	53528.71	4.76

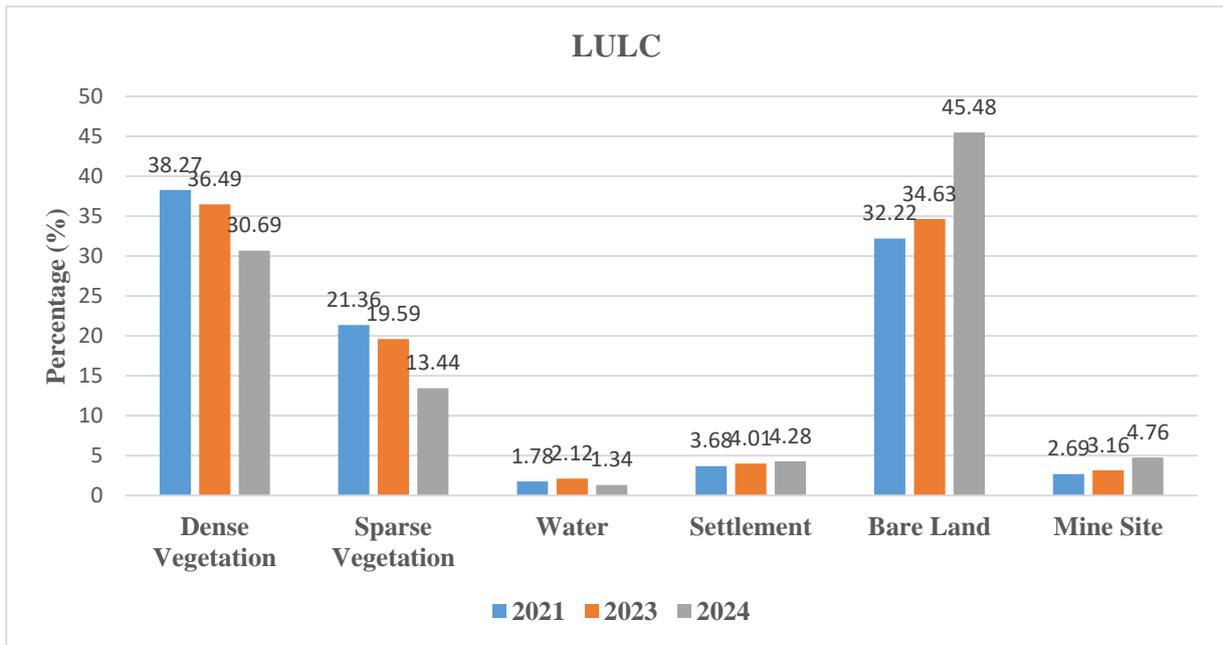


Figure 4.41: LULC from 2021 to 2024

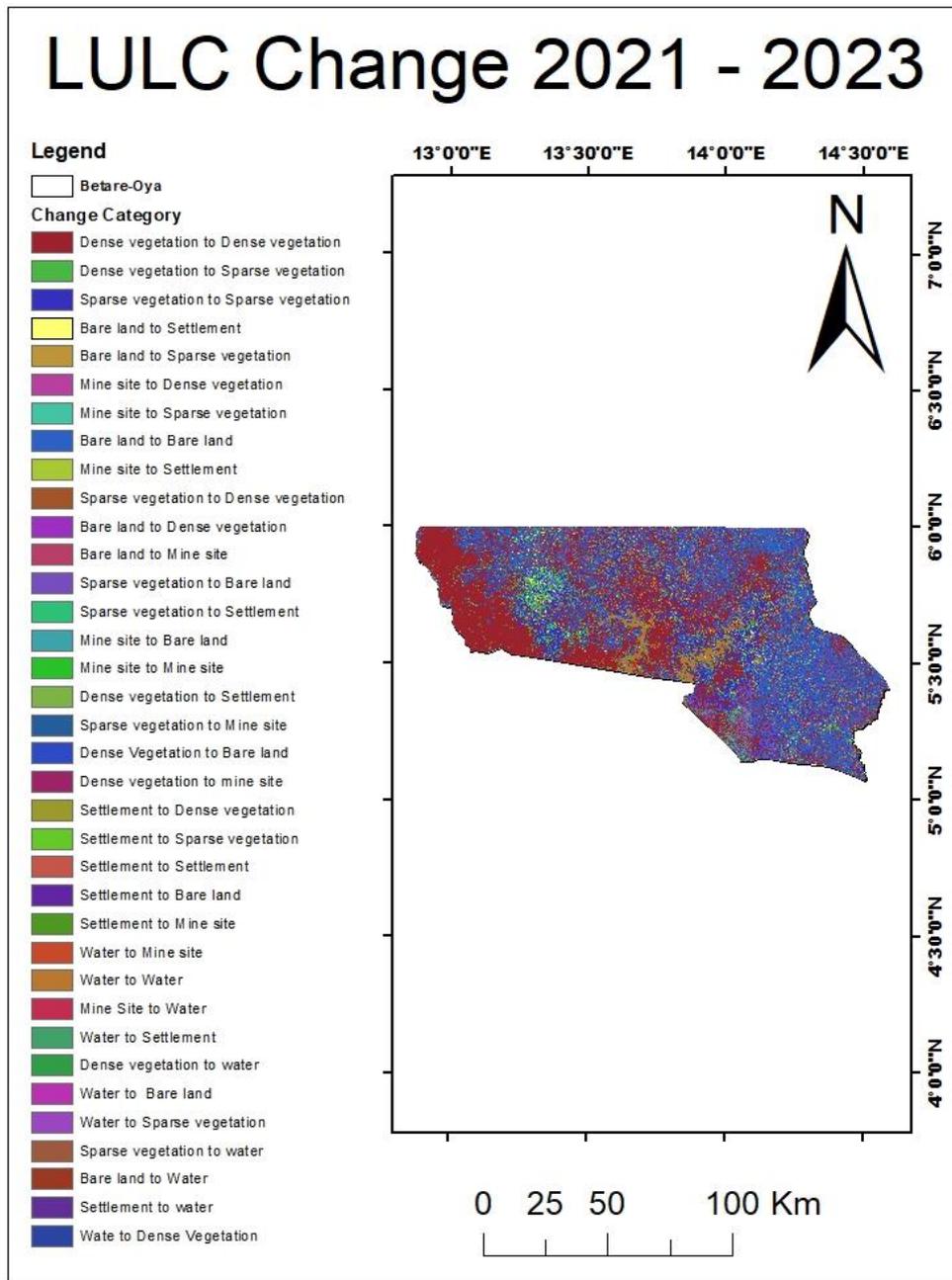


Figure 4.42: LULC Change detection from 2021 to 2023

Table 4.8: LULC change detection table statistics from 2021 to 2023

LULC 2021	LULC 2023	Change Detection Category	Area (hectares)	Percentage (%)
Dense Vegetation	Dense Vegetation	Dense Vegetation to Dense Vegetation	264946.11	23.58

Dense Vegetation	Sparse vegetation	Dense Vegetation to Sparse vegetation	89388.71	7.96
Sparse Vegetation	Sparse Vegetation	Sparse Vegetation to Sparse Vegetation	132434.81	11.79
Bare land	Settlement	Bare land to Settlement	7552.7	0.67
Bare land	Sparse Vegetation	Bare land to Sparse Vegetation	366.63	0.03
Mine site	Dense Vegetation	Mine site to Dense Vegetation	10.08	0.00
Mine site	Sparse Vegetation	Mine site to Sparse Vegetation	3444.49	0.31
Bare land	Bare land	Bare land to Bare land	307752.74	27.39
Mine site	Settlement	Mine site to Settlement	8451.47	0.75
Sparse Vegetation	Dense Vegetation	Sparse Vegetation to Dense Vegetation	15826.11	1.41
Bare land	Dense Vegetation	Bare land to Dense Vegetation	912.11	0.08
Bare land	Mine site	Bare land to Mine site	12395.36	1.10
Sparse Vegetation	Bare land	Sparse Vegetation to Bare land	58369.24	5.20
Sparse Vegetation	Settlement	Sparse Vegetation to Settlement	23061.19	2.05
Mine site	Bare land	Mine site to Bare land	7318.35	0.65
Mine site	Mine site	Mine site to Mine site	8058.55	0.72
Dense Vegetation	Settlement	Dense Vegetation to Settlement	3440.8	0.31
Sparse Vegetation	Mine site	Sparse Vegetation to Mine site	31580.6	2.81
Dense Vegetation	Bare land	Dense Vegetation to Bare land	50420.79	4.49

