Masters Program in Geospatial Technologies

AN INTEGRATED GI APPROACH FOR SPATIO-TEMPORAL MONITORING AND MAPPING ENVIRONMENTAL RISKS UNDER IMPACT OF MINES EXTRACTION

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An Integrated GI Approach for Spatiotemporal Monitoring and Mapping Environmental Risks under Impacts of Mining Extraction

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DECLARATION OF ORIGINALITY

I declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged and all the sources (published or not published) are referenced.

This work has not been previously evaluated or submitted to IFGI or elsewhere.

Munster, Germany, 26-02-2024

Boubacar Diallo

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TITLE

An Integrated GI Approach for Spatiotemporal Monitoring and Mapping Environmental Risks under Impacts of Mining Extraction

ABSTRACT

This thesis evaluates the environmental risks of mining activities in Boke Province, Guinea, using An Integrated GI Approach combining Geographic Information Systems (GIS) and remote sensing technology. The study includes neighboring municipalities, particularly those near the Sangaredji site (Dara Magnaki and Missira belonging to Telimele) in the study area, in order to provide an accurate representation of the province's environmental dynamics. The study uses a combination of remote sensing data and GIS spatial analysis to track changes in land cover and use from 1987 to 2023. Advanced remote sensing tools, including the Normalized Difference Vegetation Index (NDVI), Fractional Vegetation Cover (FVC), and Enhanced Vegetation Index (EVI), Combined Spectral Response Index (CSRI), are used to monitor changes in vegetation health, coverage and landscape fragmentation over time. Nitrogen dioxide-based air quality monitoring is also used to assess the atmospheric effects of mining operations. The methodology includes the creation of a Mining Area Evolution Map as well as a land use and land cover prediction map using the Artificial Neural Network (ANN), which provide predictive insights into future environmental trends. This integration provided a multifaceted perspective on mines extraction's impacts on the environment, which is critical for informed policymaking and sustainable mining practices.

Sustainable Development Goals (SGD):

KEYWORDS

GI approach, GIS, Remote sensing.

NDVI, EVI, FVC, Air quality, NO_2, Boke.

Mining extraction, LULC, Change detection.

Environmental risks, Boke province

Spatio-temporal, mapping, impacts.

Decision making, sustainable practices.

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Chapter I: Introduction

1.Motivation

The integration of Geographic Information Systems (GIS) with remote sensing technology has transformed environmental monitoring and management, particularly in industrial sectors such as mining. These technologies provide a dynamic and comprehensive approach to recognizing and managing the environmental issues raised by such activities. This thesis focuses on using an integrated GI approach for spatiotemporal monitoring and mapping of mining impacts in Boke Province in Guinea. This province, very rich in natural resources, has experienced significant impacts on the environment as a result of massive mining operations, emphasizing the importance of a detailed and proactive environmental management strategy. The expansion of the mining activities outside of the borders of Boke province specially the mining site of Sangaredji (East) brought to be interested in the two neighbor municipalities of the province of Telimele which Missira and Daramagnaki where there is an important part of mining activites of the CBG (companie des bauxites de Guinée/ Guinea bauxites company) and add them to our study area. GIS and remote sensing are essential in environmental science, offering tools for efficient monitoring, analysis, and visualization of ecological changes. Over the past decades, there has been notable technological progress in their development, resulting in enhanced precision and resolution of spatial data. These technologies facilitate the acquisition, retention, manipulation, and examination of geographic data, providing a comprehensive outlook on environmental matters. Remote sensing, utilizing satellite and airborne sensors, offers a comprehensive perspective of the earth's surface, enabling the monitoring of extensive regions over extended periods. The deployment of remote sensing techniques, especially Landsat imagery analysis has emerged as a robust tool to understand and monitor these changes overtime (Olorade et al., 2008). This feature is especially advantageous in regions with difficult accessibility or in situations that demand constant surveillance. GIS enhances these findings by enabling the incorporation of diverse data sets, such as socio-economic and demographic information, thereby providing a comprehensive perspective on the environmental consequences of mining. Guinea has substantial mineral resources, making its mining sector a vital contributor to the national economy. Guinea ranks among the world's top bauxite producers and has substantial reserves of high-grade iron ore, bauxite, gold and diamonds, attracting international investment and promoting related industries such as transportation, energy and construction. Bauxite deposits are present in several regions across the world. Guinea possesses the greatest bauxite reserves in the globe, reaching an outstanding quantity of 7.4 billion dry tons. The bauxite reserves in Guinea exceed the 5.1 billion dry tons in Australia, currently the world's biggest producer of bauxite (U.S. Geological Survey, 2021). However, mining activities pose environmental risks such as deforestation, water pollution, land degradation and habitat destruction. Mining activities have resulted in enduring alterations to the land surface and the hydrological cycle. Reliable information regarding vegetation structure is crucial for evaluating the impact of mining activities on ecosystems in mining regions (Zhang, Y., et al., 2016). Multiple studies have pointed out the detrimental ecological effects of mining operations worldwide, especially in tropical regions where deforestation is the primary concern. Assessing the change of forest cover resulting from mining and other human activities is essential for understanding the loss of natural ecosystems, the decline in biodiversity, and other ecological impacts, thereby, forming an important field of study within both environmental science and policy (Misra, S.K., et al., 2022).

The changing patterns of land use and cover in mining areas have direct implications on environmental sustainability and local communities' livelihoods (Olorade et al., 2008). The mining sector, especially coal mining poses significant environmental challenges that necessitate rigorous monitoring and assessment (Saini et al., 2016). The analyzes of spatial information, identifying environmental impacts, and involving communities, can promote responsible mining that balances economic growth with environmental protection and community well-being. Mining is an important sector in the world economy, producing raw minerals for a variety of businesses. However, its environmental effects are significant and varied, extending from the local to the global level. These impacts include, but are not limited to, land degradation caused by the removal of soil and vegetation, water pollution caused by the discharge of hazardous materials, air pollution caused by the release of particulate matter, and habitat destruction, which leads to biodiversity loss. As to the Regional directorate of forest environment in Boke, during a period of 62 years, the industry has deforested a total of 5,099 hectares of land, out of which about 3,218 hectares were areas of forest. Additionally, it has resulted in the devastation of a wide range of land through establishing access roads into dense forests (Sididki, S., 2019). The inclusive development international reported that 13 villages in Boke have lost their agricultural lands, resulting in a considerable drop in their income and quality of life, as well as limited access to water resources, which have been polluted, among other negative impacts with serious situation especially for the residents of Hamdallaye village, who have been informed by the CBG that they would be relocated without their consent to a former mining site that has not been fully rehabilitated (I. D.I, 2019).

The difficulty is to manage these problems while maintaining mining's economic benefits. This is especially important in developing nations, where mining may be both a major economic driver and a source of significant environmental damage. The worldwide mining industry is increasingly being scrutinized for its environmental standards, with a greater emphasis on sustainable mining. This includes developing strategies and regulations to reduce the environmental impact of mining activities while ensuring the long-term viability of natural resources. Boke is an ecologically and economically significant province due to its enormous bauxite reserves, which are the principal mineral used in aluminum manufacturing. The recent increase in mining activity in the region has brought prosperity, but it has also presented several environmental and social challenges. These challenges include deforestation, soil erosion, water contamination, air pollution, and local community disruption. Bauxite mining does not necessitate the construction of tunnels, unlike gold mining or the extraction of other mineral ores. Nevertheless, it necessitates the use of substantial excavation machinery and releases enormous amounts of dust, that pollutes the air in the surrounding areas (Sidiki, S., 2019). The region's unique biodiversity, which includes a variety of endemic species, is also under threat as mining operations increase. Boke Province's environmental governance needs to find a delicate balance between economic expansion and ecological conservation. This needs a detailed understanding of the environmental consequences, which can be effectively accomplished via an integrated GI approach. However, current research on the region is limited, with many studies providing a broad perspective rather than a specific, focused research. A comprehensive study on Boke Province is essential to establishing targeted environmental management strategy and influencing policy decisions at both local and national levels.

3. Objectives

The objective of this study, firstly is to analyze the spatial distribution of mining sites in Boke province, the spatial patterns of mining activities in the province, and to assess the environmental impacts associated with mining activities. Additionally, mapping the locations of mining sites and assessing environmental impacts, this study aims to contribute to the responsible management of Guinea's mining industry. Boke, with its rich mineral resources, is an ideal research area to understand the spatial aspects of mining. The province's diverse mining sectors, including bauxite and iron ore, provide an opportunity to consider the environmental risks and challenges associated with different types of mining operations. By conducting a comprehensive spatial analysis, the study will provide valuable information to stakeholders involved in the mining sector, including policy makers, government agencies, public mining companies and local communities, to help them make informed decisions, promote sustainable practices in Guinea's mining industry. Overall, this research aims to contribute to the sustainable development of the mining industry in Guinea by performing spatial analysis, including mapping, environmental risk assessment, and identification of facilities association for sustainable activities in increase. The integration of a Geospatial approach and remote sensing technology in this study provides valuable information and recommendations to guide the management of Guinea's mining industry and ensure a balance between development economy and environmental protection. The implementation of these practices can help Guinea to achieve a mining industry that balances economic viability with environmental responsibility, benefiting communities and preserving its natural heritage. Overall, this study aims to provide a comprehensive understanding of the spatial dimensions, environmental impacts and sustainable development potential of Guinea's mining industry. Therefore, by addressing these research goals, we can contribute to informed decision-making processes, support responsible mining practices, and guide the development of policies that promote sustainable mining in Guinea. Finally, the main objective of this study is to monitor and map the spatiotemporal impacts of mining activities in Boke province using GIS and remote sensing techniques. This includes assessing the extent of land cover change, assessing impacts on vegetation, and developing predictive models for future environmental impacts.

2. Research questions

Our study seeks to answer the following questions:

- What specific environmental risks are posed by intensive mining activities in Boke?
- How can GIS and remote sensing be utilized to monitor land cover changes resulting from mining activities in Boke?
- In what ways do Geospatial technologies help in assessing the impact of mining activities on local vegetation and air quality in the province?
- How can spatial analysis predict future environmental conditions and inform sustainable mining practices in Guinea?
- How can geospatial technologies including spatial analysis, GIS and remote sensing can be used to inform the development of sustainable mining practices, environmental management strategies, and policy-making of the spatial analysis of Boke mining to support the goals of using GI-based evaluations and remote sensing technology, and policy-making that balance economic growth together with environmental protection and community well-being?

These questions include assessing the extent and nature of land cover changes due to mining activities, identifying impacts on local vegetation, air pollution, and predicting future environmental scenarios based on current trends.
To answer this question, we will be interested in the use of Geospatial technologies like GIS and remote sensing to aiding Guinea's mining industry by providing valuable data for sustainable mining practices, environmental management, and policy-making. This study also aims to investigate the socio-economic impacts of these environmental changes, thereby providing a holistic view of the impacts of mining in Boke province. The integration of remote sensing and GIS enables multi-layered analysis that combines spatial and temporal data to provide a detailed and dynamic understanding of the environmental impacts of mining.

4. Methodology

In this study we use an integrated GI approach for spatiotemporal monitoring and mapping environmental risks under impacts of mining extraction, combining remote sensing and GIS technology. Satellite images will be analyzed to measure changes in land cover and land use patterns over time, offering a temporal perspective on the environmental effects of mining. The Landsat series from 1987 to 2023 and sentinel-5P especially for the air quality monitoring in 2018, 2020 and 2023. This will be supplemented by GIS-based spatial analysis, which will combine a variety of data sources, including environmental data etc..., to provide a more complete understanding of the effects. The study will also use predictive modeling techniques for predicting future conditions based on distinct mining activity trends. Our thesis is organized in six (6) chapters.

Chapter II: Literature review

The Environmental impact of mines will be one part of the literature review that will focus on the review of studies investigating the environmental impacts of mining activities, particularly in the context of developing countries and Guinea with similar mineral-rich environments. This research interests include deforestation due to mining activities, soil degradation due to mining activities, air pollution due to dust from mining activities, deforestation and biodiversity loss due to habitat destruction. This review highlights the importance of sustainable mining practices to minimize these impacts.
The application of GIS technology in environmental assessment and sustainable development in the mining sector is another part of our literature review. The discussion focuses on the use of GIS for spatial analysis, data integration, and visualization, highlighting the potential of GI-based techniques in identifying environmental hazards, mapping hotspots, and supporting decision-making processes. A study conducted by Olorade et al. used remote sensing techniques, particularly analysis of Landsat imagery, to map land use/cover and detect changes in the Rustenburg mining area. The methods used in this study focused on assessing and monitoring spatial patterns and dynamics of land use over time (Olorade et al., 2008). Gammage et al. conducted a study focused on improving government revenues in the mining sector through digitization. This paper proposes strategies and implications for using digital technologies for revenue collection in mining sector (Gammage et al., 2020). Wu et al. used remote sensing techniques to detect spatio-temporal changes in an open-pit mining area in Changting County, southeastern China. The methods used in the study aimed to analyze and monitor patterns of mining activity evolving over

time (Wu et al., 2019). This review also describes related research using GIS for mine-related environmental assessments, providing insight into methodologies and best practices. A study conducted by Xifengru et al. included a discussion-based approach to exploring ecology and sustainable development in the mining industry. This paper provides insight and discussion on these issues (Xifengru et al., 2011). Conducted by Feng Yu and Li Zheng, the research focused on the economic transformation of mining in Northwest China based on ecological sustainable development, used research-based approach (Yu and Zheng, 2010). This study conducted by L. Guiming, L. Cheng, W. Honzhi, W. using Pingdingshan City as a case study, focused on the ecological restoration of submerged areas in mining areas using site theory. Methods used in his study included site theory analysis to guide ecological restoration processes (Guiming et al., 2009). Shome and Manekar discussed the establishment of a green corridor to reduce pollution in the Dongri Buzurg opencast mine. The paper highlights innovative methods to mitigating mining's environmental implications, with a focus on green infrastructure in industrial areas (Shome, D., et al., 2018). Yinfei Cai, Huayang Dai, and Yixin Liu explored the visual classification of preserved entities impacted by mining operations. This research holds great importance in the realm of protecting cultural and natural heritage in mining areas, using technical tools to encourage conservation initiatives (Cai, Y., 2011). The study conducted by Lin, Wang, and Xiao provides a perceptive analysis of the changes in vegetation surrounding the Zijinshan Gold and Copper Mine in China from 1992 to 2017, applying Landsat data. The main focus is on the Normalized Difference Vegetation Index (NDVI) to assess environmental change in the mining area (Lin, M., et al., 2019). Baodong, Lixin, and Shanjun's paper introduces a method for monitoring vegetation changes and desertification in mining areas using SPOT Vegetation (VGT) NDVI data. The method classifies vegetation variation into seven levels and desertification land into five levels based on vegetation coverage, which was successfully applied to the Ningdong coal mining area (Baodong, M., et al., 2009). The research conducted by Yuxia Zhao et al. (2023) examines the impact of open-pit mining on landscape patterns and ecological conditions in the Heidaigou Mining Area, China, using remote sensing data acquisition. The study uses NDVI analysis to evaluate the health and extent of vegetation, and calculates the Remote Sensing Ecological Index (RSEI) to assess the ecological condition of the area. Statistical analysis is employed to understand the outcomes and discern patterns. An examination of different years (2006, 2011, 2016, and 2021) allows for a comparison of how landscape patterns and ecological quality have changed mining operations (Zhao, Y., et al., 2023). In their study, Lin et al. (2019) employed the NDVI index to examine vegetation variation in the vicinity of the Zijinshan Gold and Copper Mine. Their research provided valuable insights into the ecological consequences of mining operations on the health of the vegetation.

