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EVALUATING THE IMPACT OF MINING ON NATURAL VEGETATION COVER CHANGES IN LOGO LOCAL GOVERNMENT AREA, BENUE STATE, NIGERIA (2019–2023)

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ABSTRACT: *The extraction of valuable minerals necessitates extensive land clearance, which can result in the degradation of forests, grasslands, and agricultural areas with cascading effects on the environment and livelihoods. To examine the impact of mining activities on vegetal cover in Ayilamo, Akpena and Fifo, Logo Local Government Area, Benue State, Quickbird satellite imagery interpretation was used on three (3) locations between the intermittent years of 2019, 2021 and 2023. Remote sensing and GIS techniques were applied to measure vegetation loss, calculate the Rate of Conversion (RoC) of land cover in the mining sites, and identify the most affected areas. Among the nine locations studied, Ayilamo and Akpena recorded the highest RoC values for vegetation loss at -4.94 ha/year and -4.53 ha/year, respectively. Conversely, Fofi exhibited the lowest RoC at -0.36 ha/year between 2021 and 2023. Field observations corroborated these findings, showing areas of scant vegetation and bare landscapes dominated by mining pits and waste. These patterns highlight the profound ecological disruption caused by mining, with vegetation loss exacerbating soil erosion and habitat degradation. The study concluded that mining activities are a significant driver of land cover change within the study region, necessitating immediate action. Recommendations include the enforcement of stricter environmental regulations, promotion of reforestation programmes, and sustainable mining practices to mitigate further ecological degradation.*

KEYWORDS: LULC change, Mining impacts, Vegetation cover, Logo LGA, Benue State.

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INTRODUCTION

Mineral exploitation serves as a cornerstone of global socio-economic development, driving industrialisation, infrastructure growth, and employment in both developed and developing economies (David, 2002; Hilson, 2002). In several African nations, large-scale mining accounts for a significant portion of foreign exchange earnings and government revenue, while small-scale operations provide vital livelihoods for rural populations (Imasiku, 2008). However, when uncoordinated, these activities trigger severe environmental degradation, including soil erosion, heavy metal contamination, and systemic biodiversity loss (Miller et al., 2018).

A primary casualty of this industry is natural vegetation, which is essential for regulating biogeochemical cycles and maintaining soil integrity (Jenses, 2015; Adia & Rabiu, 2005). Mining-induced vegetation loss occurs through two pathways: direct clearance for site excavation and indirect physiological stress. The latter involves the deposition of chemical-laden dust on plant surfaces, which enters stomatal pores to destroy chlorophyll and disrupt photosynthesis (Maponga, 1995). Consequently, the expansion of mining activities continues to be a dominant driver of Land Use and Land Cover (LULC) transformations, necessitating rigorous monitoring of vegetative health in extractive zones.

Mining

Mining is the systematic extraction of metallic, non-metallic, and fuel minerals from the earth's crust to satisfy industrial and economic requirements (Acheampong, 2004). Historically, this practice has evolved from rudimentary prehistoric tool-crafting into a sophisticated industry dominated by two primary modalities: opencast and underground mining (Burrough, 2015; Li et al., 2021).

Opencast or surface mining remains the most prevalent global method due to its high productivity and operational safety; however, it necessitates the extensive removal of overburden through logging and clear-cutting, resulting in profound impacts on natural vegetation and land cover (USGS, 1995; Adia & Rabiu, 2008). In the Nigerian context, organized mining originated in 1903, though the 1956 discovery of oil shifted national focus away from solid minerals (Aigbedion & Iyayi, 2007). Despite this shift, the sector remains a critical regional pillar, particularly in Benue State, where limestone exploitation has driven industrial growth since the mid-20th century (Ayatse et al., 2022).

Vegetation

In ecological terms, vegetation is defined as the collective plant cover and structural assemblage of an area, encompassing both natural native species and human-maintained cultural types (Archibold, 1994; Adia & Rabiu, 2008). Unlike flora, which refers specifically to species composition, vegetation serves as a primary indicator of regional environmental and climatic conditions. Globally, these plant formations are categorized into distinct belts ranging from tropical forests to arid deserts reflecting a close dependency on latitudinal climatic gradients and moisture availability.

Within Nigeria, the vegetation follows a clear climatic zonation transitioning from southern forest belts to northern savannahs (Bryan et al., 2018). The savannah belt, which dominates the central region, is subdivided into Guinea, Sudan, and Sahel zones. Notably, the Guinea savannah is the most extensive, covering nearly half the country and encompassing states like Benue. This zone is characterised by a mosaic of tall grasses and scattered deciduous trees, serving as a transitional landscape between the lush tropical forests of the south and the increasingly arid, short-grass Sudan and Sahel savannahs of the north (Fayose & Olorunfemi, 2015).