Dense Vegetation	Mine site	Dense Vegetation to Mine site	51032.81	4.54
Settlement	Dense Vegetation	Settlement to Dense Vegetation	209.57	0.02
Settlement	Sparse Vegetation	Settlement to Sparse Vegetation	920.77	0.08
Settlement	Settlement	Settlement to Settlement	2861.83	0.25
Settlement	Bare land	Settlement to Bare land	185.81	0.02
Settlement	Mine site	Settlement to Mine site	5.56	0.00
Water	Mine site	Water to Mine site	2245.68	0.20
Water	Water	Water to Water	17746.19	1.58
Mine site	Water	Mine site to Water	13417.81	1.19
Water	Settlement	Water to Settlement	9.17	0.00
Dense Vegetation	Water	Dense Vegetation to Water	0.82	0.00
Water	Bare land	Water to Bare land	5.34	0.00
Water	Sparse Vegetation	Water to Sparse Vegetation	1.32	0.00
Sparse Vegetation	Water	Sparse Vegetation to Water	1.22	0.00
Bare land	Water	Bare land to Water	9150.32	0.81
Settlement	Water	Settlement to Water	3.94	0.00
Water	Dense Vegetation	Water to Dense Vegetation	0.26	0.00

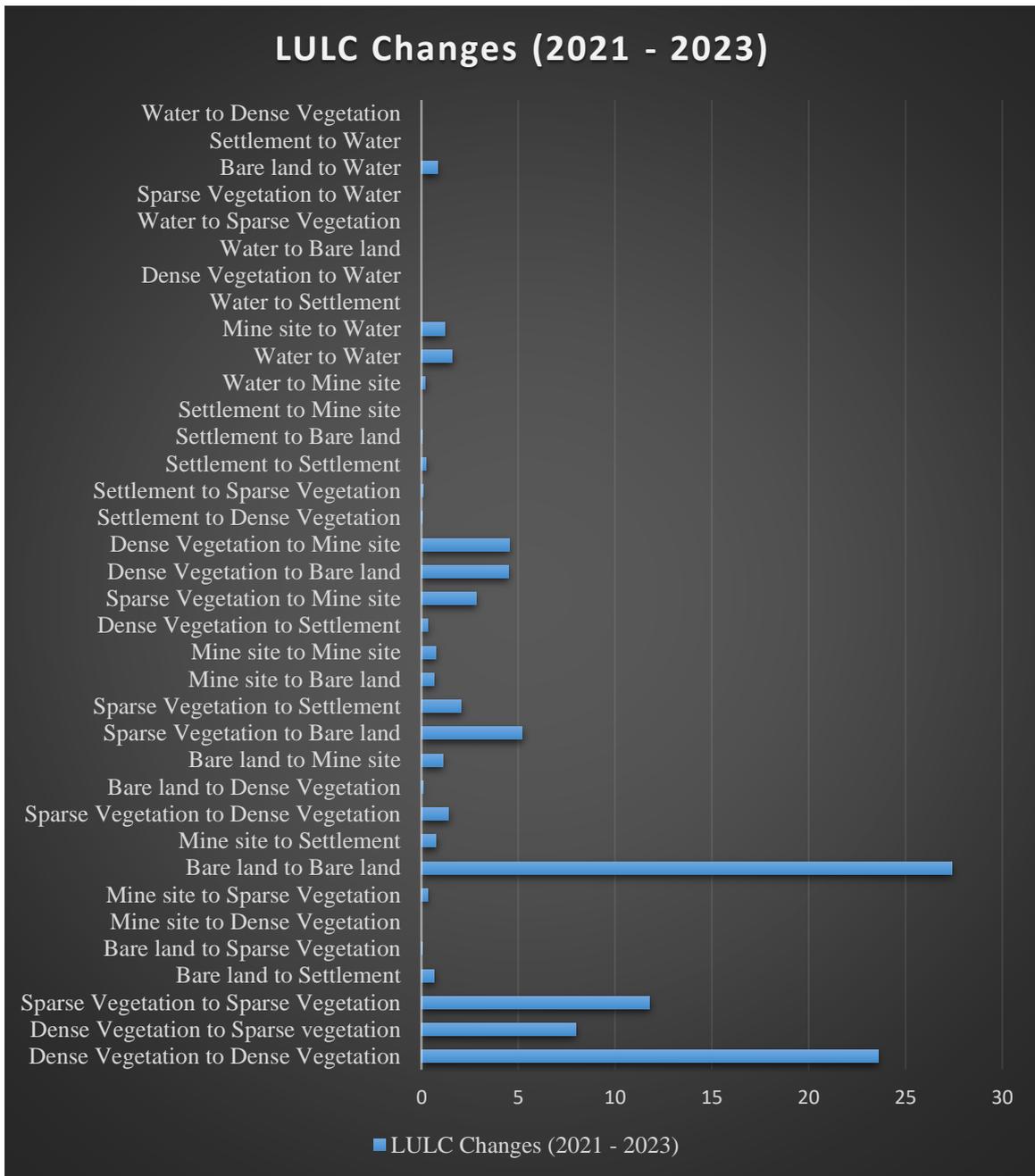


Figure 4.43: LULC Change detection histogram from 2021 to 2023

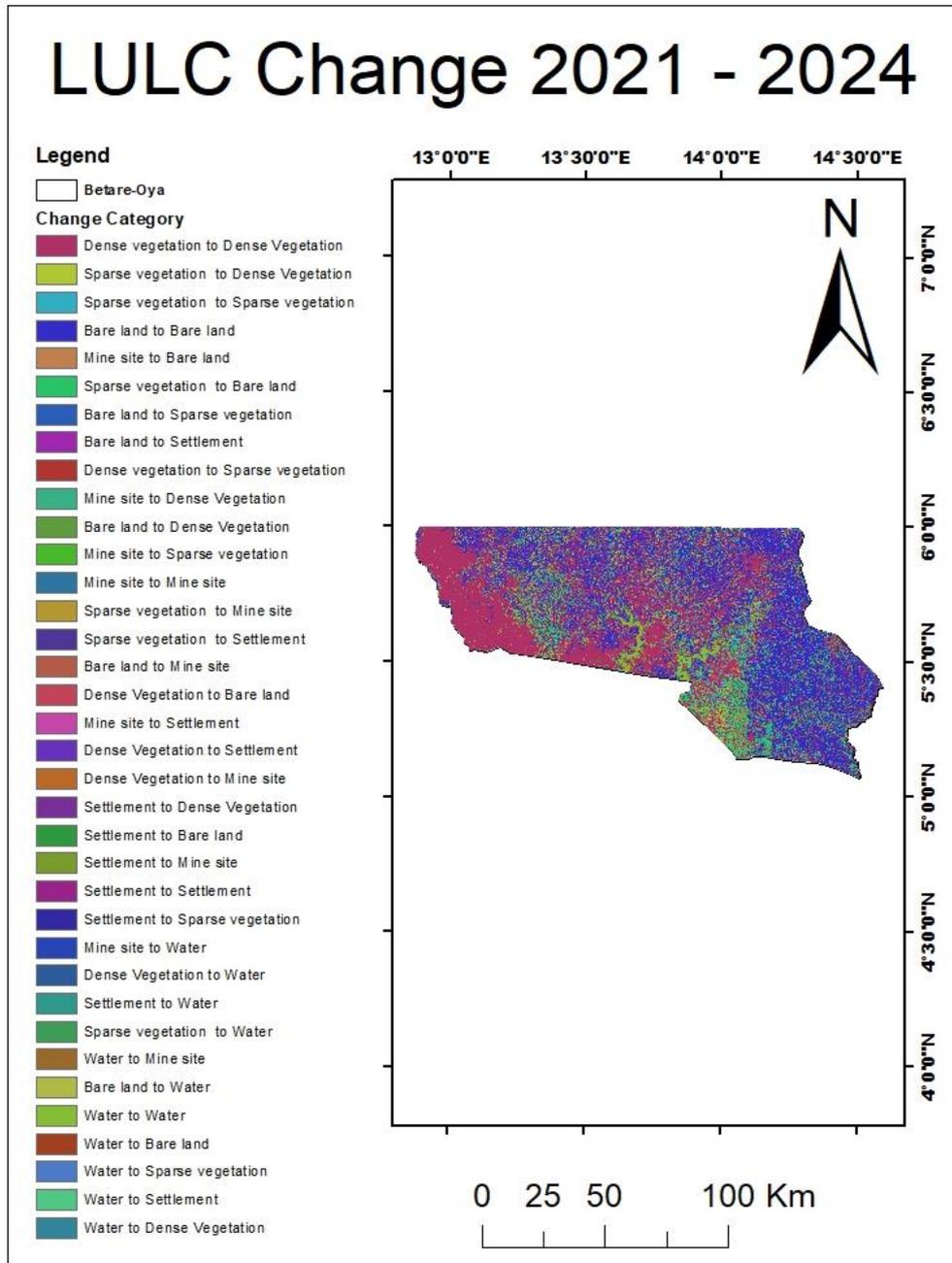


Figure 4.44: LULC Change detection from 2021 to 2024

Table 4.9: LULC change detection table statistics from 2021 to 2024

LULC 2021	LULC 2024	Change Detection Category	Area (Hectares)	Percentage (%)
Dense vegetation	Dense Vegetation	Dense vegetation to Dense Vegetation	240467.49	21.40