Bakhtiar Feizizadeh, et al. (2022) analyzed the risks of soil salinity and degradation in relation to the environmental challenges posed by the Urmia Lake Drought by using integrated geoinformatics techniques. Contributing to the corpus of knowledge on post-mining land rehabilitation, Zhang Yao and Zhou Wei (2016) investigated the relationship between vegetation recovery and various vegetation indices in reclaimed forest areas of the Pingshuo mining region. Utilizing MODIS data, Lijuan Cheng and Lin Sun (2010) examined techniques for inverting the chlorophyll content in vegetation residing in coal mining regions, thereby establishing a remote sensing method for evaluating the health of vegetation in disturbed landscapes. Fangzhou Hong et al. (2023) utilized multi-source remote sensing data to monitor vegetation and land cover changes in the Juhengzhang region, thereby contributing to the methodologies for assessing environmental changes caused by mining activities.

Chapter III: Data and Methods

In this section we will give a presentation of the study area, the data and the methods used in this study.

1- Study Area

Our study area is the Boke, a province located in the northwestern part of Guinea, which is a significant province renowned for its important bauxite mining industry. The region's strategic location at 10°56' North latitude and 14°18' West longitude has placed it at the forefront of Guinea's mining sector, particularly in the extraction of bauxite, the primary ore used in aluminum production. The abundance of bauxite has attracted considerable international investment, leading to the establishment of expansive mining operations in the region. The development of these mining activities has been accompanied by significant infrastructural growth, particularly in transportation and energy. New roads and railways have been constructed to facilitate the efficient transport of bauxite from the mines to processing facilities and export ports, boosting both the local and national economy. However, the rapid development in Boke has also brought challenges, particularly in terms of environmental impact and sustainable community growth. The increase in population due to the influx of workers and the expansion of towns near mining sites has created a dynamic yet complex social environment. In essence, Boke, with its strategic geographic coordinates, stands as a crucial component of Guinea's economic framework, playing a pivotal role in the extraction and global trade of bauxite. While it is a key driver of economic growth, it also faces the challenges of balancing development with environmental risks and community welfare due to mining operations. In summary, Boke stands as a vital area in Guinea's mining landscape, pivotal in the extraction and export of bauxite. Its role in the economic growth of Guinea is significant, as it contributes to the nation's GDP and international trade. However, it also faces challenges that need to be addressed to ensure sustainable and equitable development.

Figure1: Location of the study area

2- Data Collection

In this research, we employed a combination of remote sensing data and GIS spatial analysis to study the environmental impacts and LULC changes in the province of Boke. The remote sensing data comprised Landsat satellite imagery with 30 m resolution, spanning the period from 1987 to 2023 and Sentinel-5P for the air quality monitoring as shown on table 1. Our time series analysis hinged on the availability of these satellite images; thus, we employed Landsat 5 images for the years 1987, 2006, Landsat 8 for the years 2013, 2017 and 2023 and Sentinel-5P for the years 2028, 2020 and 2023. Additionally, topographic data (SRTM) collected form “Open Topography” have been used for creating topographical features such as slope, aspect, hillshade and roughness as well as the distance from river and roads. The road data was collected from Geofbrik.de and the hydrological data from Hydrosheds.

Satellite	Sensor	Resolution
Landsat 5 for the years 1987 and 2006	TM	30 m
Landsat 8 for the years 2013, 2017 and 2023	TM	30 m
Setinel-5P	TROPOMI	10 m

Table1: Images selection and description

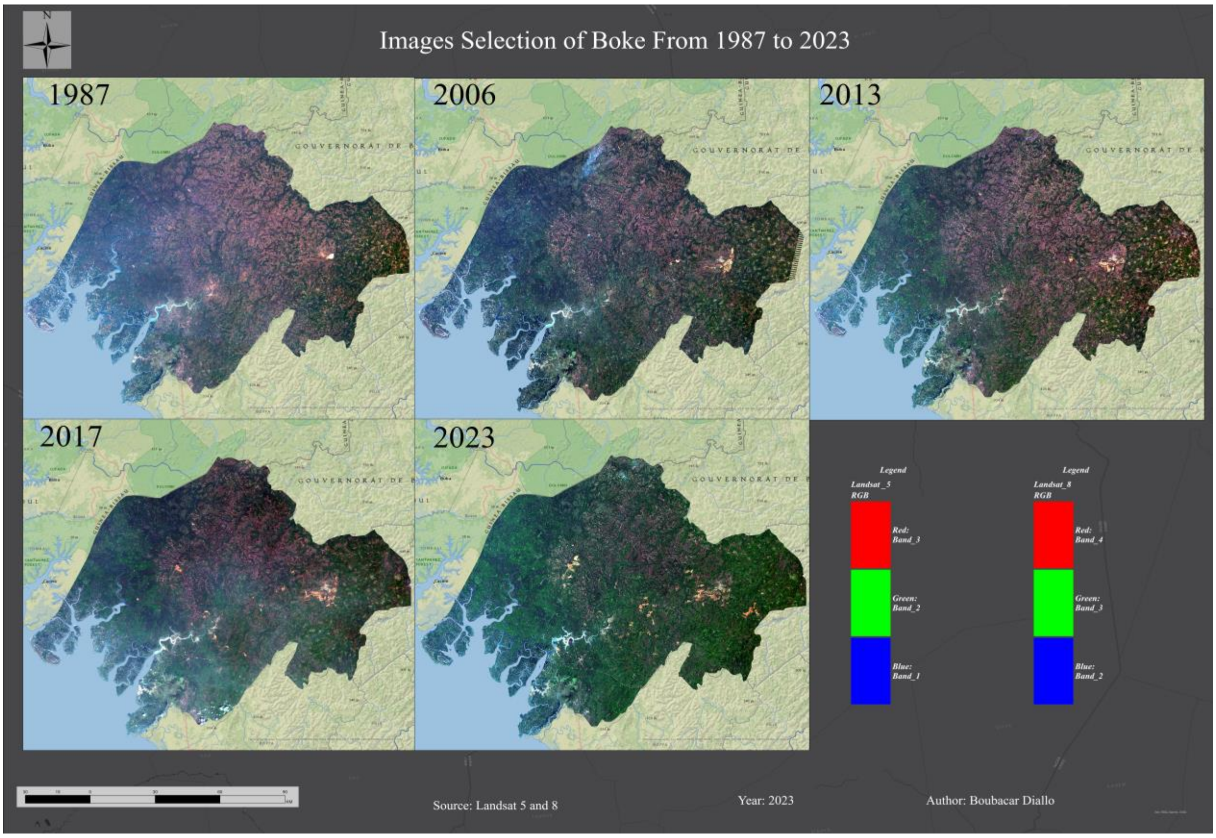

Figure 2: selected images from 1987 to 2023

3- Methods

In this study, we applied an integrated GI approach for spatiotemporal monitoring and mapping environmental risks under impacts of mining extraction, combining remote sensing and GIS technology. Satellite images from 1987 to 2023 will be analyzed to assess changes in land cover and land use patterns over time. The study will also use sentinel-5P for air quality monitoring in 2018, 2020, and 2023. GIS-based spatial analysis will be used to provide a comprehensive understanding of the effects of mining. The methods include using indices like NDVI; EVI; FVC for assessing vegetation health; coverage and fragmentation. Predictive modeling techniques will be used to predict future conditions based on mining activity trends by creating a prediction map and change detection. We leveraged the capabilities of Google Erath Engine (GEE), a cutting-edge platform that provides access to a vast array of global satellite imagery and powerful machine learning tools. Our research focuses on the comprehensive monitoring and analysis of the environmental risks and impacts and changes on LULC in Boke province from 1987 to 2023 and future changes associated to mining operations. We analyzed satellite images spanning from 1987 to 2023 to assess changes in land cover and land use patterns over time. This analysis was critical in understating the impacts of mining activities on the province's environment. Additionally, we employed the Sentinel-5P to monitor the air quality in the years 2018, 2020 and 2023 by choosing the interval between February and March, the period when the province experiences more pollution from dust due to mining activities and other activities related to transport, providing valuable insights into the environmental consequences of mining operations. Our methods involved the application of various remote sensing indices, each serving a unique purpose in our comprehensive environmental assessment. We utilized GEE's advanced algorithms to compute these indices such NDVI, EVI and FVC. An assessment of air quality and mapping of land use and land cover (LULC) were also carried out to gain a comprehensive understanding of the wider environmental effects. A mining evolution map was generated to depict the advancement of mining operations over the analyzed timeframe. Predictive modeling approaches were employed to generate a LULC (Land Use and Land Cover) prediction map, which visualizes the anticipated future condition of the province's vegetation coverage, LULC and evolution of mining area taking into account the prevailing patterns in mining activity. The study used ArcGIS Pro for detailed spatial analysis and visualization to understand the impacts of mining activities on the landscape over time. The software allowed us for precise mapping of changes in land use and land cover, tracking the evolution of mining activities and their environmental risks. ArcGIS Pro's advanced cartographic capabilities were instrumental in creating detailed maps, change detection, spatial analysis and sophisticated map layouts, which were pivotal in visualizing and communicating our findings. The combination of GEE and ArcGIS Pro in the study exemplifies the synergy that can be achieved through the integration of different technological platforms and software in environmental research, enhancing efficiency, accuracy, enabling more effective environmental management and policy decisions.

a) CSRI

The Combined Spectral Response Index were critical in assessing soil conditions. The CSRI can be computed using this formula $CSRI = \frac{B+G}{R+NIR}$ x $NDVI$. We employed the Combined Spectral Response Index (CSRI) to analyze land surface characteristics from 1987 to 2023, with a focus on the years 1987, 2006, 2013, 2017, and 2023. To improve the accuracy of the analysis, the CSRI, which uses green, blue, red, and near-infrared bands, was computed in combination with the Normalized Difference Vegetation Index (NDVI). This ensures consistency in data analysis across multiple satellite sensors and is consistent with the methodological framework presented in the study. The CSRI provides a comprehensive view of the spectral responses of both bare soil and vegetation, enabling the mapping and analysis of changes in land surface characteristics over a 36-year period. This time series analysis sheds light on environmental and ecological changes that have occurred over the years, allowing for a better understanding of long-term land surface dynamics.

b) NDVI:

The Normalized Difference Vegetation Index was used to evaluate vegetation health and coverage. The Normalized Difference Vegetation Index (NDVI) is an essential tool in remote sensing that is employed to assess the health and vegetation coverage. It is computed using the formula $NDVI = \frac{\mathrm{NIR - Red}}{NIR+Red}$, using the visible and near-infrared light reflected by vegetation. Healthy vegetation usually reflects a greater amount of near-infrared light and absorbs more visible light, resulting in higher NDVI values. The value of the index ranges from -1 to +1, with higher values indicating a healthy and dense vegetation. NDVI has extensive applications across diverse fields, primarily serving as a crucial tool for monitoring the health and density of vegetation. The NDVI is used in environmental studies to track changes in ecosystems, drought conditions, and the effects of external factors on vegetation. The NDVI accessibility is facilitated through multiple satellite platforms, enabling consistent and continuous monitoring. Due to its versatility, it is an essential component of contemporary environmental and agricultural monitoring and is used in a wide range of fields, from urban planning to climate change research. In our study case, we used the NDVI to assess and monitor the impacts of mining activities on the surrounding vegetation.

c) EVI

The Enhanced Vegetation Index was too used to assess vegetation health and coverage. The Enhanced Vegetation Index (EVI) is a remote sensing tool specifically developed to enhance the assessment of vegetation health and coverage, particularly in areas with abundant plant biomass. It improves upon the limitations of the Normalized Difference Vegetation Index (NDVI) by taking into account atmospheric conditions and amplifying the vegetation signal. The Enhanced Vegetation Index (EVI) is determined by applying the following formula $EVI = 2.5 \text{ x } \frac{(\mathrm{NIR - Red})}{(NIR+6 \text{ x } Red-7.5 \text{ x Blue} +1)}$, which takes into consideration atmospheric and background signals. It improves the representation of vegetation signals in areas with dense foliage and minimizes distortions caused by air particles and ground cover. EVI is a highly efficient method for monitoring the health, density, and vegetation coverage, particularly in areas with dense vegetation canopies. It is widely employed in agricultural management to accurately assess crop conditions and has a vital role in environmental studies, specifically in monitoring changes in ecosystems and evaluating the influence of environmental factors on vegetation health. The enhanced sensitivity of EVI in areas with high biomass makes it a favorite choice when assessing forest canopy and dense crop conditions. The effectiveness of this system in diverse ecological environments is enhanced by its ability to withstand atmospheric contaminants and background noise. In our study case, we used the EVI to compensate the NDVI into assessing and monitoring, the health, coverage, density of the vegetation and the impacts of mining activities on this vegetation.

d) FVC

The Fractional Vegetation Cover was used to assess vegetation cover and landscape fragmentation.

