OSUN GEOGRAPHICAL REVIEW

Journal of the Department of Geography,
Osun State University, Osun State, Nigeria

Volume 6, 2024

ISSN: 2695 - 1959

Published by the
Department of Geography, Osun State University,
Osun State, Nigeria

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OSUN GEOGRAPHICAL REVIEW
Published by the Department of Geography, Osun State University, Osun State, Nigeria
ISSN: 2695 - 1959 Volume 6, 2024; 48 - 58

ASSESSMENT OF MINING-INDUCED LAND DEGRADATION IN ILE-IFE, OSUN STATE, NIGERIA

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Abstract
Mining activities can lead to significant land degradation, posing environmental and socio-economic challenges in affected regions. This study aimed to assess mining-induced land degradation in Ile-Ife of Osun State, Nigeria, utilizing a comprehensive set of indicators, including slope, soil characteristics, land use/cover, soil organic carbon content, land surface temperature, normalized difference vegetation index (NDVI), and community perceptions obtained through a questionnaire survey. Remote sensing data and geographic information systems (GIS) techniques were employed to analyze land use/cover, NDVI, slope and land surface temperature variations over time, while the soil grid was analyzed to generate the soil types, quantify soil organic carbon content and other relevant soil properties. The weighted overlay analysis was used to integrate the components using the analytical hierarchical process to produce the land degradation map. The findings reveal that 89.9% of the study area has experienced significant degradation, 2.09 % has low-moderate and 8.02 % has very high degradation, all of which are related to mining activities, extremely steep slopes, and loose soil particles. The study revealed widespread concerns about environmental pollution, loss of agricultural productivity, and adverse health effects associated with mining activities. In conclusion, the findings of this study emphasize the urgent need to address mining-induced land degradation in Ile-Ife, Osun State. The integration of multi-indicator approaches, including remote sensing, GIS, and community perceptions, offers valuable insights for designing sustainable land management strategies and mitigating the adverse effects of mining on the environment and local communities.

Keywords: Mining, Land degradation, Remote sensing, Ile-Ife, Weighted overlay

Introduction

Land offers man a series of ecological services (Hardelin and Lankoski, 2018), which range from shelter, food provisioning to provisioning of natural resources for socio-economic development. In providing the ecological services, the land is sometimes overexploited, such that with time, its capacity to continue to meet the ever-increasing needs of man and the environment, both in quantity and quality, is degraded (Kertész *et al*., 2019). Land degradation describes the decline in biological or ecological productivity of land, which may arise because of human activities and/or natural factors (Eswaran, 2001). Some causes include population growth, unemployment, unsustainable agricultural practices, mining, quarrying, infrastructural development, and transportation (Fleskens and Stringer, 2014; Barbero-Sierra *et al*., 2015). Increasing human population has resulted in corresponding increase in the demand for and exploitation of natural resources, with corresponding major alterations in the land use/land cover systems (Hegazy and Kaloop, 2015).

In the Nigerian economy, the mining sector has been reported to have a significant contribution through the provision of foreign earnings, employment creation and general development (Awomeso *et al*., 2019). According to Owolabi *et al*. (2021) mining at the local level boosted the livelihood of local community people, where it provided sustenance for about 13 million locals in over 30 countries. This is in addition to the over 80 million people at the local levels whose livelihood was dependent on artisanal mining. Despite the socio-economic derivatives from the mining sector, mining activities, especially, artisanal mining has been reported to inflict numerous harms on the socio-environmental systems (Adeoye, 2016). This ranges from the loss of agricultural lands and livelihood (Eludoyin *et al*., 2017), land and water pollution, and, deforestation and forest degradation, which lead to loss of biodiversity and ecosystem services (Sonter *et al*., 2018). There were also instances of land grabbing, leading to displacement of rural people from their inherited lands, and exploitation of less privileged local people (Hausermann and Ferring, 2018; Mkodzongi and Spiegel, 2019).

Available information on the effects of mining operations on land degradation in Ile-Ife is predominantly oral and insufficient, as there has not been any dedicated effort for a long-term monitoring using modern mapping technology and tools. To overcome this inefficiency, this study integrates the remote sensing (RS) tools and Geographical Information System (GIS) data (Olorunfemi *et al*., 2018; Ak ı n and Erdoğan, 2020; Owolabi, 2020), which offers enormous capability for monitoring and assessment.

The aim of this study is to assess the effect of mining activities on land degradation in Ile-Ife, while the objectives are to identify the existing mining sites in the study area; determine the factors responsible for land degradation; delineate the mining degraded area; and examine the effects of mining activities on the local communities. The application of GIS and remote sensing as tools for data collection and analysis has a wide area of application in environmental resources management. Remote sensing data, such as Landsat TM, ETM+ and OLI/TIRS were used in change detection analysis (Weng, 2002; Bello *et al*., 2018; Adeyemi and Adeleke, 2020), to provide information on changing extents and patterns of land degradation caused by mining in the study area.