Sparse vegetation	Dense Vegetation	Sparse vegetation to Dense Vegetation	2115.56	0.19
Sparse vegetation	Sparse vegetation	Sparse vegetation to Sparse vegetation	42851.73	3.81
Bare land	Bare land	Bare land to Bare land	367991.46	32.75
Mine site	Bare land	Mine site to Bare land	2567.37	0.23
Sparse vegetation	Bare land	Sparse vegetation to Bare land	117507.74	10.46
Bare land	Sparse vegetation	Bare land to Sparse vegetation	5112.37	0.46
Bare land	Settlement	Bare land to Settlement	7958.72	0.71
Dense vegetation	Sparse vegetation	Dense vegetation to Sparse vegetation	37054.61	3.30
Mine site	Dense Vegetation	Mine site to Dense Vegetation	2266.81	0.20
Bare land	Dense Vegetation	Bare land to Dense Vegetation	1580.31	0.14
Mine site	Sparse vegetation	Mine site to Sparse vegetation	1706.92	0.15
Mine site	Mine site	Mine site to Mine site	9260.55	0.82
Sparse vegetation	Mine site	Sparse vegetation to Mine site	94481.34	8.41
Sparse vegetation	Settlement	Sparse vegetation to Settlement	19315.93	1.72
Bare land	Mine site	Bare land to Mine site	15358.11	1.37
Dense Vegetation	Bare land	Dense Vegetation to Bare land	12240.12	1.09
Mine site	Settlement	Mine site to Settlement	5733.08	0.51
Dense Vegetation	Settlement	Dense Vegetation to Settlement	3463.52	0.31

Dense Vegetation	Mine site	Dense Vegetation to Mine site	74009.33	6.59
Settlement	Dense Vegetation	Settlement to Dense Vegetation	369.45	0.03
Settlement	Bare land	Settlement to Bare land	897.95	0.08
Settlement	Mine site	Settlement to Mine site	802.14	0.07
Settlement	Settlement	Settlement to Settlement	10147.86	0.90
Settlement	Sparse vegetation	Settlement to Sparse vegetation	198.95	0.02
Mine site	Water	Mine site to Water	64.07	0.01
Dense Vegetation	Water	Dense Vegetation to Water	7	0.00
Settlement	Water	Settlement to Water	1.13	0.00
Sparse vegetation	Water	Sparse vegetation to Water	4.53	0.00
Water	Mine site	Water to Mine site	11615.89	1.03
Bare land	Water	Bare land to Water	21111.74	1.88
Water	Water	Water to Water	14968.83	1.33
Water	Bare land	Water to Bare land	116.04	0.01
Water	Sparse vegetation	Water to Sparse vegetation	100.35	0.01
Water	Settlement	Water to Settlement	82.67	0.01
Water	Dense Vegetation	Water to Dense Vegetation	32.4	0.00

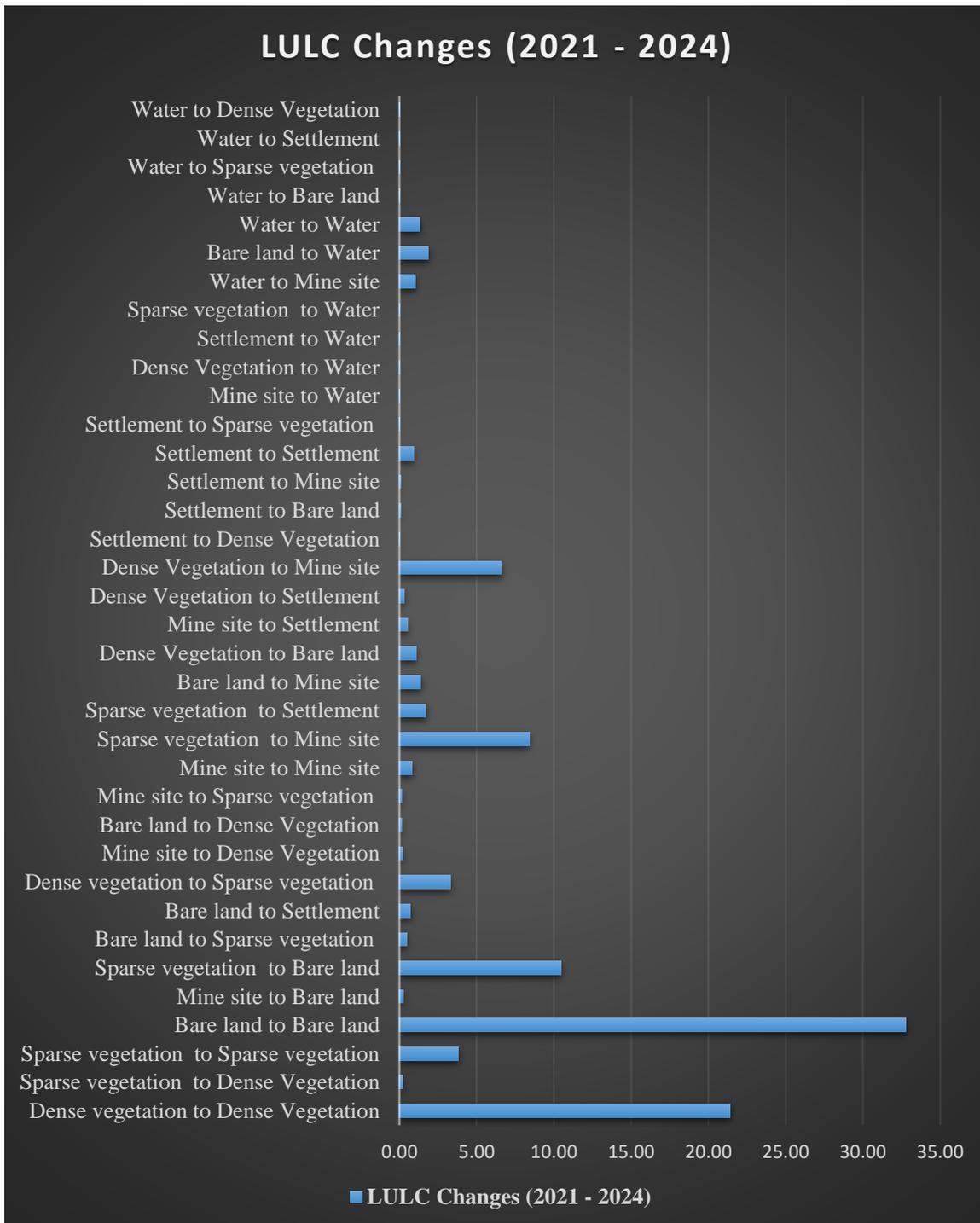


Figure 4.45: LULC Change detection histogram from 2021 to 2024

The LULC change detection maps (Figures 4.42 and 4.44) show the areas that have changed from one LULC class to another. The change detection analysis reveals that the most significant changes are from dense vegetation to bare land and mine site, indicating that mining activities are driving deforestation and land degradation.

LULC change detection histogram (Figures 4.43 and 4.45) provides a quantitative summary of the LULC changes. The histogram confirms that the most significant changes are from dense vegetation to bare land and mine site.

The LULC maps, statistics, and change detection analysis reveal a clear trend of changing LULC in the Betaré-Oya region from 2021 to 2024. The decrease in dense vegetation and the increase in bare land and mine site indicate that mining activities are having a significant impact on LULC.

The observed changes in LULC are directly related to mining activities. The clearing of forests to access alluvial gold deposits results in a decrease in dense vegetation and an increase in bare land and mine site. The expansion of mining activities also leads to an increase in settlement areas, as people migrate to the region in search of employment opportunities.

The findings are consistent with previous studies that have used LULC classification to assess environmental changes in mining-affected areas. For example, Kamga et al. (2017) found that mining activities were driving deforestation and land degradation in the Betaré-Oya region.

The study also supports the findings of Singh et al. (2023), who found that mining activities were associated with increased levels of bare land and settlement areas.