The FVC formula, denoted as $FVC = \frac{NDVI - NDVIsoil}{NDVIveg - NDVI\ soil}$ is intended to calculate the proportion of vegetation in a specific pixel of an image, which varies from 0 (indicating no vegetation) to 1 (representing complete vegetation coverage). The Fractional Vegetation Cover (FVC) is an essential metric in environmental and ecological research, offering valuable insights into the extent of vegetation cover and the degree of landscape fragmentation. The calculation primarily relies on the Normalized Difference Vegetation Index (NDVI), which is a widely accepted metric for assessing the health and density of vegetation. The significance of this calculation is based on its ability to provide a quantifiable measure of vegetation coverage across various types of
landscapes, such as forests, grasslands, and urban areas. Fractional vegetation cover (FVC) is a useful metric for assessing habitat quality, ecosystem health, and the long-term impacts of changes in vegetation. This is especially important when it comes to environmental monitoring, as FVC can be employed for assessing changes caused by human activities or natural phenomena. A significant application of FVC is in the analysis of landscape fragmentation. The process of fragmentation, which is frequently caused by urbanization, deforestation, or other modifications in land use, disrupts the continual vegetation cover, leading to wide range of biodiversity loss and changes in the ecosystem functions. FVC offers a method for assessing and visualizing this fragmentation, thus facilitating the assessment of its ecological effects. Regarding the human influence, FVC plays a crucial role in assessing the impacts of activities such as agriculture, logging, and mining on natural landscape. This information is crucial for the implementation of sustainable land-use practices and environmental legislation. The progress in remote sensing technology has additionally improved the usefulness of FVC. Satellite imagery enables efficient measurement of FVC across extensive regions, offering invaluable data for large-scale environmental monitoring and management.

e) Air Quality/ NO2

The air quality monitoring was carried out based on the Nitrogen dioxide (NO2) using sentinel-5P. Air quality assessment using Nitrogen dioxide (NO2), a significant air pollutant generated by combustion processes like vehicle emissions and industrial activities is crucial in mining areas. The NO2 is harmful to human health, causing respiratory issues and contributing to chronic lung diseases. Monitoring methods include satellites remote sensing, ground-based stations, and mobile sensors. NO2 data is assessed using trends analysis, spatial analysis using GI technology and health impact studies. The monitoring of NO2 levels is critical in order to comprehend the effects of air pollution, provide guidance for environmental policies, and inform public health planning.

f) LULC:

In our methodology, we employed supervised classification with the Support Vector Machine (SVM) classifier for every year. This method enhances the precision of land cover classification by accurately classifying satellite image data into multiple land cover classes. The SVM classifier is particularly effective in managing intricate and various datasets, offering accurate land cover classifications. We leveraged the capabilities of Google Erath Engine (GEE), a cutting-edge platform that provides access to a vast array of global satellite imagery and powerful machine learning tools. Our research focuses on the comprehensive monitoring and analysis of the environmental risks and impacts and changes on LULC in Boke province from 1987 to 2023 and future changes associated to mining operations. We analyzed satellite images spanning from 1987 to 2023 to assess changes in land cover and land use patterns over time.

g) Change Detection

In this section, we analyze changes in Land Use and Land Cover (LULC) in the Boke province between 1987 and 2023. The analysis specifically focuses on four time periods: 1987-2006, 2006-2013, 2013-2017, and 2017-2023 and the overall timeframe of 1987-2023. The analysis examines the influence of mining activities, urban expansion on the vegetation and the entire landscape. The study offers a thorough examination of land use and land cover (LULC) changes over the course of 36 years, establishing a connection between these alterations and both human activities and their resulting impacts on the environment. The study highlights the significance of continuous methodological progress in comprehending land use and land cover (LULC) changes in the Boke province.

h) Mining area evolution map

In this section of the thesis, we look at the creation of a Mining Area Evolution Map for the Boke province using the mining area in km2 of each year from 1987 to 2023. This map is intended to visually represent the expansion and progression of mining activities over a given time period. The primary goal is to demonstrate the spatial and temporal evolution of mining areas, illustrating how they transformed the province's landscape. This involved determining the locations of mining operations and tracking their expansion over time. The map depicts these changes in a clear, visual format, allowing users to easily track the progression of mining areas over time. The Mining Area Evolution Map is an important tool for understanding the impact of mining on the Boke province's landscape. It provides valuable information about the rate and extent of mining-related land cover changes, which is critical for environmental impact assessments, land use planning, and policy formulation. By visually tracking the expansion of mining areas, this map highlights the importance of careful management and planning to balance economic interests with social and environmental considerations. This map demonstrates the dynamic nature of land use in the Boke province, as well as the importance of mining activities in shaping its physical landscape.

i) LULC prediction map

In this section, we employed the Artificial Neural Network (ANN) model using the QGIS Software to predict future changes in the Land Use and the Land Cover (LULC) in the Boke province. The ANN model leverages the capabilities of neural networks for pattern recognition and nonlinear modeling to estimate land cover transition possibilities. This approach enables a detailed prediction of how current LULC trends, influenced by factors such as mining activities and urban expansion, will shape the province's future landscape. The model generates a visual predictive map of Boke province by projecting possible changes using historical LULC data. In order to support future regional planning and sustainable land management strategies, this map is essential for identifying areas that are likely to experience significant changes in the future. This study's deployment of the ANN model demonstrates a sophisticated technique for projecting future LULC scenarios based on current patterns.

Chapter IV: Results and Analysis

- **CSRI**

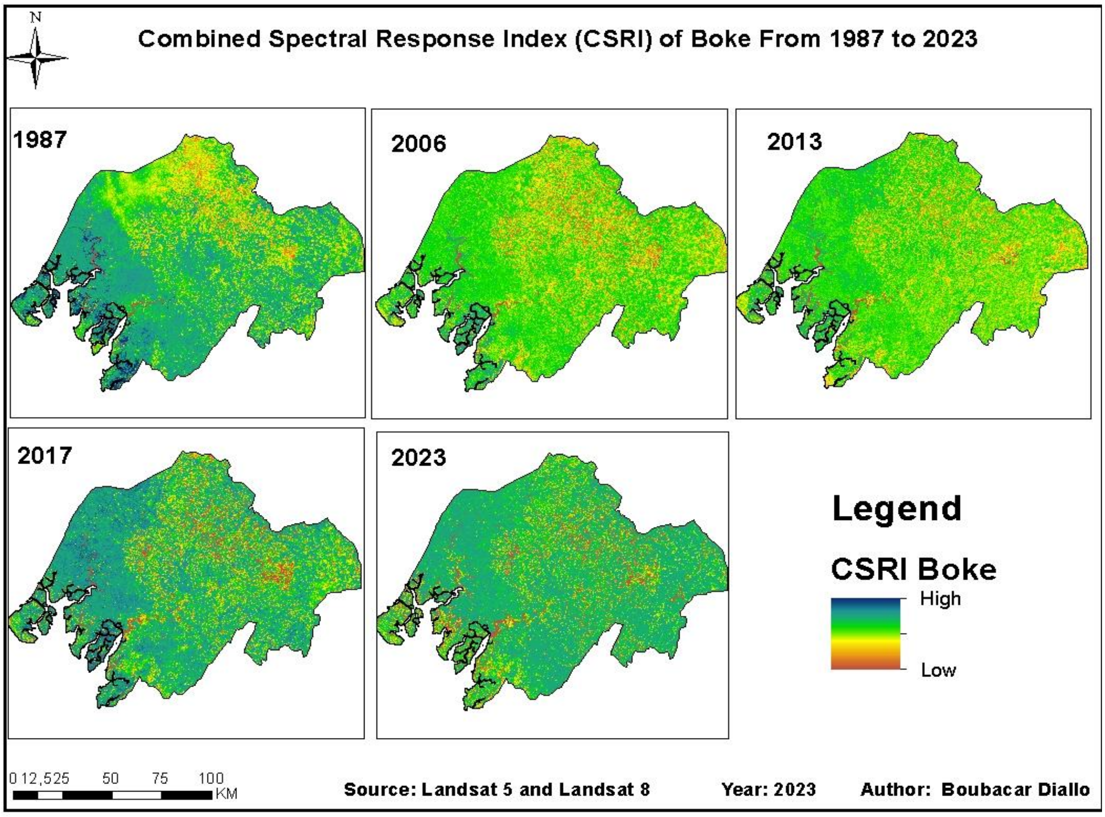

Figure 3: CSRI from 1987 to 2023

The analysis of the CSRI for Boke province reveals significant variations in soil drought levels over the study period, particularly in areas proximate to mining sites. In this study, the high values indicated low drought and dense vegetation while the low values show high drought and low vegetation. Areas adjacent to mining sites exhibit notably high soil drought levels, as indicated by low CSRI values. The results show the impacts of mining activities on soil conditions, likely due to land disturbance, soil degradation, and vegetation loss associated with mining operations. Conversely, areas distant from mining activities display lower soil drought levels as indicated by high CSRI values, reflecting comparatively healthier soil conditions. These areas likely experience less anthropic disturbance and maintain higher vegetation cover contributing to improved soil moisture retention and reduced drought stress. The CSRI analysis demonstrate the importance of remote sensing techniques for assessing soil conditions and tracking environmental changes over time. The study provides useful insights into the long-term dynamics of land surface characteristics in Boke Province, allowing for more informed decision-making in sustainable land management and resource conservation initiatives.

NDVI

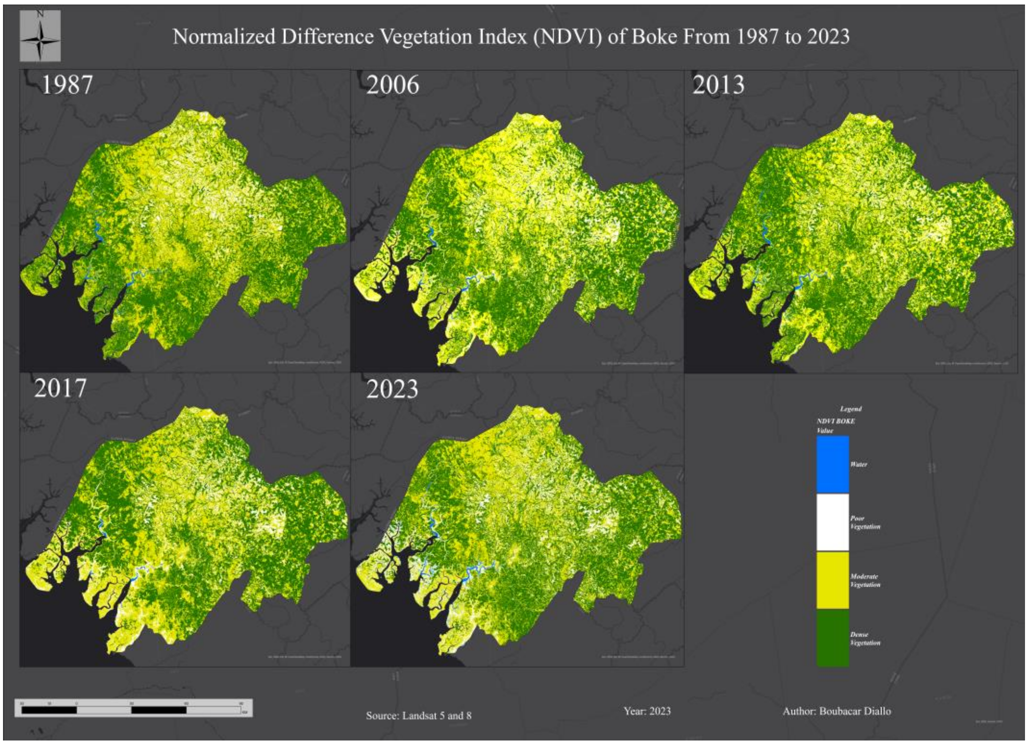

Figure 4: NDVI from 1987 to 2023

The analysis of the NDVI of Boke province offers valuable insights into the dynamics of vegetation health and coverage overtime. The NDVI shows areas of danse vegetation, moderate vegetation and low or poor vegetation. We classified the results in four (4) classes with area with values from -1 to 0 correspond to water, areas from 0.01 to 0.3 to low or poor vegetation and also to built-up areas, areas 0.31 to 0.6 to moderate vegetation and values high than 0.6 to 1 indicate the areas with danse vegetation. The analysis shows high NDVI values particularly in areas distant from mining activities indicating robust, danse and healthy vegetation. Conversely, lower NDVI values are observed in areas in proximity to mining sites, railways and built-up areas suggesting low and non-healthy vegetation, likely influenced by disturbance associated with mining activities. This analysis emphasizes how important the NDVI is as a reliable indicator for tracking the health of the vegetation and coverage, particularly when assessing the environmental impacts of mining and other human activities. It is possible to identify regions that are vulnerable to environmental degradation and guide decision-making toward sustainable land use practices by monitoring changes in the NDVI overtime.

- **EVI**

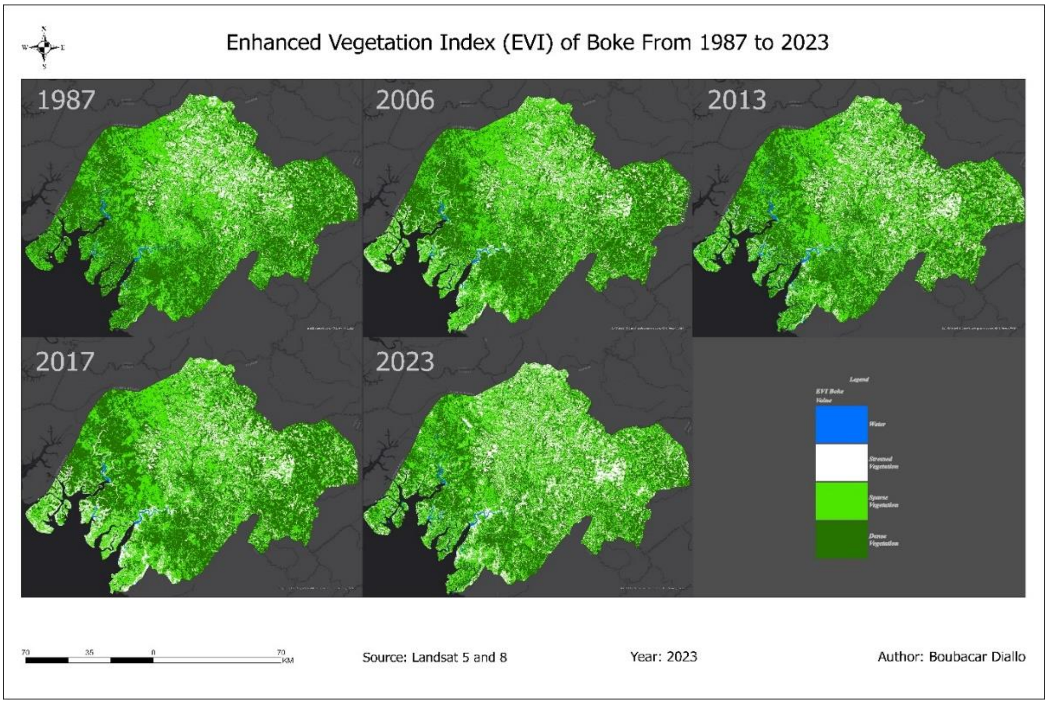

Figure 5: EVI from 1987 to 2023

The analysis based on the Enhanced Vegetation Index (EVI) shows notable impact of the mining activities on the vegetation health and coverage in the province. The EVI values ranging from -1 to 1, provides a comprehensive representation of vegetation dynamics, with higher values (>0.6) indicating dense vegetation canopies, moderate values (>0.3 to 0.6) suggesting sparse vegetation, lower values (0.1 to 0.3) stressed or non-vegetated areas and values less than 0 represent water bodies. Elevated EVI values in areas unaffected by mining activities correspond to danse and healthy vegetation cover. These high EVI values indicate dense vegetation canopies, reflective of thriving vegetation health and strong photosynthetic activity. Such areas represent undisturbed natural habitats or vegetation coverage. In contrast, areas in or close to mining sites exhibit lower EVI values indicating compromised vegetation health and reduced vegetation density. The decrease in EVI values suggests disturbance to vegetation cover caused by land clearing, soil disturbance and habitat fragmentation associated with mining activities.
The analysis of temporal trends in EVI values over the study period revealed changes in vegetation dynamics and cumulative effects of mining activities.