Mining Activities and Vegetation Cover

Mining activities have significant impacts on vegetal cover, leading to deforestation, habitat destruction, and loss of biodiversity. The effects of mining on vegetation cover are complex and influenced by various factors, including mine type, location, and rehabilitation efforts. Impacts of mining on vegetation cover include:

i. Deforestation and habitat destruction**:** Mining activities lead to widespread deforestation and habitat destruction, resulting in lost vegetation cover and biodiversity (Bryan et al., 2018).

ii. Soil erosion and degradation: Mining activities cause soil pollution and degradation, reducing vegetation cover and affecting ecosystem processes (Ladwig et al., 2017)

iii. Water pollution: Mining activities can lead to water pollution affecting vegetal survival and growth (Kuma *et al*., 2017; Miller *et al*., 2018)

iv. Fragmentation and isolation: Mining activities can fragment and isolate vegetation habitats, reducing biodiversity and ecosystem connectivity (Fayose and Olorunfemi 2005; Haddad *et al*., 2015)

Factors influencing the effect of mining on vegetal cover

The ecological impact of mining on vegetation is a multifaceted phenomenon shaped by the specific mineral type and geographical setting (Mwale et al., 2020). Local environmental variables, particularly climate and soil conditions, play a critical role in determining the degree of vegetative disturbance and the subsequent rate of ecosystem recovery (Ladwig et al., 2017). While these factors can exacerbate degradation, proactive rehabilitation efforts remain instrumental in mitigating adverse effects and fostering long-term ecological restoration (Barnes et al., 2015; Nichols et al., 2017).

Vegetation Indices

The use of vegetation indices (VIs) to assess the impact of mining activities on vegetation cover is increasingly important for environmental monitoring and rehabilitation efforts. Mining, especially surface mining, often leads to significant degradation of land and ecosystems, disrupting vegetation and soil quality. Remote sensing, through the application of various vegetation indices, provides a means to monitor these changes over time and space.

Normalized Difference Vegetation Index (NDVI)

NDVI is the most commonly used index for assessing vegetation health. It calculates the difference between the near-infrared and red bands of satellite images to evaluate the density of green vegetation. NDVI values range from -1 to +1, with higher values indicating healthier vegetation. This index is particularly useful for monitoring vegetation in areas that are impacted

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by disturbances, such as mining, as it helps quantify the extent of vegetation recovery over time.

In a study by Juanda *et al.* (2021), NDVI was used to assess the effectiveness of reclamation in a coal mine area from 2017 to 2020. The study, which analysed a 2.03 ha reclamation site, demonstrated that NDVI values showed little improvement during the first and second years of revegetation, with values less than 0.33. However, from the third year onwards, NDVI values increased significantly, reaching 0.369 in the third year and 0.417 in the fourth year. This increase in NDVI reflected a substantial improvement in vegetation health, with healthy vegetation covering 68.13% and 81.39% of the site, respectively. The study illustrates how NDVI can be a reliable tool for tracking vegetation recovery and assessing the success of reclamation efforts in mining areas (Juanda *et al.*, 2021).

Enhanced Vegetation Index (EVI)

EVI is a vegetation index that enhances the signal-to-noise ratio in areas with high vegetation density, particularly effective in forested regions. It accounts for atmospheric conditions, such as aerosols, and adjusts for the canopy background. This makes EVI more accurate than NDVI in environments where the latter might be saturated, such as dense forests or areas impacted by atmospheric pollutants.

In the study by Sun *et al.* (2024), EVI was one of the key indices used to assess the impact of mining on vegetation phenology in the Bainaimiao copper mining area. The study aimed to quantify the influence of mining activities on vegetation and to analyse the sensitivity of various vegetation indices to these activities. EVI, along with other indices, was used to track phenological changes in vegetation, which revealed significant delays in vegetation development in the mining-affected area, highlighting the extent of land degradation due to mining operations (Sun *et al.,* 2024).

Soil-Adjusted Vegetation Index (SAVI)

SAVI is particularly useful in areas with sparse vegetation, where the influence of soil background can distort the vegetation signal. By incorporating a correction factor for soil brightness, SAVI enhances the accuracy of vegetation assessments in these regions. This makes SAVI ideal for monitoring vegetation recovery in post-mining landscapes where vegetation is often sparse in the early stages of reclamation.

In a study by Bell (2015), SAVI was used to evaluate the success of vegetation rehabilitation in the Navachab Gold Mine, Namibia. The study analysed vegetation cover changes over several years using remote sensing data. SAVI proved effective in detecting subtle changes in vegetation cover, providing insights into the progress of rehabilitation efforts at the mine. It was particularly useful for tracking vegetation recovery in areas where soil exposure was still significant (Bell, 2015).