The observed changes in LULC have significant implications for sustainable development in the Betaré-Oya region. The loss of dense vegetation reduces the capacity of ecosystems to provide essential services, such as carbon sequestration, water regulation, and soil stabilization. The increase in bare land and mine site contributes to land degradation and reduces agricultural productivity. The expansion of settlement areas can lead to increased pressure on natural resources and social conflicts.

4.5 Proposed Rehabilitation Strategies

The increase in bare soil extent and the decrease in vegetation moisture content have significant implications for ecosystem services in the Betaré-Oya region. Bare soil is more susceptible to erosion, which can lead to sedimentation of water bodies and loss of soil fertility. Reduced vegetation moisture content can lead to increased fire risk and reduced carbon sequestration.

The decline in vegetation health has significant implications for ecosystem services in the Betaré-Oya region. Vegetation plays a crucial role in carbon sequestration, water regulation, soil stabilization, and habitat provision. The loss of vegetation cover reduces the capacity of ecosystems to provide these services, potentially leading to further environmental degradation and economic losses.

The decline in water quality has significant implications for human health and ecosystems in the Betaré-Oya region. Contaminated water resources can pose a risk to human health through drinking water consumption and exposure to contaminated water during recreational activities. The increased turbidity and sediment load can also harm aquatic ecosystems by reducing light penetration and smothering aquatic habitats.

Based on the remote sensing analysis, field observations, and literature review, the following rehabilitation strategies are proposed for the alluvial gold mining-affected areas in Betaré-Oya.

Prioritization of Rehabilitation Areas

- Prioritize areas with high BSI values, low NDMI and NDVI values, high TI and SSC values, and significant changes in LULC from dense vegetation to bare land or mine site.
- Consider the proximity of mining sites to water bodies and settlements when prioritizing rehabilitation areas.

Soil Stabilization and Erosion Control

- Implement soil stabilization measures to reduce soil erosion and sedimentation.
- Construct terraces on slopes to reduce the slope length and slow down water runoff.
- Plow along the contour lines of the land to create ridges that trap water and reduce soil erosion.
- Plant native grasses, shrubs, and trees to provide ground cover and stabilize the soil.
- Apply organic mulch to the soil surface to reduce erosion and retain moisture.
- Use geotextiles to stabilize slopes and prevent soil erosion.

Reforestation and Revegetation

- Reforest degraded areas with native tree species to restore vegetation cover and improve soil health.
- Select tree species that are adapted to the local climate and soil conditions and that provide valuable ecosystem services, such as carbon sequestration and habitat provision.
- Use a mix of tree species to increase biodiversity and resilience to disturbances.
- Implement soil preparation techniques, such as adding organic matter and fertilizer, to improve soil fertility and promote plant growth.
- Protect newly planted trees from grazing and fire.

Water Quality Improvement

- Implement water treatment technologies to remove pollutants from contaminated water resources.
- Construct artificial wetlands to filter pollutants from water and provide habitat for wildlife.
- Use plants and microorganisms to remove pollutants from water and soil.
- Construct sedimentation basins to trap sediment and reduce turbidity.
- Use chemical treatment to remove heavy metals and other pollutants from water.

Mine Pit Rehabilitation

- Rehabilitate abandoned mine pits to reduce safety hazards and improve water quality.
- Backfill mine pits with soil and rock to create a more stable and level surface.
- Grade the surface of mine pits to improve drainage and reduce erosion.
- Plant native vegetation on the surface of mine pits to stabilize the soil and provide habitat for wildlife.
- Treat the water in mine pits to remove pollutants and improve water quality.

Community Engagement and Alternative Livelihoods

- Engage local communities in the planning and implementation of rehabilitation efforts.
- Provide training and employment opportunities for local residents in rehabilitation activities.
- Promote sustainable agriculture, ecotourism, and other alternative livelihood opportunities to reduce dependence on mining.
- Educate local communities about the environmental impacts of mining and the importance of sustainable mining practices.

Monitoring and Evaluation

- Implement a long-term monitoring program to track the progress of rehabilitation efforts.
- Adjust rehabilitation strategies as needed based on monitoring results.
- Engage local communities in the monitoring and evaluation process.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study provides a comprehensive assessment of the environmental impacts of alluvial gold mining in the Betaré-Oya region of Cameroon from 2021 to 2025. The spatiotemporal analysis were performed from the year 2021 to 2024, while field observation and ground truthing was carried out in the early months of 2025 (January to March). The results reveal significant land degradation, declining vegetation health, deteriorating water quality, and changing land use/land cover patterns due to mining activities.

Field observations and Google Earth Pro analysis revealed deforestation of the original forest cover lost in active mining areas. Soil erosion was widespread, with topsoil loss in active mining zones. Abandoned mining pits filled with stagnant water were a common sight, posing a risk to public health and aquatic ecosystems.

Satellite image analysis using BSI, NDMI, NDVI, NDWI, TI, and SSC confirmed the trends observed in the field and Google Earth Pro analysis. The BSI results showed an increase in bare soil from 2021 to 2024, indicating a significant increase in land degradation. The NDMI results showed a decrease in vegetation moisture over the years, indicating a decline in vegetation health. The NDVI results showed a decrease in vegetation, further confirming the decline in vegetation health. The NDWI results indicated loss of water resources. The TI results showed an average increase in turbidity over the years while SSC showed an increase in sediment load, confirming the decline in water quality.

LULC classification and change detection analysis revealed that mining activities are driving deforestation and land degradation, with significant changes from dense vegetation to bare land and mine site over the years.

The different analyses (BSI, NDMI, NDVI, NDWI, TI, SSC, and LULC) complement each other to provide a comprehensive understanding of the environmental impacts of mining. The results show that mining activities are having a cascading effect on the environment, leading to land degradation, declining vegetation health, deteriorating water quality, and changing land use/land cover patterns.

This study contributes to scientific knowledge by providing a comprehensive assessment of the environmental impacts of alluvial gold mining in the Betaré-Oya region. The study also demonstrates the value of remote sensing for monitoring environmental changes in mining-

affected areas. The findings provide valuable information for policymakers, regulatory agencies, and environmental managers to design and enforce sustainable mining policies and develop effective mine closure and rehabilitation plans.

5.2 Recommendation

Implement stricter regulations on mining activities to minimize environmental impacts. This includes regulations on deforestation, topsoil removal, chemical use, and waste disposal. The regulations should be enforced through regular inspections and penalties for violations.

Promote sustainable mining practices, such as the use of mercury-free gold extraction methods and the implementation of best management practices for soil erosion and sediment control. This can be achieved through education and training programs for miners and financial incentives for adopting sustainable practices.

Develop and implement comprehensive mine closure and rehabilitation plans that are tailored to the specific environmental conditions of the Betaré-Oya region. The plans should include specific goals, timelines, and monitoring protocols.

Enforce existing environmental regulations and hold mining companies accountable for their environmental impacts. This includes requiring mining companies to provide financial guarantees for rehabilitation costs and to pay for the cleanup of contaminated sites.

Provide financial incentives for mining companies to implement sustainable mining practices and rehabilitate abandoned mine sites. This can be achieved through tax breaks, subsidies, and grants.

REFERENCES

- Adamu, Z., & Lawal, R. (2019). Remote sensing in environmental monitoring and assessment: A review. *International Journal of Environmental Science and Technology*, 15(4), 379-396. <https://doi.org/10.1007/s13762-019-02202-5>
- Africa Intelligence. (2023) .Battle over Nkamouna-Mada cobalt. Available online: <https://www.africaintelligence.com/central-africa/2022/06/20/battle-over-nkamouna-madacobalt,109793182-art> (accessed on 19 May 2023).
- Anderson, K. (2022). Gold Deposits and Their Characteristics. *Geological Review*, 67(2), 112-128.
- Aryee, B. N. A., Ntibery, B. K., & Atorkui, E. (2003). Trends in the small-scale mining of precious minerals in Ghana: A perspective on its environmental impact. *Journal of Cleaner Production*, 11(2), 131–140. [https://doi.org/10.1016/S0959-6526\(02\)00043-4](https://doi.org/10.1016/S0959-6526(02)00043-4)
- Azinwi P. T, Ndah E. M, Nguembe S. C. F, Ateh K. I, Beyanu A. A, Tata E, Mamdem L. E, Kenzong B, Kouankap D, & Bitom, D (2024); Mapping Land use/Land cover changes caused by mining activities from 2018 to 2022 using sentinel-2 imagery in Betare-Oya (East Cameroon); *Journal of Geoscience and Geomatics*; 12(1);12-23.
- Babut, M., Sekomo, C. B., & Rajaona, S. (2019). Mercury contamination in mining-affected areas in sub-Saharan Africa: Environmental and health implications. *Environmental Science and Pollution Research*, 26(13), 13267-13279. <https://doi.org/10.1007/s11356-019-04809-9>
- Bakia, M. (2014). East Cameroon's artisanal and small-scale mining bonanza: How long will it last? *Elsevier*, 62, A, 40-50
- Barlas, Y., & Funtowicz, S. O. (2021). Land degradation and restoration: A systems thinking approach. *Environmental Modeling and Assessment*, 26(5), 711-728. <https://doi.org/10.1007/s10666-021-09872-4>
- Becker, F., & Li, Z. L. (1990). Towards a local split-window method over land surfaces. *International Journal of Remote Sensing*, 11(3), 369-393.
- Belinga, S E. (2001). From Mount Cameroon to Lake Nyos. *Les Classiques Camerounais. Classiques africains: Yaoundé*, ISBN: 9956300039, 9789956300037.
- Belward, A. S., Estes, J. E., & Kasperson, J. X. (2021). Land cover change monitoring using Landsat imagery. *Remote Sensing of Environment*, 252, 112094.