- **FVC**

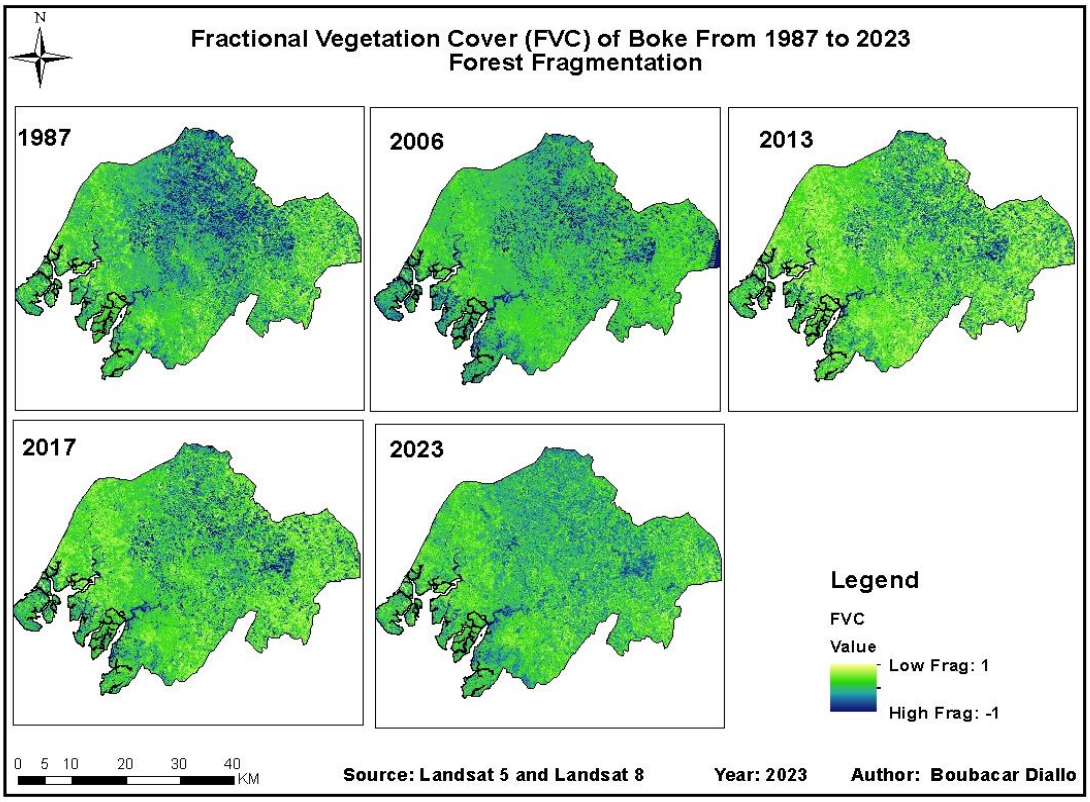

Figure 6: FVC from 1987 to 2023

The analysis of the fractional vegetation cover (FVC) in Boke province highlights significant landscape fragmentation and disruption of vegetation cover, particularly in and near mining areas. In areas proximate to mining sites, FVC values approach 0% (-1 correspond to 0%) indicating minimal to no vegetation cover due to the direct impact of mining activities on the land clearance and habitat destruction. Conversely, in areas farther from mining activities, FVC values reach 100%, reflecting uninterrupted and healthy vegetation cover. This stark contrast in FVC values underscores the detrimental effects of mining landscape and vegetation integrity. The process of mining including land clearance, excavation, and infrastructure development, disrupts the natural vegetation cover leading to habitat loss, biodiversity decline and ecosystem degradation. Such fragmentation poses significant ecological challenges, including reduced connectivity between habitats. We notice that, in 1987 there is high fragmentation in the northern part of the province which is not associated to mining activities but due to a period of drought that affected the region in 1980s.

Air Quality (NO2)

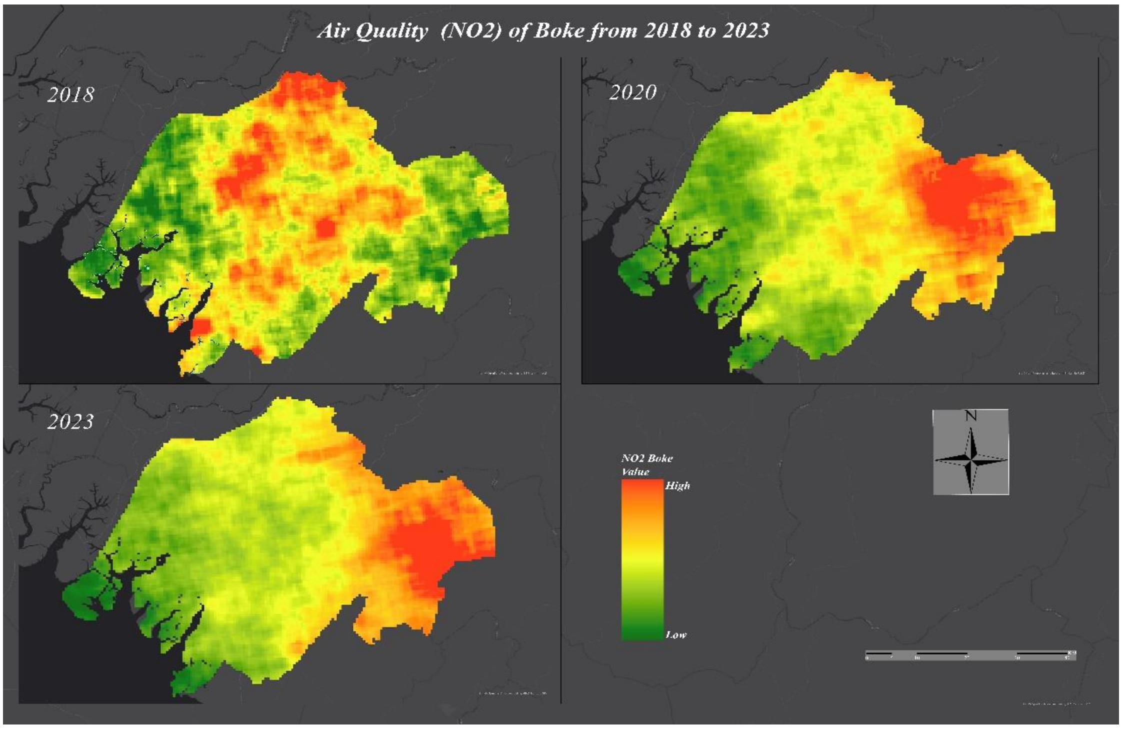

Figure 7: Air quality (NO2) from 2018 to 2023

Air quality monitoring involves the systematic and continuous assessment of various pollutants present in the air, including nitrogen dioxide (NO2), which can be particularly relevant in areas with mining activities. In our study, the analysis of the spatial distribution of NO2 concentrations helped in the identification of hotspots of pollution near mining sites and the assessment of the extent of dispersion of pollutants in the surrounding areas. High NO2 concentrations are observed near in close proximity to mining activities, with decreasing concentrations as distance from the source increases. We can observe that the NO2 concentrations fluctuate with changes in mining operations, such increased activity during peak production periods or decreased emissions during shutdowns. The monitoring of NO2 levels in the vicinity of mining sites allowed to detect any increases in NO2 concentrations resulting from mining activities.

LULC

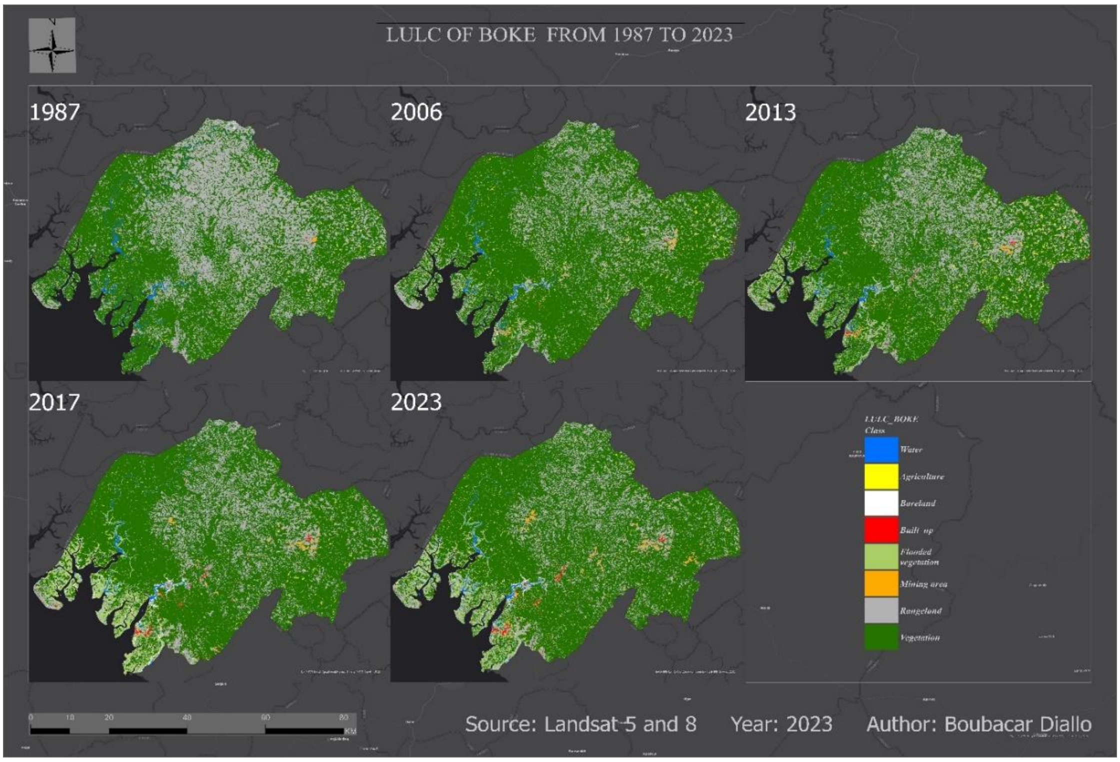

Figure 8: LULC from 1987 to 2023

Accuracy Assessment of LULC from 1987 to 2023 (SVM)

Year	Accuracy	Kappa Index
1987	0.926453876	0.899074532
2006	0.914632196	0.886328093
2013	0.935089652	0.917654932
2017	0.978765098	0.955790346
2023	0.945987236	0.927845038

Table 2: Accuracy assessment of LULC from 1987 to 2023

This table presents the accuracy and the kappa index values for the SVM classifier applied to the LULC data for the years 1987, 2006, 2013, 2017 and 2023.
The accuracy measures the overall correctness of the classifier's predictions. It is calculated as the ratio of correctly classified instances to the total number of instances. High accuracy values indicate that the classifier performed well in accurately classifying land cover types. The accuracy values range from 0 to 1, with one representing perfect classification. Across all the years, the SVM classifier achieved relatively high accuracy, ranging from approximately 91.5% (2006) to 97.9% (2017). This suggests that the classifier performed well in classifying land cover types for each respective year.
The kappa index, also known as Cohen's Kappa coefficient, measures the agreement between the classifier's predictions and the actual observations while accounting for the agreement occurring by chance. It provides a more robust measure of classification performance, especially when dealing with imbalanced datasets. The Kappa index values range from -1 to 1, where 1 indicates perfect agreement, 0

indicates equivalent to chance and negative values indicate agreement worse than the chance. The Kappa index values for all the years are high, ranging from approximately 0.886 (2006) to 0.956 (2017). This indicates substantial agreement between the classifier's predictions and the actual observations, with values closer to 1 indicating high agreement.
The SVM classifier demonstrated strong performance in accurately classifying LULC data across all years, as evidenced by both high accuracy and kappa index values. These results suggest that the SVM classifier is effective in capturing the spatial patterns and dynamics of land cover changes overtime, which is essential for various applications such as land management, environmental monitoring and urban planning.

- **Area in Km2 from 1987 to 2023**

Class	Area in Km2 1987	Area in Km 2006	Area in Km 2013	Area in Km 2017	Area in Km 2023	Evolution
Agriculture	82	195	215	89	152	
Bareland	17	27	16	84	50	
Built_up	9	22	43	56	55	
Flooded veget	84	198	376	765	602	
Mining area	6	13	17	37	65	
Rangeland	4395	2243	2862	2298	2156	
Vegetation	8135	9952	9204	9402	9638	
Water	124	98	117	120	133	
Grand Total	12850	12850	12850	12850	12850	....

Table 3: Area in Km2 of LULC from 1987 to 2023

- **Area in Km2 from 1987 to 2023**

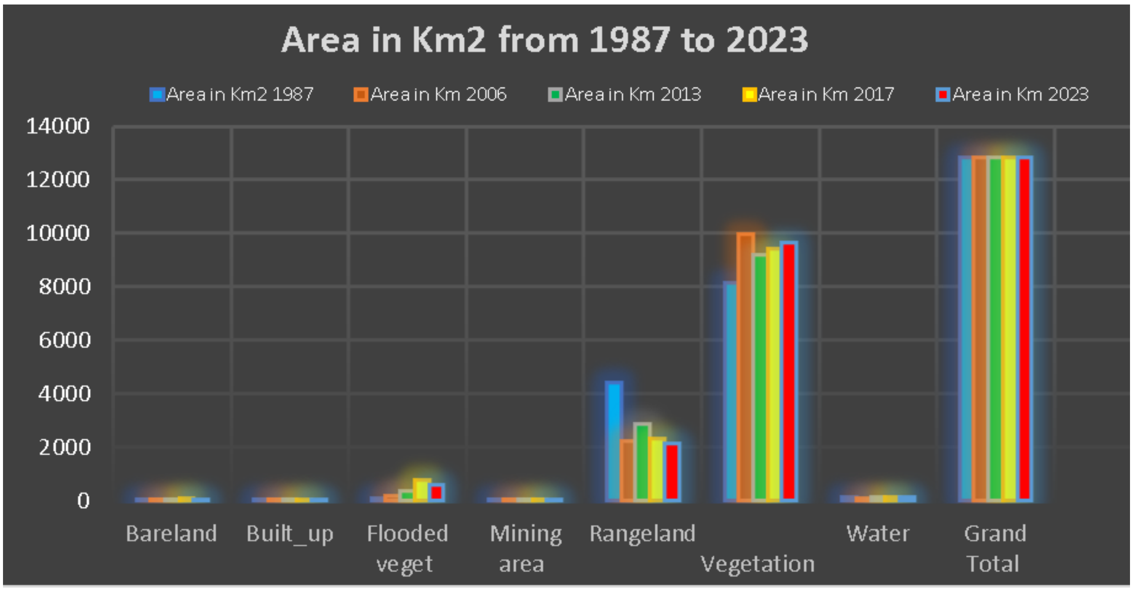

Figure 9: Area in Km^2 of LULC from 1987 to 2023

The table and the bar graph show land use and land cover changes across various classes (agriculture, bareland, built-up, flooded vegetation, mining area, rangeland, vegetation and water bodies) over different years from 1987 to 2023, measured in square kilometers. Additionally, there is a column on the table with graphical representations of the evolution of the trends over time for each category.
There is an initial increase in agricultural land from 82 km² in 1987 to 215 km² in 2013. However, from 2013 to 2023, the area decreases significantly to 152 km². The

trends show a peak in in 2013, followed by a decline, suggesting recent reductions in agricultural land use.