Theoretical Framework

This study is grounded in the theories of environmental change, resource management, and human-environment interactions. It adopts the theory of environmental determinism and possibilism to explain how human actions shape forest resources in the Logo Local Government Area. Environmental determinism suggests that natural conditions influence human activity, while possibilism argues that human intervention can alter the environment through policy and resource use (Bridgman & Dragovich, 2019).

MATERIALS AND METHODS

Research Design

This study employed a quasi-experimental time series design to monitor forest resource changes in Logo Local Government Area, Benue State, from 2019 to 2023, taking intermittent years of 2019, 2021 and 2023. This is most suitable for a concise understanding of the spatial and temporal dynamics of LULC changes, to provide insights into the environmental effect and inform sustainable land management strategies for the future.

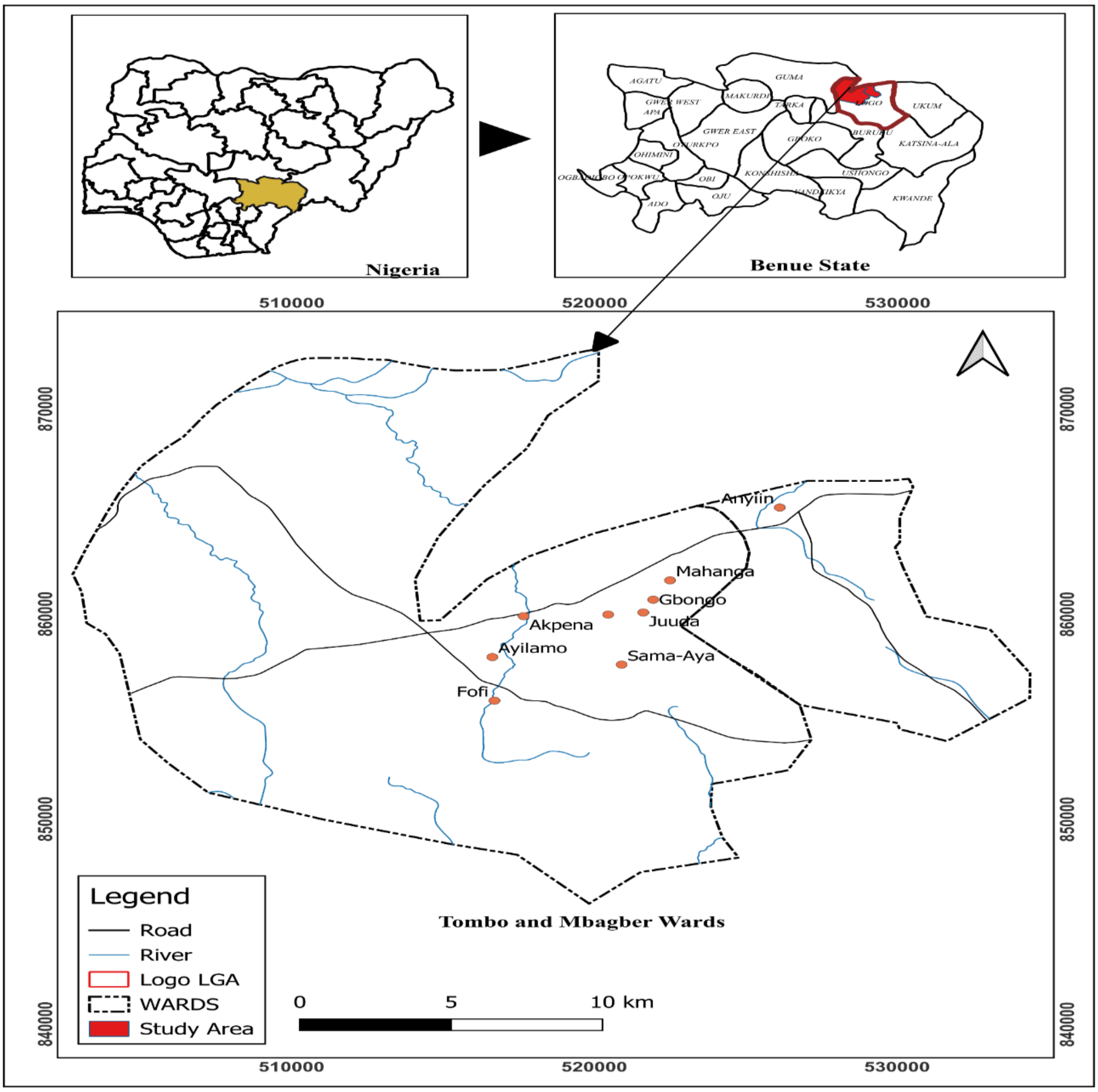
The study employed a purposive sampling technique to select specific communities within the Logo Local Government Area (LGA), Benue State, Nigeria. The communities Ayilamo, Akpena and Fofi were chosen based on the presence of active or visible mining activities. This approach enables a more detailed examination of areas undergoing significant land cover transitions due to mining, which affects natural vegetation and other land cover types. Each selected community represents a site where the effect of mining on vegetal cover can be observed, thus providing valuable data for spatial and temporal analysis of land use dynamics. In selecting these areas, considerations were made for observable mining activities.