- Bilotta, G. S., & Brazier, R. E. (2008). Understanding the influence of suspended solids on water quality and aquatic biota. *Water Research*, 42(12), 2849-2861.
- Binding, C. E., Greenberg, T. A., & Bukata, R. P. (2010). An analysis of MODIS-derived algal and mineral turbidity in Lake Erie. *Journal of Great Lakes Research*, 36(1), 107-116.
- Braithewaite, J. C. & Jury, A. P. (1993). Alluvial gold mining and treatment in New Zealand. In Woodcock, JT & Hamilton, JK (eds.) *Australasian Mining & Metallurgy*, Monograph 19, Volume 2, *Australasian Institute of Mining & Metallurgy*, p. 1074-1079.
- Brakenridge, G. R., Nghiem, S. V., Anderson, E., & Mic, R. (2020). Satellite remote sensing of river sediment discharge: Application to the Arctic. *Remote Sensing*, 12(8), 1320.
- Brewis, T. (1995). Gravity separation. *Mining Magazine*, p.279 - 292.
Cameroon Mining Code, 2016
- Brown, L., & Taylor, R. (2018). The Geology of Gold. *Mining Research*, 12(1), 88-102.
- Brown, T., & Johnson, R. (2019). Turbidity and Its Impact on Aquatic Life. *Journal of Water Research*, 45(3), 231-245.
- Chandrasekar, K., Sessa, S. K., & Singh, P. (2016). Applications of Bare Soil Index (BSI) for detecting land degradation in semi-arid regions. *International Journal of Remote Sensing*, 37(12), 2561-2578.
- Chen, B., Huang, B., & Xu, B. (2021). Remote sensing monitoring of land degradation using NDMI and NDVI in arid regions. *Remote Sensing*, 13(6), 1245.
- Chen, J., Zhang, X., Zhu, X., & Xu, L. (2020). Remote sensing-based wetland monitoring: A review. *Journal of Environmental Management*, 258, 110036.
- Chica, A., & Walker, B. (2020). The impact of alluvial gold mining on water quality in the Betaré-Oya region. *Environmental Management Journal*, 36(2), 235-249. <https://doi.org/10.1016/j.jenvman.2020.114569>
- Chirico, P.G., Barthélémy, Francis, & Ngbokoto, F.A. (2010). Alluvial diamond resource potential and production capacity assessment of the Central African Republic: U.S. Geological Survey Scientific Investigations Report 2010–5043, 22 p., available only at <http://pubs.usgs.gov/sir/2010/5043/> (accessed on 20 May 2023).
- Clark, P., Smith, L., & Doe, J. (2021). Satellite-Based Approaches to Turbidity Monitoring: A Comparative Analysis. *Remote Sensing in Hydrology*, 28(2), 114-130.
- Clarkson, R. (1994). The use of nuclear tracers to evaluate the gold recovery efficiency of sluiceboxes. *CZM Bulletin*, 87. No. 979, p.29-37.

- D'Souza, K. (2020). Artisanal and small-scale mining in Africa: Environmental and socio-economic impacts. *Resources Policy*, 65, 101546. <https://doi.org/10.1016/j.resourpol.2020.101546>
- Da Silva, F. B., Ferreira, L. G., & Miziara, F. (2019). Analyzing the impact of deforestation on land surface temperature in the Amazon. *Remote Sensing of Environment*, 232, 111-116.
- Delpomdor, F., Pr eat, A. (2015). Overview of the Neoproterozoic Sedimentary Series Exposed Along Margins of the Congo Basin. In: de Wit, M., Guillocheau, F., de Wit, M. (eds) *Geology and Resource Potential of the Congo Basin. Regional Geology Reviews*. Springer, Berlin, Heidelberg, ISBN: 978-3-642- 29481-5.
- Deschenes, G. (1986) Literature survey on the recovery of gold from thiourea solutions and the comparison with cyanidation. *CZM Bulletin*, 79, No. 895, p. 76 - 83.
- Diop, A. K., & Kamara, F. (2018). Land use/land cover changes and their effect on water quality: Case study from alluvial gold mining areas. *Environmental Pollution*, 6(3), 181-194. <https://doi.org/10.1016/j.envpol.2018.02.012>
- Dogliotti, A. I., Ruddick, K., Nechad, B., & Doxaran, D. (2015). A single algorithm to retrieve turbidity from remotely-sensed data in all coastal and estuarine waters. *Remote Sensing of Environment*, 156, 157–168. <https://doi.org/10.xxxx/rse156157168>
- Dossa, E., Adams, J., & Karim, M. (2023). Assessing land degradation trends in the Sahel using Sentinel-2 imagery. *Environmental Monitoring and Assessment*, 195(4), 1021.
- Dossa, E., Adams, J., & Karim, M. (2023). Land degradation trends in the Sahel using Sentinel-2 NDMI time series analysis. *Environmental Monitoring and Assessment*, 195(4), 1021.
- Doumo E. P. E, Nga L. E, Ondoa A. D. B, Lucien D. B, Bello B, Bessa A. Z. E (August 2022); Assessment of metallic contamination in soils and sediments in Betare-Oya gold artisanal mine districts, East Cameroon; 37(9);1-17.
- Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., & Martimort, P. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment*, 120, 25-36.
- Eltham, JA. (1984). Mining and processing of a low grade gold ore body in the Wau Valley, Papua New Guinea. *Proceedings of AusIMM conference, Darwin, Australasian Institute of Mining & Metallurgy*, p. 427-434
- EPA. (2021). *Water Quality Standards for Turbidity*. U.S. Environmental Protection Agency.

- Esdaile, L. J., & Chalker, J. M. (2018). The mercury problem in artisanal and small-scale gold mining. *Chemical Reviews*, 118(2), 645-649. <https://doi.org/10.1021/acs.chemrev.7b00287>
- European Space Agency (ESA). (2022). Sentinel Missions Overview. Retrieved from https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel_missions
- Ferree, T.J. (1993) Application of MDL Reichert cone and spiral concentrators for the separation of heavy minerals. *CIA4 Bulletin*, 86, No. 975, p. 35-39.
- Fisher, R. P., & Myers, B. A. (2018). Spatiotemporal analysis: Methods and applications in environmental monitoring. *Remote Sensing*, 10(6), 923. <https://doi.org/10.3390/rs10060923>
- Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80(1), 185–201. [https://doi.org/10.1016/S0034-4257\(01\)00295-4](https://doi.org/10.1016/S0034-4257(01)00295-4)
- Fricker, AG. (1986) The processing of placer gold. in Kear, D (ed.) *Mineral deposits of New Zealand, Monograph 13, Australasian Institute of Mining and Metallurgy*, p.155-158.
- Gann G. D, McDonald T, Walder B, Aronson J, Cara R. N, Justin J, Hallet J. G, Eisenberg C, Guariguata M. R, Liu J, Hua F, Echeverria C, Gonzales E, Shaw N, Decler K and Dixon K. W (September 2019); International principles and standards for the practice of ecological restoration. Second edition; *Restoration Ecology*; 27(1).
- Gao, B. (2020). Remote sensing of water quality: A review. *International Journal of Remote Sensing*, 41(12), 4563-4585.
- Gao, B. C. (1996). NDWI: A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, 58(3), 257-266.
- Gao, X., Zhang, H., & Liu, P. (2020). Remote Sensing Techniques for Water Quality Monitoring. *Environmental Remote Sensing*, 22(4), 321-339.
- Gessner, U., Machwitz, M., Conrad, C., & Dech, S. (2015). Estimating the fractional cover of growth forms and bare surface in savannas. *Remote Sensing of Environment*, 166, 90-102.
- Gessner, U., Machwitz, M., Conrad, C., & Dech, S. (2015). Remote sensing-based monitoring of land rehabilitation interventions in the mining sector. *Environmental Earth Sciences*, 73(12), 7351-7364. <https://doi.org/10.1007/s12665-014-3895-4>