The bareland fluctuates with an increase from 17 km² in 1987 to 27 km² in 2006, then a decrease to 16 km² in 2013. A notable increase occurs by 2023 with bareland expanding to 50 km².

The area of built-up land consistently increases from 9 km² in 1987 to 55 km² in 2023. The trend in built-up reflects a steady growth, which indicates urban expansion or development.

The flooded vegetation category shows significant growth, from 84 km² in 1987 to 765 km² in 2017, then a slight reduction to 602 km² in 2023. The trend, despite the recent decrease shows a strong overall upward, indicating increased flooding or expansion of wetlands over time.

The mining area exhibits a steady increase from 6 km² 1987 to 65 km² 2023 in 2023. The trend shows an overall upward, suggesting continued or increasing mining activities.

There is considerable decrease in rangeland, from 4395 km² in 1987 to 2156 km² in 2023, suggesting a continuous decrease in rangeland, implying a significant loss of rangeland over the years due to mining activities.

The area of vegetation increases from 8135 km² in 1987 to 9402 km² in 2017, with a slight decrease to 9368 km² in 2023.

The water-covered area fluctuates slightly but show a general increase 124 km² in 1987 to 133 km² in 2023.

The evolution demonstrates how land cover and land use have changed throughout time, with growing urban areas and decreasing rangelands signifying changes in agricultural land and urbanization. Increases in mining areas and flooded vegetation could be a result of both economic activity and environmental changes. These trends reflect factors such as urbanization, economic change, and environmental impacts.

Change Detection

LULC Change Detection of Boke from 1987 to 2023

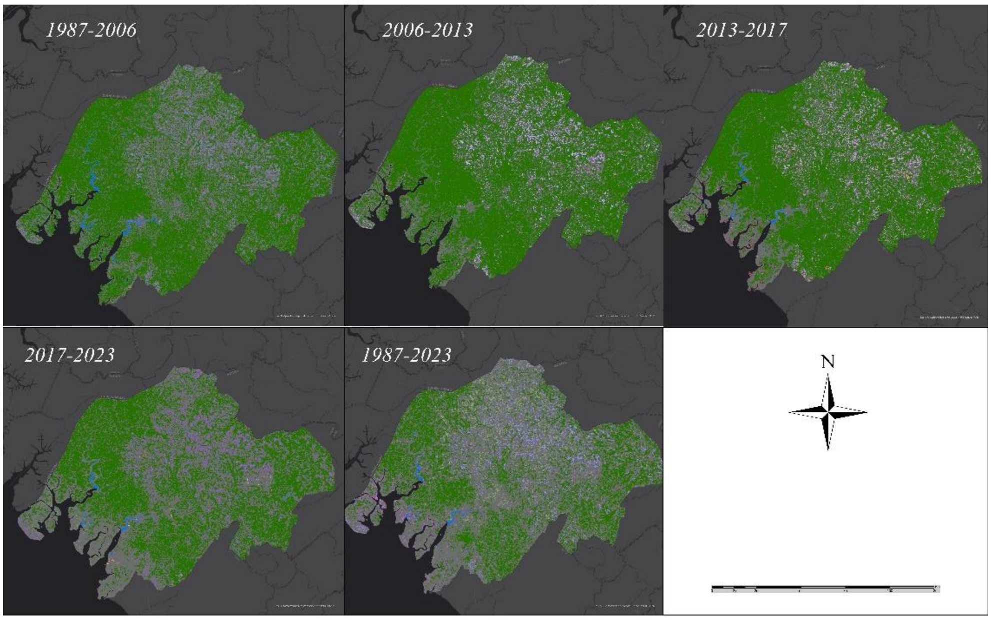

Figure 10: Change detection map from 1987 to 2023

In this part, we will give a focus on the changes occurred with mining areas. In examining the changes on land cover, with respect to mining areas over the period from 1987 to 2006, we analyze the dynamics of land use transitions to and from mining areas. Our interpretations will focus on how other land cover classes have transformed into mining areas, signifying an expansion of mining activities, as well as how mining areas have transitioned into other land cover classes. These transition s are critical for understanding the environmental and economic impacts of mining activities on the landscape. We will delve into the numerical data to elucidate these patterns of change and to draw insights from shifting mosaic of land use.

Change Detection 1987-2006

Year	2006								
	Class	Agriculture	Bareland	Built_up	Flooded V	Mining ar	Rangeland	Vegetation	Water	Grnd Total
	Agriculture	3,86	0,01	0,49	0,02	0,02	1,25	73,93	0,00	79,58
	Bareland	0,08	4,43	0,27	0,51	0,01	8,35	1,77	0,56	15,99
	Built_up	0,09	2,04	1,14	0,11	0,04	4,05	0,90	0,20	8,57
	Flooded V	1,92	1,54	0,39	10,01	0,06	32,46	35,72	1,55	83,65
	Mining area	0,04	0,13	0,01	0,00	3,01	2,24	0,09	0,02	5,54
	Rangeland	55,10	11,13	8,93	16,18	8,27	1907,16	2355,01	2,09	4363,87
	Vegetation	133,83	5,20	10,86	163,69	1,96	264,82	7475,85	9,03	8065,24
	Water	0,22	1,96	0,01	7,18	0,00	21,91	7,82	83,47	122,57
1987	Grand Total	195,14	26,43	22,10	197,70	13,38	2242,24	9951,08	96,92	12745,00

Table 4: Area in Km2 of change detection from 1987 to 2006

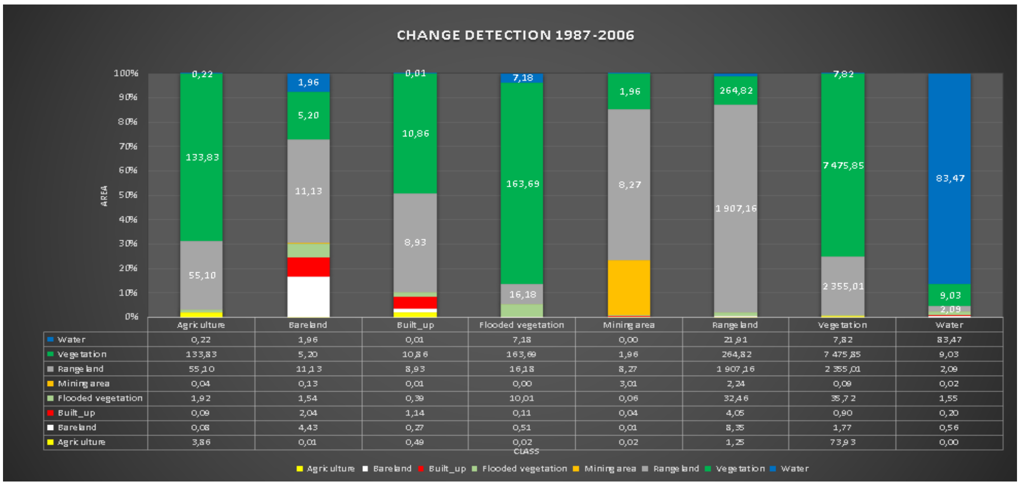

Figure 11: Area in Km2 of change detection from 1987 to 2006

A small amount of land, 3.01 km² that was classified mining area in 1987 remained as mining area in 2006 and the total area of mining in 2006 is13 km².
The majority of the mining area in 2006 come from what was the rangeland in 1987, with 8.27 km² being converted to from rangeland to mining area. The second largest change to mining areas comes from the vegetation class, with 1.96 km². A smaller but still notable amount of mining area in 2006 comes from bareland, with 0.13 km² that has transitioned to mining area. The transition from agriculture and built-up to mining area is insignificant with 0.1 km². There is no transition from water to mining area. Only 3.01 km² of land that was mining area has transitioned to rangeland in 2006.
No other land use categories have significant transitions from mining areas in 2006.

Change Detection 2006-2013

Year	2013									
	Class	Agriculture	Bareland	Built_up	Flooded V	Mining a	Rangeland	Vegetation	Water	Grnd Total
	Agriculture	19,14	0,00	2,61	2,62	0,13	35,39	135,24	0,00	195,1517
	Bareland	0,03	4,58	1,80	0,85	0,36	9,84	0,27	9,14	26,87359
	Built_up	3,15	0,21	6,53	0,36	0,06	3,46	8,32	0,03	22,11951
	Flooded V	0,14	0,34	0,18	144,79	0,00	30,57	21,26	0,81	198,0845
	Mining area	0,04	0,04	0,19	0,01	6,28	6,62	0,19	0,01	13,37595
	Rangeland	10,16	7,15	22,31	67,97	7,44	1 941,05	170,82	16,02	2242,937
	Vegetation	179,24	0,60	7,35	158,56	2,91	802,64	8 799,14	1,04	9951,47
	Water		2,73	0,01	0,51	0,01	5,28	0,06	89,43	98,02405
2006	Grand Total	211,91181	15,6567	40,9708	375,68146	17,18205	2834,8525	9135,3026	116,48	12748,04

Table 5: Area in Km2 of change detection from 2006 to 2013

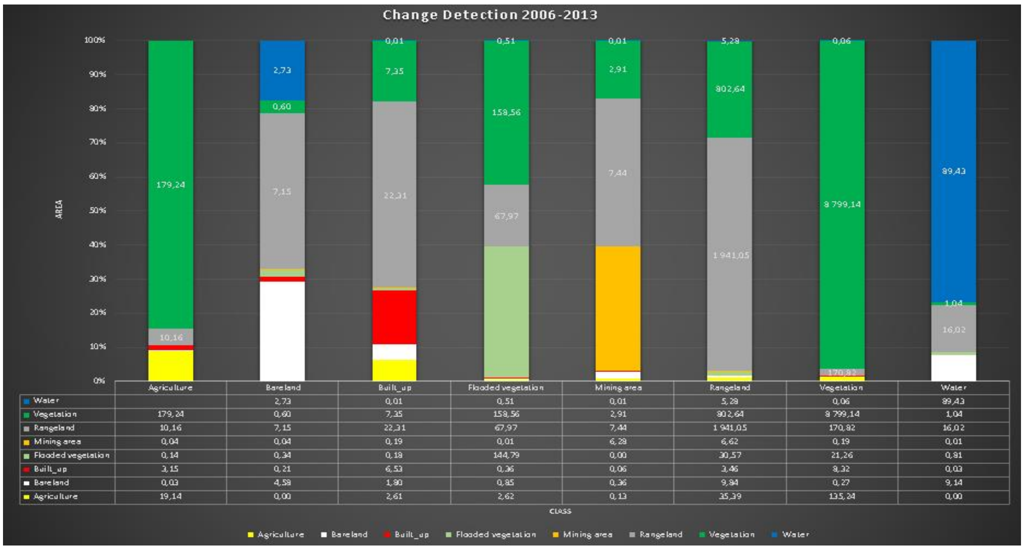

Figure 12: Area in Km2 of change detection from 2006 to 2013

A portion of 6.28 km² of land that was classified mining area in 2006 remained as mining area in 2013 and the total area of mining in 2013 is17 km².
The majority of the mining area in 2013 come from what was the rangeland in 2006 with 7.44 km² being converted to from rangeland to mining area. The second largest change to mining areas comes from the vegetation class, with 2.91 km². A smaller but still notable amount of mining area in 2013 comes from bareland, with 0.36 km² and agriculture, with 0.13 km² that has transitioned to mining area. The transition from agriculture, water and built-up to mining area is insignificant with 0.01 km² each one. There is an insignificant transition from water to mining area and for the reverse.
A notable area of 6.62 km² of land that was mining area has transitioned to rangeland in 2013 There is an insignificant transition of other land use categories from mining areas in 2006, with only 0.19 km² of vegetation and 0.19 km² of built-up.