Data used in this study were primarily spatial, including multi-temporal Quickbird satellite imagery for 2019, 2021, and 2023 (sourced from Google Earth Pro), a topographic map of Benue State, and ground truth data obtained through GPS and photographs. Image acquisition occurred between November and March (year) to minimise cloud interference. Ancillary data, such as high-resolution imagery, were also incorporated to aid in classification accuracy.

The Study Area

Geographically, Logo Local Government Area (LGA) is situated in the Northwestern region of Benue State, Nigeria. Logo LGA shares borders with Nasarawa State. It has Ukum LGA as its eastern neighbour and Guma LGA as its western neighbour. Furthermore, Logo shares a southwest boundary with Katsina-Ala LGA and Buruku LGA on the southern part. This LGA is part of the Tiv-speaking region of Benue and consists of multiple communities, including but not limited to where the study was conducted: Ayilamo, Akpena, Fofi, Gbongo (Gbango), Ikpaagia, Juuda, Mahanga, Anyiin, and Sam-Aya. Residents of these nearby LGAs frequently trade, cultivate, and exchange cultures with their counterparts across these borders, which contribute to the socioeconomic connections in the area.

Figure 1: Maps Showing Nigeria, Benue State and Logo LGA in the Study Area



Data Analysis Techniques

Image Pre-Processing

Satellite images were pre-processed to enhance usability. These involved subsetting based on the area of interest and re-geo-referencing in ArcGIS (Xu *et al.*, 2019).

Image Classification

A supervised classification approach with the Maximum Likelihood Classification (MLC) algorithm was utilised. The classification process involved:

i. **Training Data Selection:** Field visits and high-resolution imagery from Google Earth were used to identify representative samples for each land cover class (Guo *et al.*, 2020).

ii. **Classification Execution:** The MLC algorithm assigned pixels to the respective classes based on spectral signatures, optimising accuracy for vegetation and non-vegetation classes (Jensen, 2015). This method is effective in distinguishing the probability of a pixel belonging to a specific land cover class, which aids in identifying changes accurately over time (Belgiu & Drăguţ, 2016).

Using classified images, land cover changes were analysed based on the study's objectives. The classified images were used to measure changes in vegetation cover, expansion in mining areas and its impact on adjacent land covers, conversion rates of vegetation and grasslands to mining sites and shifts in LULC percentage compositions.

Change Detection

Change detection analysis was conducted to measure the changes in natural vegetation cover from 2019 to 2023/2024. The formula used for calculating the change in area for each LULC class is:

$$\text{Change in Area} = Area_{Final} - Area_{Initial} \qquad 1$$

Where:

$Area_{Final}$= Area of the LULC class in the later year

$Area_{initial}$= Area of the LULC class in the earlier year

This calculation was performed for each location to quantify the extent of vegetation loss or gain.

Rate of Change

To analyse the rate at which natural vegetation and grasslands are being converted to mining sites, the rate of change was calculated using the formula:

$$\text{Rate of Change} = \frac{Change\ in\ Area}{Time\ Period} \qquad 2$$

Where:

Change in area is as defined in Equation 1.

The time period is the number of years between the initial and final measurements.

Assessment of LULC Composition Shifts

To assess the shifts in percentage composition of each LULC type, the percentage of each category was calculated as follows:

$$\text{Percentage Composition} = \left(\frac{Area\ of\ LULC\ Type}{Total\ Area}\right) \times 100\% \qquad 3$$

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Table 1: Satellite Data Characteristics

Data Type	Acquisition Date	Resolution	Source
Quickbird	January 2019	0.5 m	Google Earth Pro
Quickbird	March 2021	0.51 m	Google Earth Pro
Quickbird	January 2023	0.5 m	Google Earth Pro

Classification Scheme

The classification scheme used in this study integrated aspects of both the FAO (2010) and Anderson *et al.* (2001) classification frameworks, adapted to meet the objectives of examining natural vegetation, grassland reduction, and identifying mining-impacted areas. This framework enabled the study to effectively categorise land cover types relevant to land use changes observed between 2019 and 2023. The following four classes were defined:

i. **Natural Vegetation (Forest):** This class includes areas with dense tree cover, typically comprising species such as *Khaya senegalensis*, *Isoberlina doka*, and *Daniella olivera*. These areas are characterized by canopy coverage of over 10% and tree heights exceeding 5 meters, representing mature forest areas as well as preserved gallery forests along watercourses. This category was essential for measuring vegetation reduction across the study period.