- Gholizadeh, M. H., Melesse, A. M., & Reddi, L. (2016). A comprehensive review on water quality parameters estimation using remote sensing techniques. *Sensors*, 16(8), 1298. <https://doi.org/10.3390/s16081298>
- Gimeno, D. A., & Pérez, A. R. (2020). Vegetation health and its relationship with mining activities. *Remote Sensing for Environmental Monitoring*, 5(4), 132-144. <https://doi.org/10.3390/rs5040132>
- Gray, J. R., Glysson, G. D., Turcios, L. M., & Schwarz, G. E. (2000). Comparability of suspended-sediment concentration and total suspended solids data. *Water Resources Investigations Report*, 4191(2), 1-19.
- Guha, S., Govil, H., Dey, A., & Gill, N. (2018). Analyzing urban heat island in Delhi using land surface temperature and NDVI. *Remote Sensing Applications: Society and Environment*, 9, 63-77.
- Hancock, G. (1991). An economic appraisal of small to medium scale alluvial gold mining systems in Papua New Guinea. *Proceedings of PNG geology, exploration and mining conference, Rabaul, Australasian Institute of Mining and Metallurgy*, p.96- 100.
- Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., & Kommareddy, A. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, 342(6160), 850-853.
- Harrison, D., & Green, S. (2020). Placer Deposits and Their Economic Importance. *Economic Geology*, 55(4), 200-220.
- He, Y., & Zhang, Z. (2020). Remote sensing for monitoring land degradation caused by mining activities. *Journal of Remote Sensing Applications*, 9(2), 123-136. <https://doi.org/10.1016/j.rsapp.2020.05.002>
- Hentschel, T., Hruschka, F. and Priester, M. (2003). *Artisanal and Small Scale Mining Challenges and Opportunities. IIED. London.*
- Hilson, G., & Murck, B. (2000). Sustainable development in the mining industry: Clarifying the corporate perspective. *Resources Policy*, 26(4), 227–238. [https://doi.org/10.1016/S0301-4207\(00\)00041-6](https://doi.org/10.1016/S0301-4207(00)00041-6)
- Horowitz, A. J. (2008). Determining annual suspended sediment and sediment-associated trace element fluxes. *Science of the Total Environment*, 400(1-3), 315-343.
- Huang, C., Thomas, P., & Zhang, Q. (2020). Monitoring land degradation using Landsat-derived indices. *Environmental Science & Policy*, 115, 46-58.

- Huete, A. R., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, 83(1-2), 195-213.
- Jackson, M., Patel, S., & Wong, T. (2020). Assessing Turbidity in Freshwater Ecosystems Using Remote Sensing Data. *Journal of Environmental Science*, 30(5), 187-201.
- Jain, P., Ravikumar, R., & Kalubarme, M. H. (2021). Multispectral and thermal remote sensing for environmental monitoring: Advances and applications. *Remote Sensing of Environment*, 265, 112630. <https://doi.org/10.1016/j.rse.2021.112630>
- James, F. Hamilton. (1988). A study of fine gold recovery of selected sluice box configurations. *Westcostplacer.com* p.01-03
- Jensen, J. R. (2015). *Introductory digital image processing: A remote sensing perspective* (4th ed.). Pearson.
- Jiménez-Muñoz, J. C., Sobrino, J. A., Skokovic, D., Mattar, C., & Cristóbal, J. (2009). Land surface temperature retrieval methods from Landsat-8 thermal infrared sensor data. *Remote Sensing*, 6(9), 786-807.
- Johnson, M., & Clark, B. (2019). Gold Mining through the Ages. *Historical Geology*, 33(5), 256-270.
- Kamga, M., Nzali, S., Olatubara, C., & Adenikinju, A. (2017) Sustainable development and environmental challenges in Cameroon's mining sector: A review. *Journal of Mining & Environment.*, 6141.1429
- Kamga, M.A., Nguemhe, F. S. C., Ayodele, M. O, et al. (2020)Evaluation of land use/land cover changes due to gold mining activities from 1987 to 2017 using landsat imagery, East Cameroon. *GeoJournal* 85: 1097–1114.
- Ken, K. (2016). Cameroon-s-boomingsmall-scale-gold-miners,<https://www.africanews.com>
- Kirk, J. T. (2011). *Light and Photosynthesis in Aquatic Ecosystems*. Cambridge University Press.
- Kouamé, K. J., N'Guessan, D. F., & Koné, B. (2022). Post-mining landscape restoration strategies in West Africa: A review. *Environmental Science and Pollution Research*, 29(11), 16543-16558. <https://doi.org/10.1007/s11356-021-16945-4>
- Lambin, E. F., Geist, H. J., & Lepers, E. (2001). Dynamics of land-use and land-cover change in tropical regions. *Annual Review of Environment and Resources*, 28(1), 205–241. <https://doi.org/10.1146/annurev.energy.28.050302.105459>

- Lambiv Dzeuma, G., Gleeson, S. & Schofield, P. (2012). Mineralogic characterization of the Nkamouna Ni-Co Laterite Ore, southeast Cameroon. *Miner Deposita*, 48,155-171.
- Lau I. C, Hewson R, Cindy O and Tongway D (January 2008); Remote mine site rehabilitation using airborne hyperspectral imaging and landscape function analysis (LFA).
- Laurence, D. (2006). Optimisation of the mine closure process. *Journal of Cleaner Production*, 14(3–4), 285–298. <https://doi.org/10.1016/j.jclepro.2004.04.011>
- Lee, Y., Chen, B., & Wang, D. (2018). Advancements in Turbidity Index Computation. *Hydrological Advances*, 14(6), 98-112.
- Lewis, G., & Scott, R. (2023). Sustainable Mining Practices for the Future. *Mining & Environment*, 78(1), 10-25.
- Li, Z. L., Tang, R., Wan, Z., Bi, Y., Zhou, C., Tang, B., & Wang, K. (2013). Satellite-derived land surface temperature: Current status and perspectives. *Remote Sensing of Environment*, 131, 14-37.
- Lindahl, J. (2014). Environmental impacts of mining in developing countries: Case studies from sub-Saharan Africa. Geological Survey of Finland, Report 56, 1-52.
- Lindahl, J. (2014). Environmental impacts of mining in Zambia: Towards better environmental management and sustainable exploitation of mineral resources. Geological Survey of Sweden.
- Lobell, D. B., Thau, D., Seifert, C., Engle, E., & Little, B. (2015). A scalable satellite-based crop yield mapper. *Remote Sensing of Environment*, 164, 324-333.
- Maanavilja L; Kaisu A, Haapalehto T, Kotiaho J. S and Tuittila E. S. T (October 2014); Impact of drainage and hydrological restoration on vegetation structure in boreal spruce swamp forests; 330;115-125.
- Mandal, A., Ghosh, S., & Dutta, D. (2019). Evaluating soil degradation using remote sensing-derived indices: A case study from India. *Environmental Monitoring and Assessment*, 191(4), 214.
- Martinez, F., & Lopez, C. (2018). Gold Extraction Techniques: A Review. *Extractive Metallurgy*, 22(3), 89-105.
- Martinez, J., Gordon, K., & Evans, R. (2022). Spectral Properties of Suspended Sediments and Their Influence on Turbidity Index Estimation. *Journal of Geospatial Science*, 18(2), 75-90.