Change Detection 2013-2017

Year	2017								
	Class	Agriculture	Bareland	Built_up	Flooded V	Mining area	Rangeland	Vegetation	Water	Grnd Total
	Agriculture	3,32	0,00	4,17	0,21	0,19	7,50	199,91	0,00	215,30
	Bareland	0,00	7,58	1,25	0,64	0,11	2,37	0,01	3,71	15,67
	Built_up	0,31	0,26	17,90	0,09	0,31	15,54	8,69	0,04	43,14
	Flooded V	0,13	6,60	0,77	307,07	0,24	37,44	21,24	1,98	375,47
	Mining area	0,03	0,02	0,29	0,00	11,91	4,88	0,05	0,01	17,18
	Rangeland	6,89	56,73	14,27	92,80	16,17	1933,42	726,93	14,41	2861,62
	Vegetation	78,14	0,84	17,03	359,78	7,36	295,03	8444,96	0,47	9203,60
	Water	0,00	12,06	0,22	3,45	0,27	1,79	0,02	98,62	116,42
2013	Grand Total	88,81	84,09	55,90	764,03	36,58	2297,95	9401,81	119,24	12848,40

Table 6: Area in Km2 of change detection from 2013 to 2017

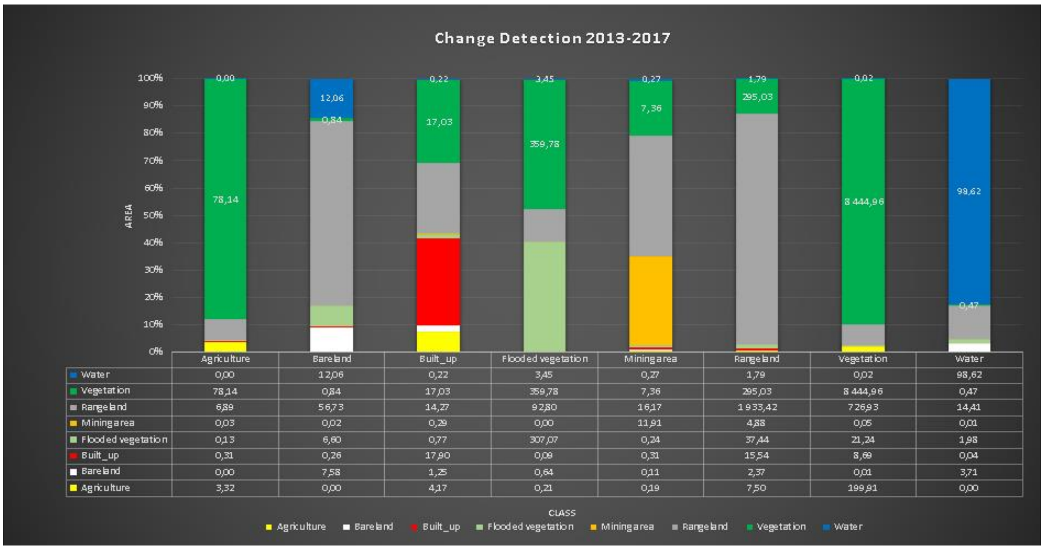

Figure 13: Area in Km2 of change detection from 2013 to 2017

A portion of 11.91 km² of land that was classified mining area in 2013 remained as mining area in 2017 and the total area of mining in 2017 is 36 km².
The majority of the mining area in 2017 come from what was the rangeland in 2013 with 16.17 km² being converted to from rangeland to mining area. The second largest change to mining areas comes from the vegetation class, with 7.36 km². A smaller but still notable amount of mining area in 2013 comes from bareland, with 0.11 km² and agriculture, with 0.19 km² that has transitioned to mining area. The transition from water and built-up to mining area is insignificant. There is an insignificant transition from water to mining area and for the reverse. A notable area of 4.88 km² of land that was mining area has transitioned to rangeland in 2017. There is an insignificant transition of other land use categories from mining areas in 2017, with only 0.05 km² of vegetation and 0.29 km² of built-up.

Change Detection 2017-2023

Year	2023									
	Class	Agriculture	Bareland	Built_up	Flooded V	Mining ar	Rangeland	Vegetation	Water	Grnd Total
	Agriculture	7,41	0,01	1,35	0,04	0,17	5,76	74,08	0,00	88,82
	Bareland	0,00	19,66	0,05	4,86	0,05	38,37	0,20	20,87	84,07
	Built_up	2,56	0,98	25,31	0,26	1,16	15,30	9,52	0,81	55,90
	Flooded V	0,17	5,93	0,04	470,43	0,03	174,14	108,91	4,38	764,05
	Mining area	0,25	0,12	0,56	0,04	16,43	17,50	1,52	0,15	36,58
	Rangeland	15,14	15,68	16,08	42,98	24,52	1 636,96	538,27	8,30	2 297,92
	Vegetation	126,03	0,28	10,96	81,45	22,76	255,26	8 904,87	0,17	9 401,79
	Water	0,01	7,16	0,04	1,47	0,01	12,65	0,05	97,81	119,21
2017	Grand Total	151,57	49,82	54,40	601,53	65,14	2 155,95	9 637,42	132,49	12 848,32

Table 7: Area in Km2 of change detection from 2017 to 2023

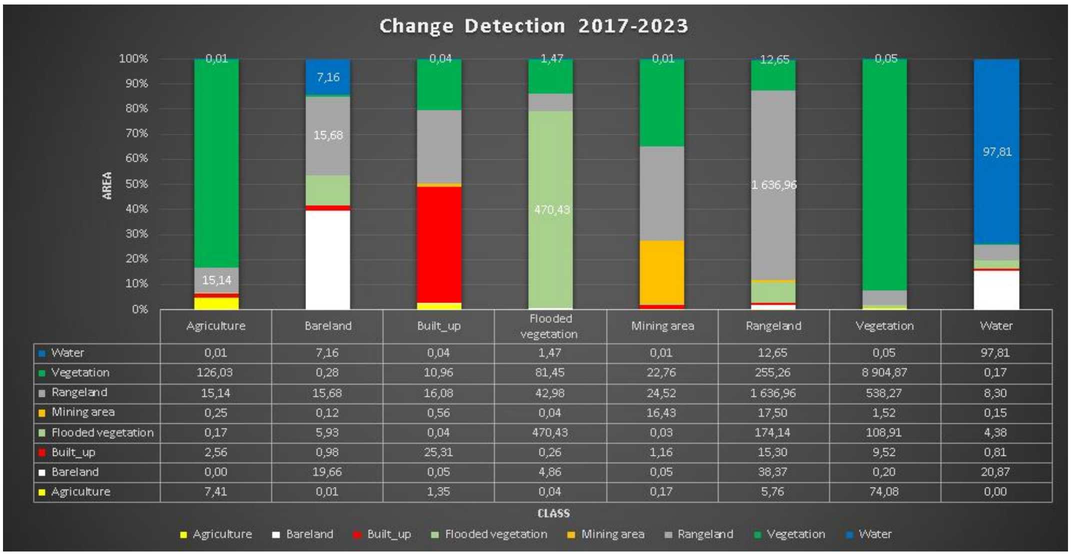

Figure 14: Area in Km2 of change detection from 2017 to 2023

A portion of 16.43 km² of land that was classified mining area in 2017 remained as mining area in 2023 and the total area of mining in 2023 is 65 km².
The majority of the mining area in 2023 come from what was the rangeland in 2017 with 24.52 km² being converted to from rangeland to mining area. The second largest change to mining areas comes from the vegetation class, with 22.76 km². A smaller but still notable amount of mining area in 2023 comes from bareland, with 0.05 km² and agriculture, with 0.17 km² that has transitioned to mining area. The transition from water (0.01 km²) and built-up (1.16 km²) to mining area is insignificant. There is an insignificant transition from water to mining area and for the reverse. A notable area of 17.50 km² of land that was mining area has transitioned to rangeland in 2023. There is an insignificant transition of other land use categories from mining areas in 2023, with only 1.52 km² of vegetation and 0.56km² of built-up.

Change Detection 1987-2023

Year	2023									
	Class	Agriculture	Bareland	Built_up	Flooded Veg	Mining a	Rangeland	Vegetation	Water	Grand Total
	Agriculture	4,20	0,01	0,27	0,05	0,13	2,53	74,88	0,01	82,07
	Bareland	0,05	0,99	0,27	0,99	0,02	8,18	1,60	3,89	15,98
	Built_up	0,06	0,86	2,00	0,19	0,07	3,11	0,95	1,34	8,59
	Flooded Veg	0,85	4,22	0,92	14,08	0,23	32,78	26,47	4,20	83,75
	Mining area	0,01	0,02	0,05	0,20	1,05	2,58	1,60	0,03	5,54
	Rangeland	34,18	22,09	32,61	44,03	43,73	1 682,01	2 517,33	18,19	4 394,16
	Vegetation	112,17	16,23	18,22	531,03	19,82	404,90	7 009,95	20,79	8 133,10
	Water	0,06	5,20	0,02	10,66	0,09	19,40	4,44	82,68	122,55
1987	Grand Total	151,56249	49,61713	54,3619	601,215104	65,1377	2155,4876	9637,2205	131,13	12845,7351

Table 8: Area in Km2 of change detection from 1987 to 2023

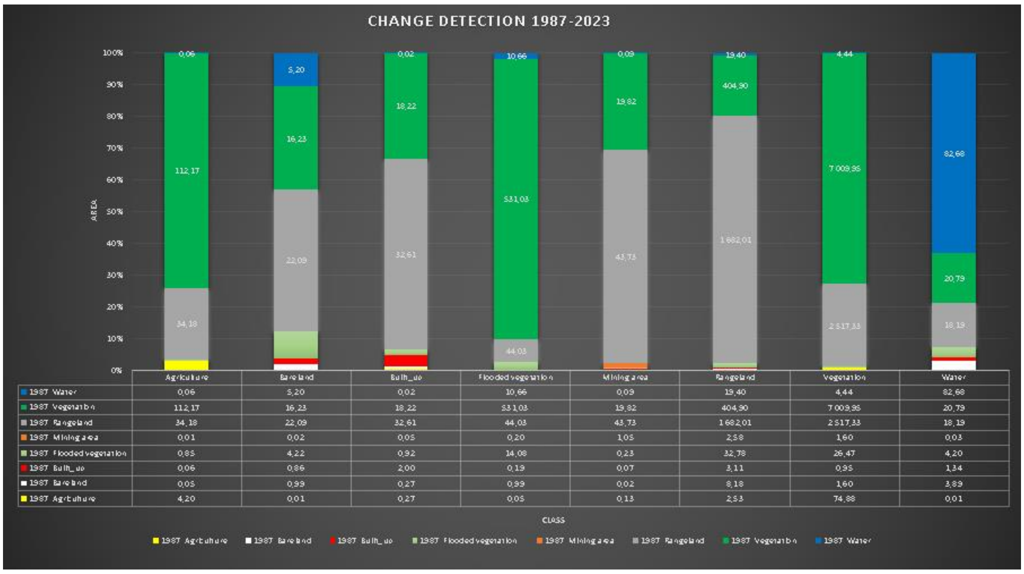

Figure 15: Area in Km2 of change detection from 2013 to 2017

A portion of 1.05 km² of land that was classified mining area in 1987 remained as mining area in 2023 and the total area of mining in 2023 is 65 km².
The majority of the mining area in 2023 come from what was the rangeland in 1987 with 43.73 km² being converted to from rangeland to mining area. The second largest change to mining areas comes from the vegetation class, with 19.82 km². A smaller but still notable amount of mining area in 2023 comes from bareland, with 0.02 km² and agriculture, with 0.13 km² that has transitioned to mining area. The transition from water (0.09 km²) and built-up (0.07 km²) to mining area is insignificant. There is an insignificant transition from water to mining area and for the reverse. A notable area of 2.58 km² of land that was mining area has transitioned to rangeland in 2023. There is an insignificant transition of other land use categories from mining areas in 2023, with only 1.60 km² of vegetation and 0.05 km² of built-up.

- **Number of ports for each year from 1987 to 2023**

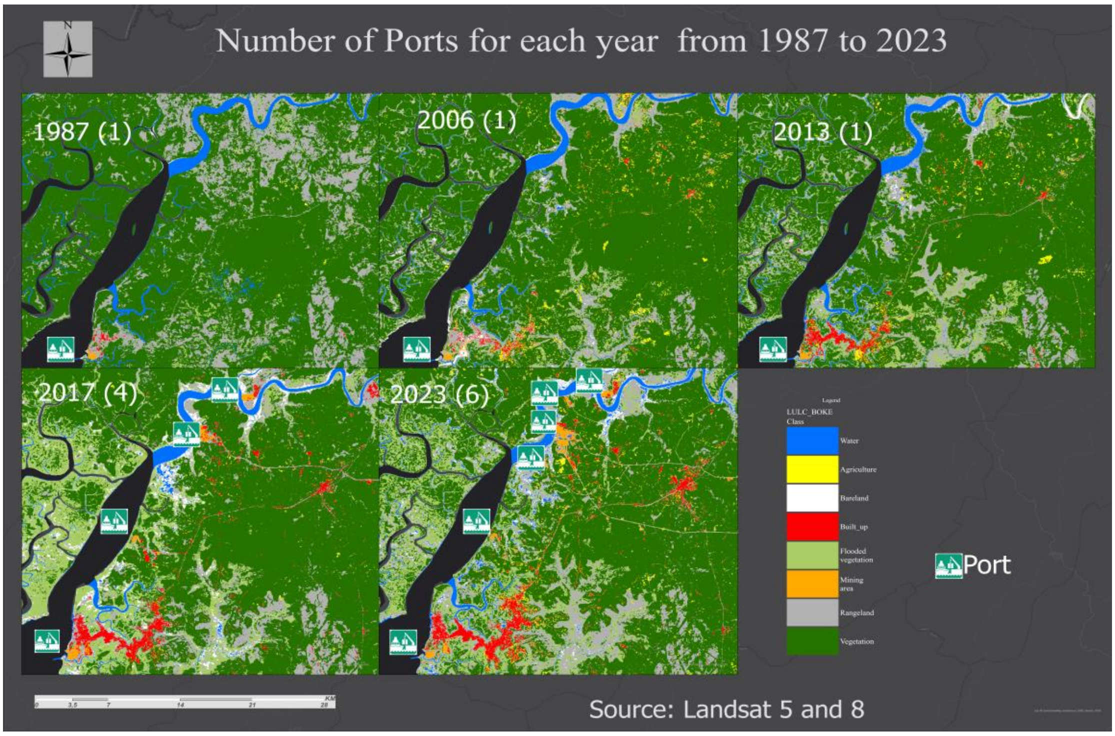

Figure 16: Number of ports for each year from 1987 to 2023

In this part, we analyze the increase of the number of mining ports over a period spanning from 1987 to 2023 as depicted in the satellite imagery sourced from Landsat 5 and 8. The progression indicates substantial infrastructural development within the mining sector, reflecting changes in economic activities and potentially the volume of mineral resource extraction and trade.

From 1987 to 2013, there is only one mining port visible each year's image. This consistency suggests that for a long period, the mining infrastructure in terms of ports facilitates remained unchanged.

In 2017, the number of mining ports increased to four. This indicates a significant development in mining infrastructure within the four-period year since 2013.

In 2023, the number of mining ports has further increased to six. The continued increase in the number of ports suggests an expanding mining sector requiring more facilities to handle the exports related to mining activities.

The existence and expansion of ports, particularly in mining areas, may be linked to changes in various land use and land cover types, such as increased built-up areas or changes in vegetation cover (deforestation). The increase of mining ports from 1987 to 2023 reflect also the growth and intensification of mining operations, possibly due to the increased demand for mineral resources such as bauxite in Boke province and the economic growth. This growth may have environmental implications, such as the impact on coastal ecosystems and water quality, and socio-economic implications, including employment and local economic development.