ii. **Grassland:** This category covers land dominated by grasses and herbaceous plants, often utilised for grazing livestock or agricultural activities. Grassland in the study area also includes mixed farming zones where land frequently shifts between cultivation and fallow, resulting in modified vegetation with lower density. The grassland category provides insight into natural vegetation converted for agricultural use and tracks reductions in non-forested vegetation.

iii. **Mining Site:** This class represents areas heavily modified for the purpose of mineral extraction. Mining sites display significant disturbances to the natural environment, typically characterised by bare soil, open pits, and limited vegetation cover. The mining site classification was critical for quantifying the extent of land cover changes driven by mining activities and assessing impacts on surrounding natural vegetation and grasslands.

iv. **Built-Up Area:** This class includes urbanised or developed land, encompassing residential areas, roads, and infrastructural developments within the selected communities. Built-up areas are identified by their high density of impervious surfaces, distinguishing them from natural vegetation and open land types.

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RESULTS

The Changes in Natural Vegetation cover and percentage composition of LULC from 2019 to 2023 in each location

This objective aims to examine how the relative proportions of key land use land cover (LULC) types namely mining, natural vegetation, and grassland have evolved across the study locations from 2019 to 2023. The data clearly indicates that mining activities have been a major factor influencing the shifting composition of land cover in most areas. By assessing these percentage changes, we can better understand the spatial transformation occurring due to mining expansion and its impact on natural vegetation and grassland.

Ayilamo Study Site

Table 2 shows the statistical evidence of land use/land cover (LULC) classification from 2019 to 2023, with natural vegetation, grassland, and mining sites as the land cover types. In 2019, natural vegetation covered 14.15 hectares, accounting for 20.95% of the total land area, while grassland made up the majority with 46.46 hectares (68.77%). Mining activities were also present, occupying 6.94 hectares (10.28%). Fig. 2 (2019) illustrates the spatial representation of this period, showing natural vegetation (deep green), grassland (light green), and mining areas (red), with grassland being the dominant land cover type.

By 2021, there was a significant reduction in natural vegetation to 5.1 hectares (7.55%), reflecting a sharp decline in vegetative cover. Grassland, however, increased substantially to 55.46 hectares (82.10%), suggesting either vegetation conversion or seasonal changes. Mining activities remained relatively stable, covering 6.99 hectares (10.34%). As shown in Fig. 2 (2021), grassland (light green) became more expansive, while natural vegetation (deep green) shrank, and mining areas (red) remained relatively unchanged.

In 2023, the natural vegetation cover partially recovered, increasing to 9.65 hectares (14.29%), indicating a slight regrowth or rehabilitation in certain parts of the landscape. Grassland reduced to 49.24 hectares (72.89%), while mining activities expanded further, occupying 8.66 hectares (12.82%). Fig. 2 (2023) spatially reflects these changes, with the mining areas (red) slightly expanding, natural vegetation (deep green) appearing in more patches, and grassland (light green) remaining widespread but less dominant than in 2021. Plate 1 shows the field evidence of mining activity in the area, including exposed soil surfaces, excavated pits, and scattered vegetation.

Table 2: Ayilamo Quantitative LULC Values from 2019–2023

Land Cover Classes	Year	Area (Ha)	Percentage (%)
Natural Vegetation	2019	14.15	20.95
	2021	5.1	7.55
	2023	9.65	14.29
Grass Land	2019	46.46	68.77
	2021	55.46	82.1
	2023	49.24	72.89
Mining Site	2019	6.94	10.28
	2021	6.99	10.34
	2023	8.66	12.82

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Figure 2: Ayilamo Land Cover Analysis of 2019–2023