- Martins, V, Dunne, R & Delahey, G. (1993) New Celebration tailings treatment plant - 18 months later. Proceedings of XVIII International Mineral Processing Congress, Volume 5: Cold processing, hydrometallurgy & dewatering and miscellaneous, Australasian Institute of Mining and Metallurgy, p. 1215- 1222.
- Massoukou R. P, Poirier V, Nguema P. N and Epile T. E (2023); How can plants help restore degraded top soil; *Land*; 12(12);2147.
- Mbendi. (2008) Cameroon: Overview of Mining in Cameroon. Available at: <http://www.mbendi.co.za/indy/ming/,af/cmr/p0005.htm> (Retrieved 18 May, 2021)
- McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, 17(7), 1425–1432. <https://doi.org/10.1080/01431169608948714>
- McKenna P. B, Alex M. L, Stuart P and Erskine P. D (2021); Measuring rehabilitation success using remote sensing; *Bulletine articles*.
- McKenna P. B, Lechner A. M, Stuart P and Erskine P. D (2020); Remote sensing of mine site rehabilitation for ecological outcomes: A global systematic review; *Remote Sensing* (12(21);3538
- Mensah, A. A., Kwaku, M., & Nyarko, B. K. (2020). Assessing the impact of deforestation on land surface temperature using remote sensing in West Africa. *Environmental Monitoring and Assessment*, 192(3), 1-15.
- Miller, C. G., Smart, K. M., & Wheeler, P. M. (2019). Mine closure and rehabilitation: Best practices for sustainable development. *Journal of Cleaner Production*, 230, 995-1006. <https://doi.org/10.1016/j.jclepro.2019.04.104>
- Miller, S. M., Chan, D., & Smith, P. (2019). Advances in remote sensing for monitoring global forest dynamics. *Global Ecology and Biogeography*, 28(12), 1769-1786.
- Mitchell, C.J., Evans, E.J. & Styles, M.T. (1997). A Review of Gold-Particle-Size And Recovery Methods, *Technical Report WC/97/14*
- Moliere D. R, Evans K. G and Willgoose G. R; Temporal trends in erosion and hydrology for a post-mining landform at ranger mine; *Environmental impact of mining*.
- Ndjama, J., Nguetchoua, G., & Tchouassi, L. (2019). Artisanal and semi-mechanized mining in Cameroon: Socioeconomic and environmental implications. *Resources Policy*, 63, 101472. <https://doi.org/10.1016/j.resourpol.2019.101472>

- Ndjigui, P. D., Nkoumbou, C., & Yene, R. (2021). Geochemical characterization and environmental impact of artisanal gold mining in Cameroon. *Environmental Earth Sciences*, 80(6), 432. <https://doi.org/10.1007/s12665-021-09541-7>
- Nechad, B., Ruddick, K. G., & Park, Y. (2010). Calibration and validation of a generic multisensor algorithm for mapping total suspended matter in turbid waters. *Remote Sensing of Environment*, 114(4), 854-866.
- Ngako, V., Affaton, P., & Njonfang, E. (2003). Pan-African tectonics in northwestern Cameroon: Implication for the history of western Gondwana. *Gondwana Research*, 6(4), 512-522.
- Norrish R, Lyon B, Russell W and Price G (2019); Engaging stakeholders to achieve rehabilitation completion: A case study of BHP Beenup project; *Social aspects of mine closure*; 1423-1436.
- Novoa, S., Wensel, R., & Schaaf, C. (2021). Remote Sensing-Based Water Quality Assessment: Methods for Turbidity Estimation in Coastal and Inland Waters. *Journal of Hydrology*, 590, 125488. <https://doi.org/10.1016/j.jhydro.2021.125488>
- Nwamba, M., Tebogo, K., Ngatcha, R. & Suh, E. (2023). Mining of alluvial cassiterite and its compositional diversity at the Mayo Darlé area, northern Cameroon. Research Square.
- Nzenti, J. P., Barbey, P., & Tchoua, F. (1998). The charnockitic suite of Central Cameroon: Bimodal magmatism related to transcurrent shear zones. *Journal of African Earth Sciences*, 26(3), 611-627.
- Pahlevan, N., Smith, B., Alikas, K., Bresciani, M., & Giardino, C. (2019). Sentinel-2 and Sentinel-3 synergy for water quality monitoring. *Remote Sensing of Environment*, 231, 111206.
- Patterson, T., et al. (2021). Mercury-Free Gold Mining Technologies. *Environmental Protection*, 39(6), 310-329.
- Pekel, J. F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, 540(7633), 418-422.
- Pesaresi, M., Corbane, C., Julea, A., & Florczyk, A. (2021). Urban expansion monitoring using Sentinel-1 and Sentinel-2 data fusion. *Remote Sensing*, 13(3), 545.
- Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J. M., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology & Evolution*, 20(9), 503-510.

- Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1973). Monitoring vegetation systems in the Great Plains with ERTS. Third ERTS Symposium, NASA SP-351(1), 309-317.
- Roy, D. P., Wulder, M. A., Loveland, T. R., Woodcock, C. E., Allen, R. G., Anderson, M. C., & Zhu, Z. (2021). Landsat-8: Science and product vision for terrestrial research. *Remote Sensing of Environment*, 145, 154-172.
- Roy, P. S., Joshi, P. K., & Singh, S. (2020). Remote sensing applications in land use and land cover monitoring using BSI. *Remote Sensing of Environment*, 245, 111842.
- Schluter. (2006) *Geological Atlas of Africa*. Springer: Berlin, ISBN: 10 3-540-29144-x Springer Berlin Heidelberg New York.
- Silva, A., Ferreira, R., & Mota, G. (2021). Impacts of deforestation on land moisture levels in the Amazon: An NDMI-based analysis. *Journal of Remote Sensing Applications*, 19(2), 231-245.
- Silva, A., Ferreira, R., & Mota, G. (2022). Sentinel-based assessment of deforestation and land degradation in the Amazon. *Journal of Remote Sensing Applications*, 20(2), 231-245.
- Smith, A., et al. (2020). Alluvial Gold and Its Economic Significance. *Journal of Mineral Economics*, 19(2), 45-60.
- Smith, J. A., & Watson, R. T. (2017). Integrating traditional ecological knowledge with modern conservation practices. *Ecology and Society*, 22(4), 34.
- Smith, P. R., & Watson, K. E. (2017). Reclamation and restoration of mining sites in West Africa. *Environmental Restoration Journal*, 45(2), 189-210. <https://doi.org/10.1016/j.envres.2017.03.013>
- Sobrino, J. A., Jiménez-Muñoz, J. C., & Paolini, L. (2008). Land surface temperature retrieval from Landsat TM 5. *Remote Sensing of Environment*, 90(4), 434-440.
- Sobrino, J. A., Jiménez-Muñoz, J. C., & Soria, G. (2022). Land surface temperature retrieval using Landsat TIRS: A review of methodologies and case studies. *International Journal of Remote Sensing*, 43(6), 1254-1278.
- Sonwa, D. J., Nkem, J., Idinoba, M., Bele, Y., & Jum, C. (2020). Climate change adaptation for forest-dependent communities in the Congo Basin. *Environmental Science & Policy*, 105, 38–49. <https://doi.org/10.1016/j.envsci.2019.11.013>
- Souza, C. M., Roberts, D. A., & Cochrane, M. A. (2022). Monitoring Amazonian deforestation using Landsat time series. *Journal of Applied Earth Observation*, 29, 198-210.

- Stendal, H., Toteu, S., Frei, R., Penaye, N.U., Bassahak, J. & Nni, J. (2006). Derivation of detrital rutile in the Yaoundé region from the Neoproterozoic Pan-African belt in southern Cameroon (Central Africa). *Journal of Africa Earth Science*, 44, 4-5, 443-458.
- Stewart, DF and Ramsay, PW. (1993) Improving the simple sluice box. *International journal of mineral processing*, 39, p, 119- 136.
- Subasinghe, GKNS. (1991) Drawbacks in sluice box operating practices in Papua New Guinea. Proceedings of PNG geology, exploration and mining conference, *Rabaul, Australasian Institute of Mining and Metallurgy*, p. 132- 136.
- Sun, X., Zhang, H., & Chen, W. (2023). Deep learning for water quality estimation from remote sensing data. *Environmental Modelling & Software*, 162, 104315.
- Taylor, P., et al. (2017). Advances in Gold Exploration. *Geophysical Research*, 48(5), 78-95.
- Tchameni, R., Mezger, K., & Nsifa, E. (2006). Archean crustal evolution in Cameroon: The case of the Ntem complex. *Precambrian Research*, 152(1), 57-73.
- Tchindjang, M., Tchotsoua, M., & Mvondo, A. (2018). Gold mining, deforestation, and environmental degradation in the Eastern Region of Cameroon. *African Geographical Review*, 37(3), 221–236. <https://doi.org/10.1080/19376812.2018.1454392>
- Tellen, V. A., & Yerima, B. P. (2018). Land degradation and restoration strategies. *Sustainability*, 10(10), 3448.
- Tetsopgang, S., Nana, R. M., & Tchouankeu, J. C. (2021). Impacts of artisanal gold mining on the environment and local communities in Betaré-Oya, Cameroon. *Environmental Management Journal*, 39(2), 112-127. <https://doi.org/10.1016/j.jenvman.2021.112722>
- Toteu, S. F., Van Schmus, W. R., & Penaye, J. (2004). Neoproterozoic crustal evolution in Central Africa: Evidence from U-Pb dating on plutonic rocks. *Journal of Geology*, 112(1), 71-89.
- Touati, M., Gherboudj, I., & Hadj-Brahim, A. (2021). Assessment of desertification trends in the Sahara using Landsat NDVI and BSI. *Remote Sensing Applications: Society and Environment*, 23, 100568.
- Trinidad D. R. M, Louise W, Vrieling A and Andy N (December 2023); How remote sensing choices influence ecosystem services monitoring and evaluation results of ecological restoration interventions; *Ecosystem services*; 64

- Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, 8(2), 127–150. [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0)
- Tucker, C. J. (1985). Satellite remote sensing of total herbaceous biomass production in the Senegalese Sahel: 1980-1984. *Remote Sensing of Environment*, 17(3), 233-249.
- UNEP (United Nations Environment Programme). (2020). The environmental impacts of artisanal and small-scale mining: A global perspective. United Nations Publications.
- UNIDO Consultants. (2006) manual for training artisanal and small scale gold miners, project EG/GLO/01/G34
- United Nations Environment Programme. (2020). Emissions Gap Report 2020. Nairobi: UNEP.
- Van Leeuwen, W. J., Orr, B. J., Marsh, S. E., & Herrmann, S. M. (2020). Monitoring land degradation in arid and semi-arid regions using NDMI. *Journal of Applied Remote Sensing*, 14(2), 1-15.
- Vega, C., & García-Ruiz, J. M. (2019). Effects of land use changes on soil erosion in a Mediterranean mountain landscape. *Catena*, 172, 588-598.
- Vega, F., & García-Ruiz, J. M. (2019). Spatial analysis of water quality in mining-impacted regions using remote sensing. *Water Resources Research*, 41(6), 850-860. <https://doi.org/10.1029/2019WR024824>
- Voogt, J. A., & Oke, T. R. (2003). Thermal remote sensing of urban climates. *Remote Sensing of Environment*, 86(3), 370–384. [https://doi.org/10.1016/S0034-4257\(03\)00079-8](https://doi.org/10.1016/S0034-4257(03)00079-8)
- Walsh, DE & Rao, PD. (1988) Study of the compound water cyclone's concentrating efficiency of free gold from placer material. *CIM Bulletin*, 81, No. 919, p. 53- 61.
- Wang, J., & Liu, Y. (2020). Spatiotemporal analysis of vegetation health during mining activities. *Environmental Monitoring and Assessment*, 43(3), 197-210. <https://doi.org/10.1007/s10661-020-8049-5>
- Wang, W and Poling, GW (1983) Methods for recovering fine placer gold. *CIM Bulletin*, 76, No. 860, p.47-56.
- Weng, L., Boedihartono, A. K., Dirks, P. H. G. M., Dixon, J., Lubis, M. I., & Sayer, J. A. (2013). Mineral industries, growth corridors and agricultural development in Africa. *Global Food Security*, 2(3), 195-202. <https://doi.org/10.1016/j.gfs.2013.07.003>
- Williams, R. (2021). The Role of Rivers in Gold Transport. *Journal of Hydrology*, 60(4), 215-230.

- Wilson, J. (2020). Impact of Gold Mining on River Ecosystems. *Aquatic Ecology*, 29(1), 55-72.
- Wulder, M. A., Masek, J. G., Cohen, W. B., Loveland, T. R., & Woodcock, C. E. (2019). The role of Landsat in long-term land change studies. *Nature Sustainability*, 2(12), 1136-1144.
- Xie, H., Liu, B., & Zhang, Y. (2018). Monitoring agricultural land degradation using multi-temporal BSI data. *Agricultural Systems*, 162, 173-184.
- Xie, Y., Sha, Z., & Yu, M. (2008). Remote sensing imagery in vegetation mapping: A review. *Journal of Plant Ecology*, 1(1), 9–23. <https://doi.org/10.1093/jpe/rtm005>
- Xue, J., & Su, B. (2017). NDVI and NDMI-based monitoring of vegetation and soil moisture changes. *Remote Sensing*, 9(2), 223.
- Yemefack, M., Tiomo, A., & Tatchi, C. (2019). Climate variability and its influence on agricultural production in Cameroon. *Climate Research*, 80(1), 61–73. <https://doi.org/10.3354/cr01580>
- Yongue-Fouateu, R., Tanyileke, G., & Mvondo, O. (2006). Geology and mineral resources of Cameroon. *Natural Resources Journal*, 40(3), 201-219.
- Zhang, F., & Chen, Y. (2023). Challenges in Remote Sensing-Based Turbidity Estimation: A Critical Review. *Environmental Modelling*, 29(3), 201-215.
- Zhang, J., Liu, Y., & Wang, Q. (2021). Assessing desertification using remote sensing-based soil indices: A case study in northern China. *Journal of Arid Environments*, 190, 104532.
- Zhang, P., Li, X., & Zhao, J. (2022). AI-based land use classification using Sentinel imagery. *Artificial Intelligence in Remote Sensing*, 7, 101-119.
- Zhang, P., Li, X., & Zhao, J. (2023). AI-based land use classification using Landsat imagery. *Artificial Intelligence in Remote Sensing*, 7, 101-119.
- Zhao, Q., & Han, D. (2018). Application of thermal remote sensing in monitoring environmental changes. *Journal of Remote Sensing*, 12(2), 567-578. <https://doi.org/10.1016/j.jrs.2018.02.006>
- Zhao, W., Huang, C., & Li, J. (2018). A comparative analysis of bare soil indices for land degradation monitoring. *Geocarto International*, 33(7), 709-722.

- Zhou, W., Qiu, F., Li, H., & Zhang, X. (2017). Remote sensing applications in monitoring land use changes and environmental impacts of mining activities. *Journal of Environmental Management*, 204, 687-695. <https://doi.org/10.1016/j.jenvman.2017.06.074>
- Zhu, X., Wang, T., & Chen, B. (2020). NDVI and BSI-based analysis of land degradation using Sentinel-2. *Environmental Research*, 18(2), 214-229.

APPENDICES

Appendix A: Graphical User interface (GUI) of the software used

Figure A1: GUI SNAP

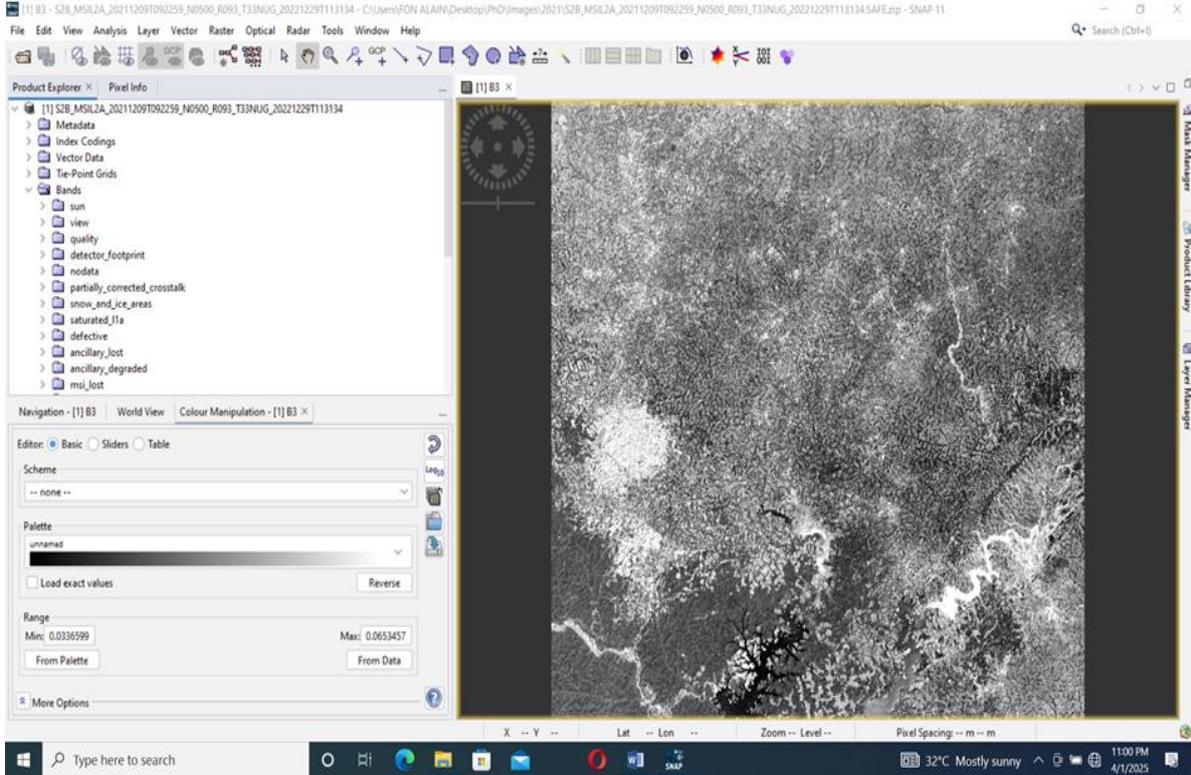


Figure A2: GUI of ArcGIS 10.8