Mining area evolution map

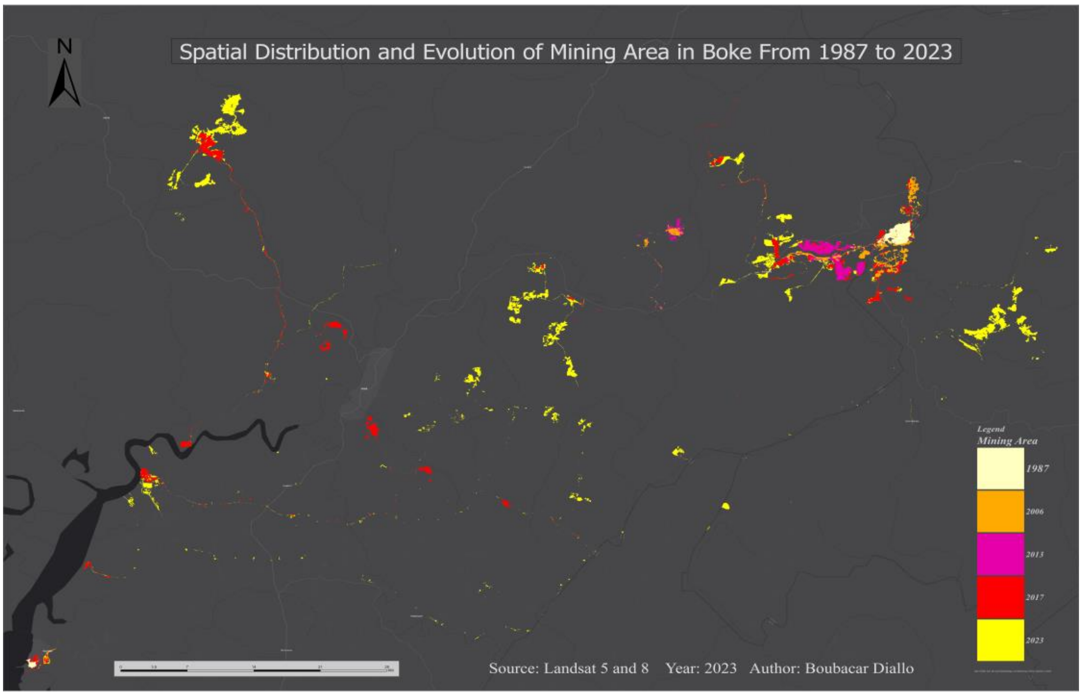

Figure 17: Evolution of mining area in Km2 from 1987 to 2023

This map shows the spatial distribution and evolution of mining sites and activities in province from 1987 to 2023. We can observe that in 1987, there was only one mining sites in the eastern part of the province and one port for the mineral exportation. In 2023, we can observe that the mining sites considerably increased and are disturbed all over the province.

Class	Area in Km2 1987	Area in Km 2006	Area in Km 2013	Area in Km 2017	Area in Km 2023
Mining area	6	13	17	37	65

Table 9: Mining area in Km2 from 1987 to 2023

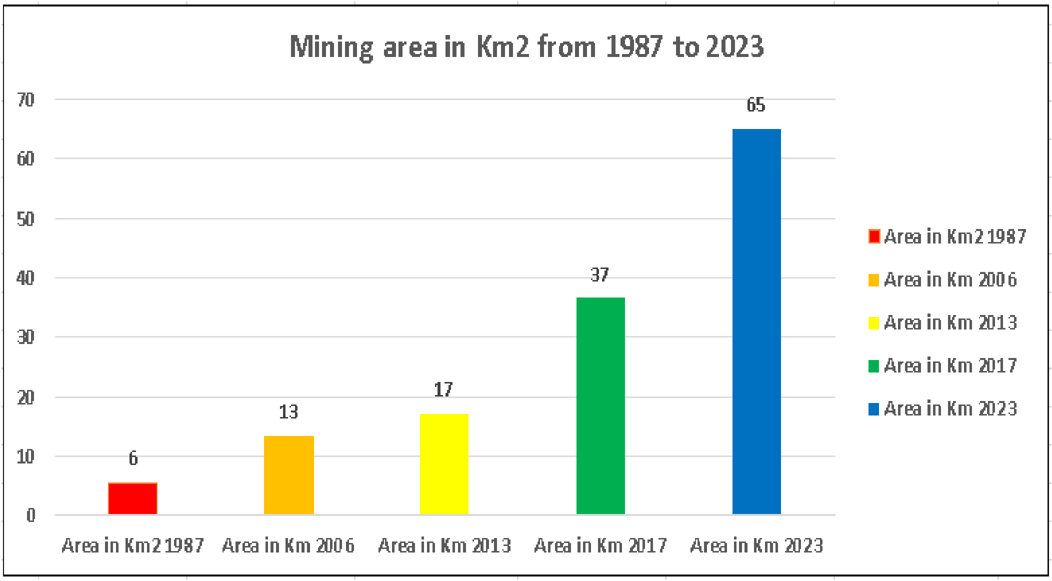

Figure 18: Evolution of mining area in Km2 from 1987 to 2023

The table and the bar graph show the area covered by mining activities in km² for each selected year from 1987 to 2023. The data on the table as visualized on the bar graph illustrate the growth of the mining area over the years. The mining increased from 6 km² in 1987 to 13 km² in 2006. It increased to 17 km² in 2013, then expanding to 37 km² in 2017 and finally, reaching 65 km² in 2023.
The mining activity in the Boke region has increased significantly over the last 36 years. The map shows not only an increase in the number of mining sites, but also the expansion of existing ones. The tabular data and bar graph quantitatively confirm this trend, demonstrating that the area has grown consistently, with the most significant growth occurring in the last decade of the dataset. This expansion could be fueled by rising global demand for minerals, advanced mining technologies, or the discovery of new mineral deposits in the Boke region. The increased mining activity suggests significant economic development for the region, which could be combined with infrastructure investments, such as the observed increase in ports. However, expanding mining areas can have environmental impacts such as land degradation, deforestation, and pollution, all of which can have an impact on local ecosystems and communities. The evolution of these mining areas, as seen in satellite imagery, could be a useful tool for monitoring environmental impact and establishing future planning and mitigation strategies to ensure sustainable mining practices.

- **Deforested Area** (overlaying Mining area 2023, Vegetation 1987-2006 and Rangeland 2006)

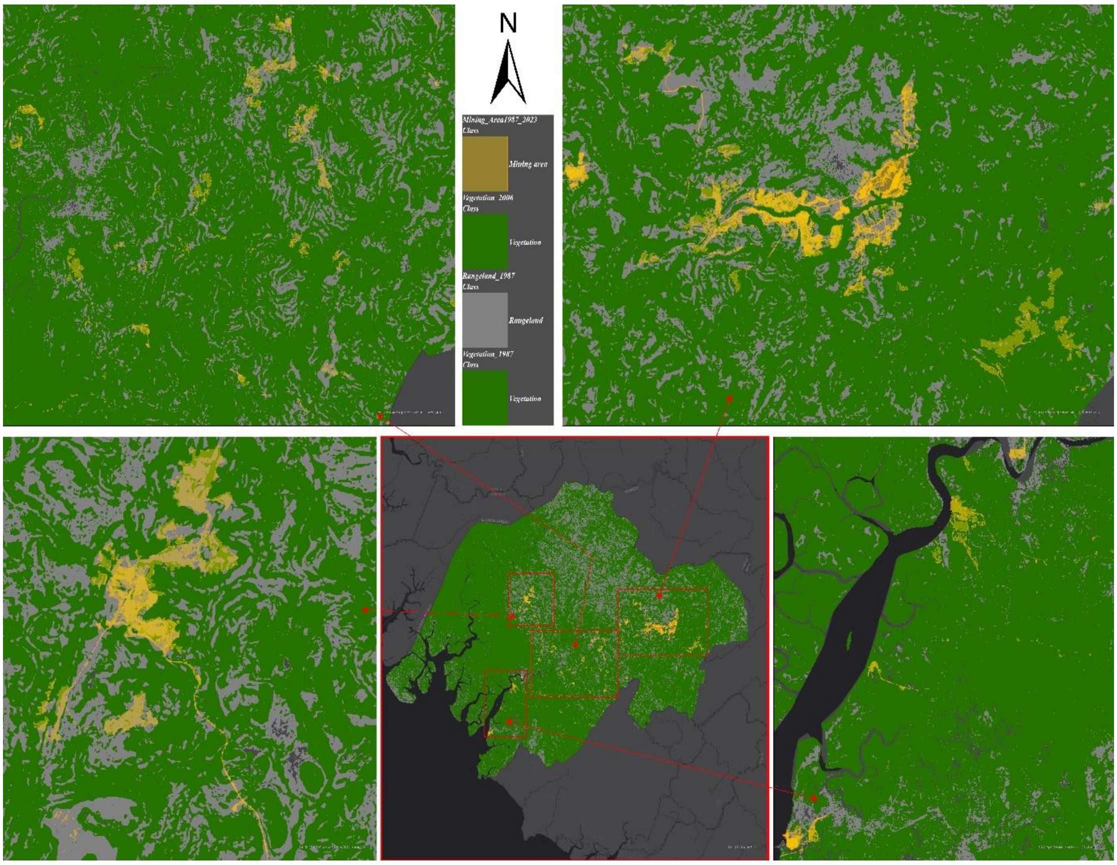

Figure 19: Deforested area from 1987 to 2023

The provided map is an analytical tool for assessing deforestation as mining activities expand. It is divided into four panels: the central large panel provides an overview, while the left and right panels provide detailed views of specific regions. The map uses color coding to represent different land classifications, with mining areas for 2023 being particularly highlighted. The yellow areas designated as mining zones in 2023 are dispersed across the map, implying that mining activities have expanded to new areas and possibly intensified in existing ones. Green areas represent vegetation cover between 1987 and 2006, which was most likely rich in flora prior to significant mining expansion which caused deforestation. In 2006, rangeland areas were also marked, which were typically used for grazing; however, any overlap with mining areas in yellow indicated a conversion from rangeland to mining. To indicate where deforestation has occurred, the map overlays mining areas over earlier vegetation and rangeland. The spatial distribution indicates that mining activities, which have increased by 2023, are a major driver of land-use change in this province. The large proportion of the yellow areas in comparison to the green areas suggests a significant impact on vegetation and potentially rangeland. The map provides a stark visual representation of the environmental impact of mining activities, aiding conservationists, policymakers, and planners in understanding the extent of deforestation and strategizing mitigation measures such as reforestation or sustainable mining practices.

- **Deforested Area** (overlaying Mining area 2023and Vegetation 1987-2006)

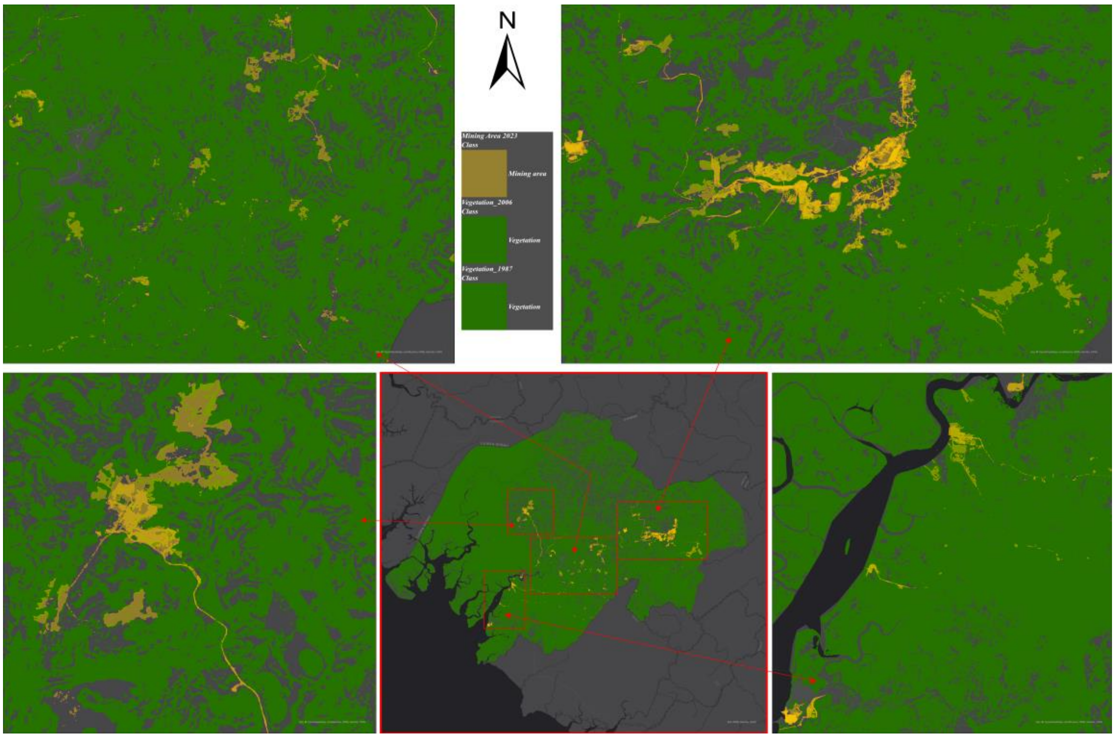

Figure 20: Deforested area from 1987 to 2023

The map depicts the deforestation caused by mining activities between 1987 and 2023. Yellow areas indicate mining zones that have grown significantly, absorbing previously vegetated areas. Green areas depict vegetation from 1987 to 2006, reflecting the natural landscape before mining expansion. The overlay analysis reveals that deforestation is evident where yellow overlays green, indicating that these areas have been cleared for mining operations. The map's panel structure provides a broad overview of the region, with smaller panels focusing on areas of high mining activity and deforestation. The map shows a clear environmental impact, with mining activities reducing green vegetated areas and driving land-use change, which has ecological impacts. This visualization emphasizes the negative environmental impacts of mining expansion and the need for sustainable mining practices and effective land management strategies to reduce deforestation and protect natural habitats.