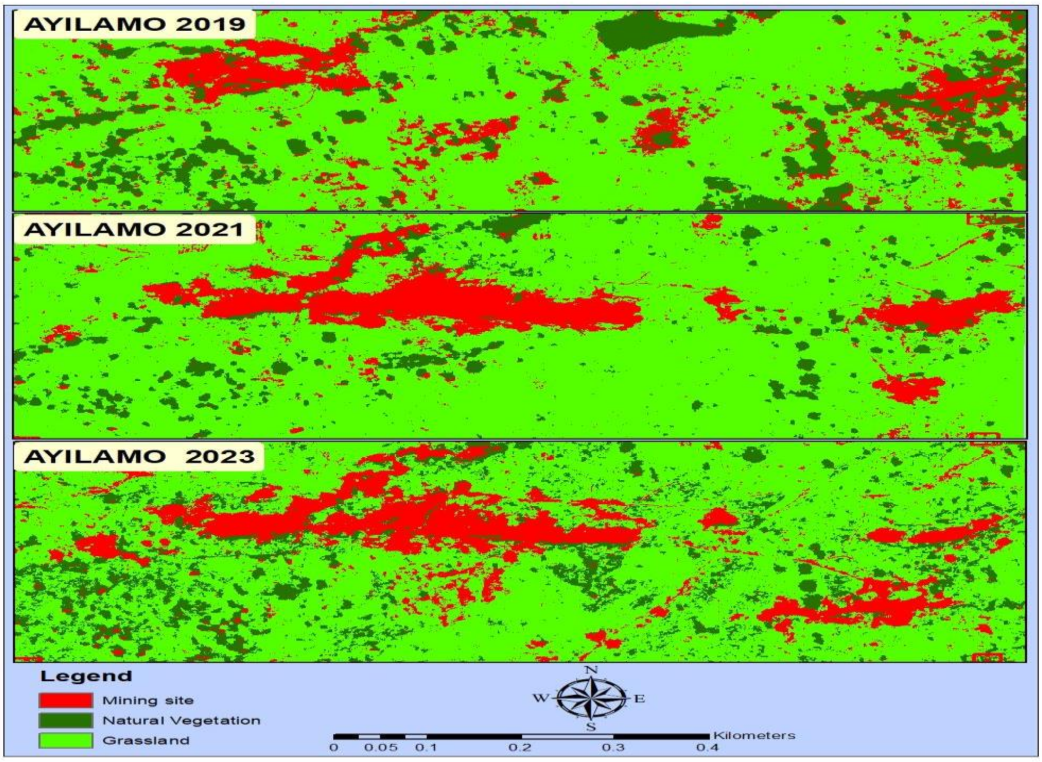

Plate 1: Ayilamo Study Site showing Degraded Landscape with scanty Vegetation due to Mining

Akpena Study Site

Table 3 shows a more gradual shift from natural vegetation and grasslands towards mining. In 2019, natural vegetation covered 8.18 hectares (37.26%), and grassland accounted for 13.77 hectares, representing 62.74% of the total 21.95 hectares. By 2021, mining areas had started to emerge, covering 3.29 hectares (14.98%), while natural vegetation increased slightly to 14.17 hectares (64.59%), and grassland decreased to 4.49 hectares, representing 20.45%. A whopping area of 9.28 hectares initially covered by grassland was lost within these two years, possibly as mining activities crept in. This shift continued in 2023, when mining expanded to 4.87 hectares (22.17%), natural vegetation shrank to 4.3 hectares (19.6%), and grassland decreased further to 12.78 hectares (58.22%). The overall data indicate that mining activity has gradually encroached on both natural vegetation and grasslands in Akpena, though grassland remains the dominant land cover type despite the growing mining footprint.

Figure 3 shows the land cover type; areas covered with deep green indicate natural vegetation, and the areas covered with light green indicate areas covered by grassland. In 2019, there was no sign of mining activity shown with red. From 2021, mining activities sprang up, and by 2023, both deep and light green areas were taken over hugely by red, showing the effect of mining activities on vegetal cover. These changes reflect the significant encroachment of mining on both natural vegetation and grassland, although grassland remains the largest land cover type. Plate 2 shows a degraded landscape with scanty vegetation due to mining. As the overburden is removed for excavation activities, the natural vegetation and grassland land cover types are lost to mining.

Table 3: Akpena Quantitative LULC Values from 2019–2023

Land Cover Classes	Year	Area (Ha)	Percentage (%)
Natural Vegetation	2019	8.18	37.26
	2021	14.17	64.59
	2023	4.3	19.6
Grass Land	2019	13.77	62.74
	2021	4.49	20.45
	2023	12.78	58.22
Mining Site	2021	3.29	14.98
	2023	4.87	22.17

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Figure 3: Akpena Land Cover Analysis of 2019–2023

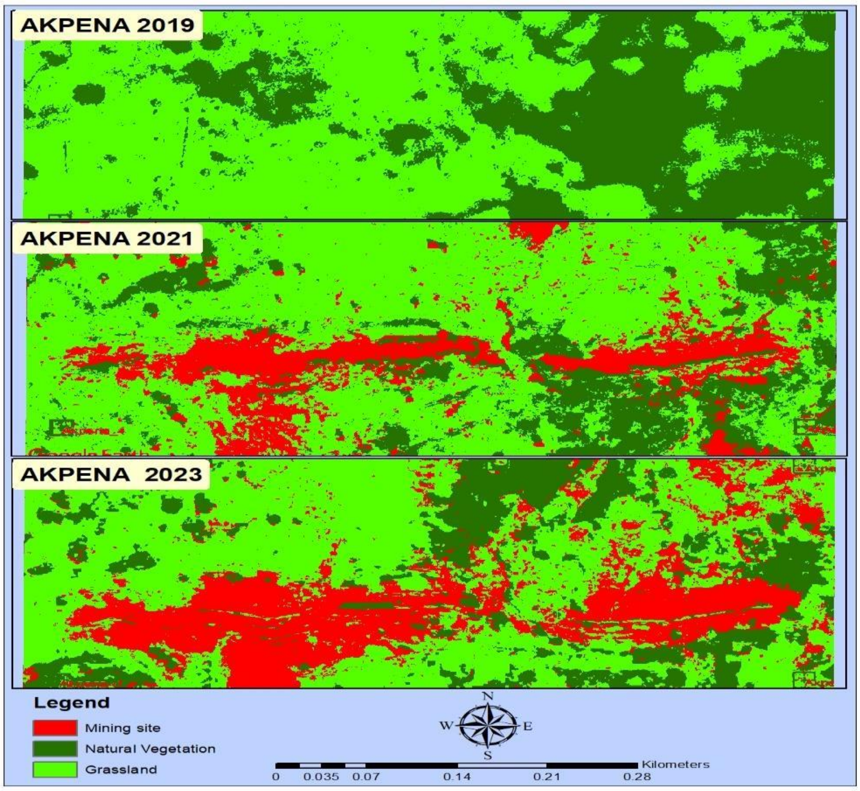

Plate 2: Akpena study site showing a degraded landscape with scanty vegetation due to mining

Fofi Study Site

In Table 4, the LULC changes reflect a notable impact of mining on both natural vegetation and grassland. In 2019, natural vegetation dominated with 3.51 hectares, representing 53.56%, and grassland covered 3.05 hectares, representing 46.44% of the total 6.56 hectares. However, by 2021, mining began to appear, covering 0.93 hectares, taking up to 14.11%, while natural vegetation decreased to 0.93 hectares (14.17%), and grassland increased to 4.7 hectares (71.68%). By 2023, mining expanded slightly to 1.01 hectares (15.45%), natural vegetation increased marginally to 1.3 hectares (19.81%), and grassland coverage remained high at 4.25 hectares (64.71%). This result suggests that mining in Fofi has led to a shift away from natural vegetation, though grassland remains a significant land cover class, indicating less dramatic land cover changes compared to other locations.

Figure 4 shows the land cover analysis. It has a deep green colour that covers about 14.17% of the total area, representing the natural vegetation, and grassland is represented with light green, covering up to 71.68% of the total area covered in 2019. In this year of no disturbance (2019), mining activities had not set in. In 2021, however, red portions set in, representing 14.17% of the area taken over by mining activities. By 2023, mining activities, represented with red portions, had taken over about 1.01 hectares, representing 15.45% of the total land cover. Grassland decreased to 64.71%, showing the slow but steady impact of mining on both natural vegetation and grassland. Plate 3 displays The Fofi study site showing mining pits and scanty vegetation, taken in 2023.

Table 4: Fofi Quantitative LULC Values from 2019–2023

Land Cover Classes	Year	Area (Ha)	Percentage (%)
Natural Vegetation	2019	3.51	53.56
	2021	0.93	14.17
	2023	1.30	19.81
Grass Land	2019	3.05	46.44
	2021	4.7	71.68
	2023	4.25	64.71
Mining Site	2021	0.93	14.11
	2023	1.01	15.45

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Figure 4: Fofi Land Cover Analysis of 2019–2023