- **LULC prediction map**

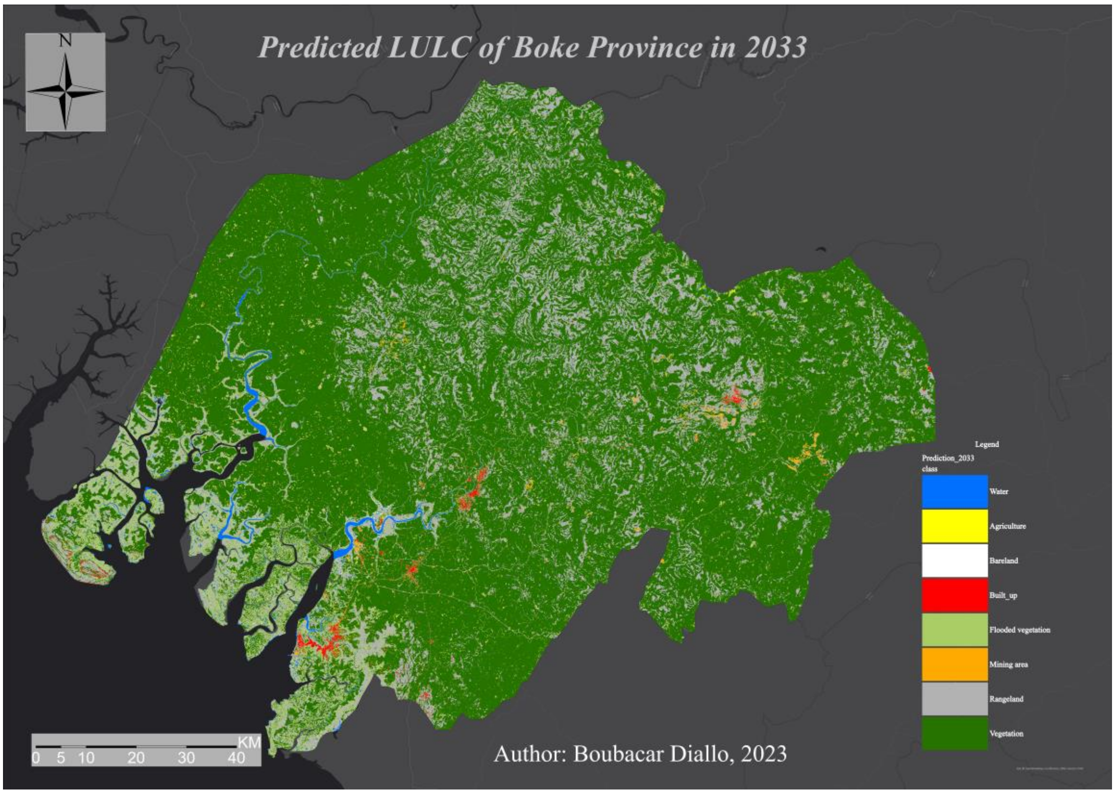

Figure 21: Prediction map of Boke province in 2033

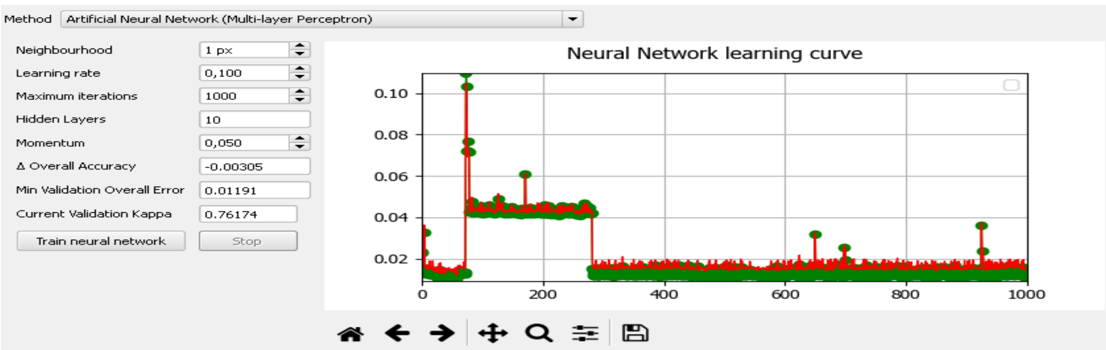

Figure 22: Neural network learning curve graph

The current validation Kappa statistic of 0.76174 indicates a high level of agreement between the model's classifications and the observed validation data, suggesting that the Artificial Neural Network (ANN) model is performing well. The Kappa statistic particularly valuable since it gives a more nuanced measure of accuracy by accounting for the chance of agreement, thus offering a more robust evaluation of the model's predictive capabilities than simple accuracy would.

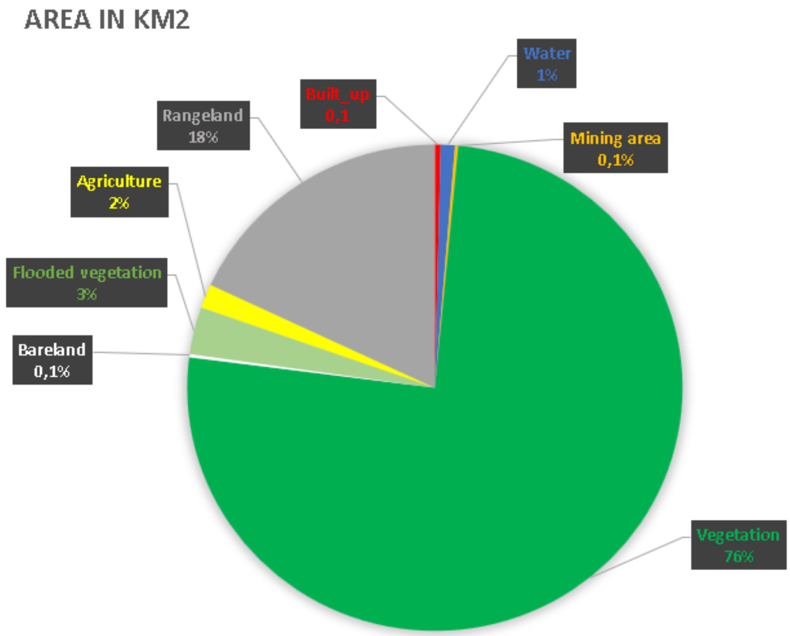

Figure 23: Area in km² of LULC of Boke in 2033

These three (3) figures provide useful information on the future of LULC in Boke.
This pie chart shows the area covered by various land use categories, based on projections for 2033. The vegetation dominates, covering 76% of the area. Rangeland (18%), the flooded vegetation (3%) and agriculture (2%) are the next largest categories. Water bodies, built-up areas, and mining sites each constitute a very small fraction of the total area, at 1% or less.
The neural network that has been trained to predict the future LULC distribution in Boke province demonstrated a high agreement the model's classifications and the observed validation data. The results show that in 2033, the majority of the land in the province remain as vegetation as indicated on the pie chart, with only minor changes in other land use classes, like agricultural land, built-up and mining areas. The prediction for 2033 and the shift in land use dynamics become apparent. Notably, the yellow areas representing mining activities are reduced, which may suggest a decline in lining operations. This decrease could also result from various factors including depletion that limit extractive activities. A reduction in mining operations can lead to less disruption of the natural landscape, potential recovery of local ecosystems, and a decrease in pollution and land degradation.
In summary, the predicted LULC map for 2033 suggest positive a positive environmental outcome with a reduction in mining areas and the preservation of extensive vegetated regions. At the same time, it also indicates continued economic and infrastructural development as seen by the expansion of built-up areas. This balance is delicate and would require ongoing, adaptive management to ensure that the natural environment and human development can coexist in harmony. It is also important to note that predictions are based on models that rely on current trends and the actual future LULC will be possibly influenced by a variety of factors including political decisions, economic shifts, and unforeseen events.
The analysis provides valuable insights for future environmental management and development policies in Boke province enabling the prediction of land distribution, which can guide urban planning, sustainable mining and development practices, and environmental conservation efforts.

Chapter V: Discussion

The comprehensive research of the environmental risks of mining activities in Boke province from 1987 to 2023, through the lens of various environmental indices and land use/land cover (LULC) changes, has provided critical insights into the dynamic interplay between human activities and the natural environment. The study utilized a range of remote sensing techniques, including the Combined Spectral Response Index (CSRI), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Fractional Vegetation Cover (FVC), alongside air quality (NO2) monitoring and detailed LULC assessments, to evaluate the impacts of mining operations.

The findings highlight a clear dichotomy in soil moisture and vegetation health between areas proximate to and distant from mining sites. High CSRI values in distant areas indicated healthier soil conditions, while low values near mining sites pointed to increased soil drought levels and vegetation stress, evidencing the detrimental effects Of mining on soil and vegetation health. This pattern was corroborated by NDVI and EVI analyses, which showed diminished vegetation health and coverage near mining operations, reflecting the adverse impacts of land disturbance and habitat fragmentation caused by mining.

Furthermore, the FVC analysis revealed significant landscape fragmentation and loss of vegetation cover, particularly in areas close to mining operations, underscoring the extensive ecological disruptions induced by mining. Air quality analysis, focusing on NO2 levels, highlighted pollution hotspots near mining sites, indicating the environmental hazards associated with mining activities.

The accuracy assessment of LULC classification using the SVM classifier demonstrated high reliability in capturing the spatial patterns and dynamics of land cover changes overtime, affirming the methodological soundness of the study. Change detection analysis provided a granular view of how mining activities have transformed the landscape, with a significant conversion of rangeland and vegetation to mining areas, highlighting the encroachment of mining operations on the natural habitats.

A notable transformation has been observed in the rangeland of Boke, which has experienced the most considerable decline among all land cover types due to mining expansion. From a sprawling 4395 km² in 1987n rangeland coverage has plummeted to 2156 km² in 2023. This significant reduction reflects the extensive conversion to mining areas, accounting for 43.73 km² of the total mining area in 2023, a change that was not initially anticipated. The rangeland, traditionally serving as grazing grounds and natural habitats, is now at the forefront of land repurposing, bearing the brunt of industrial encroachment.

When it comes to the vegetation trends, the coverage initially presented a resilient front, increasing from 8135 km² in 1987 to 9402 km² in 2017, before experiencing a marginal decrease to 9368 km² by 2023. Despite the overall growth, the vegetation class has not been immune to the impacts of mining. There has been a notable shift of 19.82 km² of vegetation into mining areas by 2023. This trend is indicative of deforestation and habitat disruption, yet the slight recovery in vegetation cover towards the end study period offers a glimmer of hope for environmental restoration.

The mining sector has seen an aggressive expansion, with the area under mining surging from a mere 6 km² in 1987 to an expansive 65 km² by 2023. The mining sites have not only increased in number but also in the scope, reflecting an intensive scale of operations. The consistent growth is attributed to a confluence of factors, including global mineral demand especially for the bauxite, technological advancements, and

possible new mineral deposit discoveries. This also has been minored in the infrastructural domain, with the number of mining ports escalating from one single port in 1987 to six by 2023, which also increased the number of rail ways across all the province, underscoring the intensification of mining and its environmental footprint.
The direct correlation between mining activities and land use change is starkly evident in the data. Mining activities have precipitated the most profound alterations in land cover, reshaping the province’s physical and economic landscape.
Despite the economic boom, this expansion comes at an ecological cost, manifesting in land degradation, deforestation, and pollution, thus posing risks to local ecosystems and communities.
The analysis, which used GIS and remote sensing data, revealed significant changes in land use and land cover (LULC) over the study period, with the expansion of mining areas resulting in reduced vegetation and altered natural landscapes. These findings have implications for environmental sustainability in the Boke province, highlighting the trade-off between economic benefits from mining activities and visible environmental degradation, such as deforestation, soil erosion, and pollution. The study assesses the effectiveness of the integrated Geographic Information System (GIS) approach in monitoring and predicting environmental risks, emphasizing its advantages and disadvantages. It also investigates the role of technological advancements in increasing the accuracy of environmental monitoring. The utility of predictive models, as illustrated by the LULC prediction maps, is discussed in terms of future planning and policymaking. Mining-induced changes in land use patterns have far-reaching consequences for local communities, including altered livelihoods, reduced access to natural resources, and the possibility of social conflict. The health risks associated with environmental degradation, particularly those involving air and water quality, are thoroughly examined. Comprehensive environmental impact assessments, stringent regulatory frameworks, and active community participation in decision-making are among the policy recommendations. Future research directions include longitudinal studies on mining's long-term ecological and socioeconomic impacts, the development of sophisticated models for predicting environmental and health risks, and an integrated Geographic Information (GI) approach to complex environmental monitoring and management.

Chapter: VI: Conclusion

In conclusion, this part summarizes the key findings and their implications for environmental management in the Boke province. The study highlights the importance of GIS and remote sensing technologies in understanding and managing the environmental impacts of mining activities. The spatiotemporal analysis provided a comprehensive view of changes in land use and vegetation cover, highlighting mining's extensive environmental impact, which went from 6 km² 1987 to 65 km² 2023. The findings from this study, underscore the profound multifaceted impacts of mining activities on the environment in Boke province. While mining operations have contributed to economic development, evidenced the expansion of mining areas and the increase in number of mining ports from one 1987 to six 2023, they have also led to significant environmental degradation. This includes increased soil drought levels, reduced vegetation cover, landscape fragmentation and elevated air pollution levels. The temporal trends revealed through various environmental indices and LULC changes highlight the importance of integrating remote sensing and geospatial analyses in environmental monitoring and management. These tools have proven effective in assessing the impacts of anthropogenic activities on land surface characteristics, offering a basis for informed decision-making in sustainable land management and conservation efforts. Looking forward, the predicted LULC for 2033 offers a cautiously optimistic scenario, with a potential reduction in mining areas and preservation of vegetated areas, suggesting possible environmental recovery with 76% coverage in vegetation and 18% in rangeland. However, this positive outlook is contingent upon a delicate balance between economic development and environmental stewardship, necessitating adaptive management strategies. In light of these findings, it is imperative for policymakers, environmental managers, and stakeholders in the mining sector to consider the long-term ecological and socio-economic implications of mining activities. There is a critical need for comprehensive land use planning and the adoption of environmentally sustainable mining technologies and practices to safeguard the ecological integrity and natural heritage of Boke province for future provinces. This thesis contributes to the growing body of knowledge on the environmental impacts of mining and demonstrates the utility of remote sensing and geospatial analysis as indispensable tools for environmental monitoring and management. It provides a foundation for future research and basis for informed decision-making in the pursuit of sustainable development and environmental conservations in mining-affected areas. The thesis concludes that sustainable mining practices are critical to balancing economic growth and environmental conservation. It promotes the use of effective environmental management strategies, informed by GIS and remote sensing analyses, to mitigate the negative effects of mining activities. The study highlights the importance of continuous monitoring and adaptive management approaches in protecting the natural environment and ensuring the well-being of local communities.

Despite the large corpus of research on the environmental impacts of mining, studies focused on specific areas, particularly those with distinct ecological and socioeconomic characteristics about Boke, are rare. The lack of localized research restricts the establishment of customized environmental management measures. The available literature frequently adopts a broad approach that may not be completely applicable to the unique conditions of Boke. This study intended to provide a comprehensive analysis of the environmental repercussions of mining in this the province by combining GIS and remote sensing. This specific focus is crucial when it comes to develop efficient strategies that are responsive to the unique ecological and social realities of Boke Province. The importance of this study stems from its potential contributions to environmental management and monitoring. By focusing on a specific area with unique ecological and socioeconomic characteristics, the study gives findings that are potentially transferable to other similar regions. The findings could help to shape environmental policy as well as management strategies, resulting in the development of sustainable mining operations. Furthermore, this research could serve as a framework for how integrated GI techniques can be properly used in environmental monitoring and management, particularly in areas affected by extensive industrial activity such as mining.

Finally, the thesis underlines the potential of integrated GI approaches to provide useful insights for policymaking and future research. It suggests areas for future research, such as the long-term socioeconomic effects of mining and the development of more advanced predictive models for assessing environmental risk in mining regions. The conclusion emphasizes the importance of interdisciplinary approaches to addressing complex environmental challenges in regions such as Boke province.

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