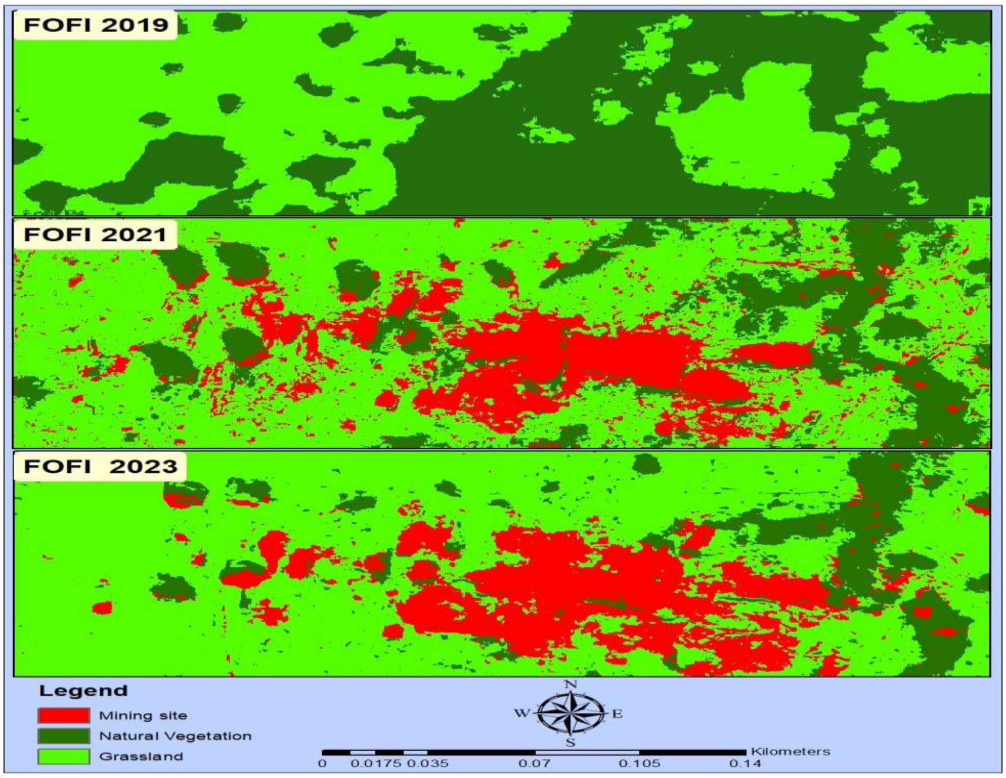

Plate 3: Fofi study site showing mining pit and scanty vegetation

DISCUSSION

Changes in Natural Vegetal Cover from 2019 to 2023 across each Location

In Ayilamo, the land cover dynamics from 2019 to 2023 show a clear shift from natural vegetation and grassland towards mining activities. The continuous decrease in natural vegetation and the simultaneous expansion of mining activities align with findings by Merem *et al.* (2017), who observed significant vegetation loss in Niger State due to rapid mining expansion. Similarly, the reduction in natural vegetation highlights the environmental degradation linked to mining, which corresponds to the deforestation trends identified by Mkaanem (2015) in Mbayion, Gboko.

The land use and land cover (LULC) data for Akpena reveal a more gradual transition from natural vegetation and grassland to mining activities. Akpena's gradual shift, however, underscores the variable pace of mining impacts compared to other locations like Ayilamo.

In Fofi, the LULC changes reflect a notable impact of mining on both natural vegetation and grassland. Mining activities have led to a consistent decrease in natural vegetation, a pattern also observed in studies such as Aminu *et al.* (2023), where sand mining in Agila District caused similar vegetation and soil degradation.

Percentage Composition of LULC Type from 2019 to 2023 in each Location

In Ayilamo, the impact of mining on land cover is pronounced. Natural vegetation, which constituted 24.97% in 2019, declined to 11.64% by 2023, while mining expanded to 27.30%. Grassland, previously dominating at 75.03%, shrank to 61.06% over the same period. This mirrors findings by Mkaanem (2015), who observed substantial vegetation loss due to limestone mining in Gboko, indicating that resource extraction consistently disrupts vegetative cover.

In Akpena, natural vegetation decreased from 37.26% in 2019 to 19.6% in 2023, while mining increased to 22.17%. Grassland, initially covering 62.74%, declined to 58.22%. Similar to the situation in Ayilamo, mining has progressively altered the landscape. Unanaonwi and Amonum (2017) reported a comparable decline in vegetation diversity near mining operations in Gboko, highlighting the broader ecological impacts.

Fofi showed a slower expansion of mining activities, rising from 14.11% in 2021 to 15.45% in 2023. Natural vegetation fluctuated slightly, but grassland decreased significantly, suggesting that mining encroachment is ongoing but less severe compared to Ayilamo and Akpena. Dalil *et al.* (2017) reported a similar gradual decline in vegetation in Kogi State due to cement production, reinforcing the notion that mining-induced land degradation progresses at varying rates depending on site-specific factors.

CONCLUSION AND RECOMMENDATIONS

This study utilised satellite imagery and GIS techniques to assess the impact of mining on land use and land cover (LULC) across nine locations in Logo LGA, Benue State, between 2019 and 2023. The findings reveal a significant and widespread decline in natural vegetation, most notably in Akpena and Ayilamo, where mining expansion directly replaced green cover. While grassland areas fluctuated based on the timing of extraction, the overall trend confirms that mining is the primary driver of environmental degradation in the region. Spatial analysis further highlights an accelerating Rate of Conversion (RoC), with mining footprints expanding significantly, specifically in Akpena, which grew from 14.98% to 22.17% at the expense of critical natural ecosystems.

To mitigate these impacts, the study recommends the urgent implementation of reafforestation programmes and the strengthening of regulatory frameworks, including mandatory Environmental Impact Assessments (EIA). Land use zoning policies should be established to protect critical habitats from indiscriminate mining activity. Furthermore, sustainable extraction practices and soil restoration initiatives are essential to foster ecosystem recovery. The study also suggests future research into the chemical interactions between mining byproducts and local flora to better understand the mechanisms behind grassland conversion and long-term environmental toxicity.

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