Study Area

Ile-Ife is located between Latitudes 7° 27"N and 7° 3"N and Longitudes 4° 32"E and 4° 40"E (Figure 1). It occupies an area of about 172 Km^2 with a projected population of 423,000 and a growth rate of 3.42 % (https://www.macrotrends.net/global-metrics/cities/ 21991 /ife/)

Mining activities cut across the local communities in the eastern axis of Ile-Ife, which comprised of Mokuro, Kajola, Idujimoti, Lukosi, Alaba Egi, Abata Egba, Okerembete, Wanikin and Aiye Coker. According to Montimore (1975) and Adejuwon (1979), the climatic condition of the town is tropical, differentiated into wet and dry seasons. Outside the apparent effect of climatic variation, the rainy/wet season typically falls between the months of March and October, and is characterized by an annual rainfall of 1200–1500mm, while the dry season is typically between November and February of every year. The long rainfall season conditions the area as a tropical rainforest characterized by high commercial valued trees, such as *Milicia excelsa*, *Entandrophragma cylindricum*, as well as tall grasses. Similarly, the temperature ranges between 27 and 32 °C, with temperature maximum recorded in April. Consequently, the relative humidity is between 50 and 80 %. The area is characterized by protruding hills of between 366 and 394 meters above the mean sea level. Fadare (2000) described the geology of the area as a schist belt, and undifferentiated schist, pegmatized schist, gneisses and migmatites with pegmatites. The soils are tropical ferruginous red soil with both sandy and clayey texture. The local people, predominantly of the Yoruba-speaking tribe, are typically farmers, who engage in subsistent farming as well as in the production of food and cash crops, such as *Theobroma cacao*, *Elaeis guineensis*, *Gambeya africana* and *Coffea brevipes*. Some of the locals also engage in games as a means of livelihood.

Methodology

The datasets for the analysis include Nigeria shape file, Shuttle Radar Topography Mission-Digital Elevation Model (SRTM-DEM) of Nigeria, Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) satellite imagery, Digital soil map of Nigeria and soil organic carbon. The SRTM-DEM and Landsat 8 OLI/TIRS of resolutions 30 m and 100 m was downloaded from https://earthexplorer.usgs.gov/. The digital soil map was downloaded from https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/faounesco-soil-map-of-the-world/en/ and soil organic carbon was downloaded at 250 m resolution through the online International Soil Reference and

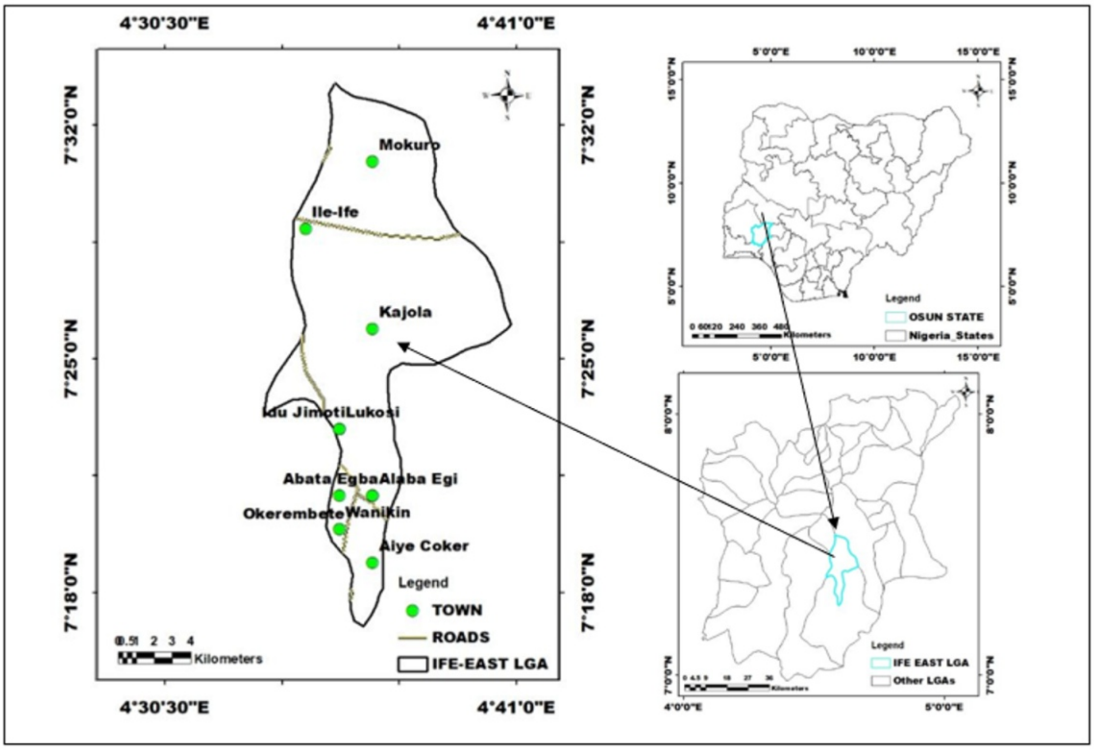

Figure 1: The study Area

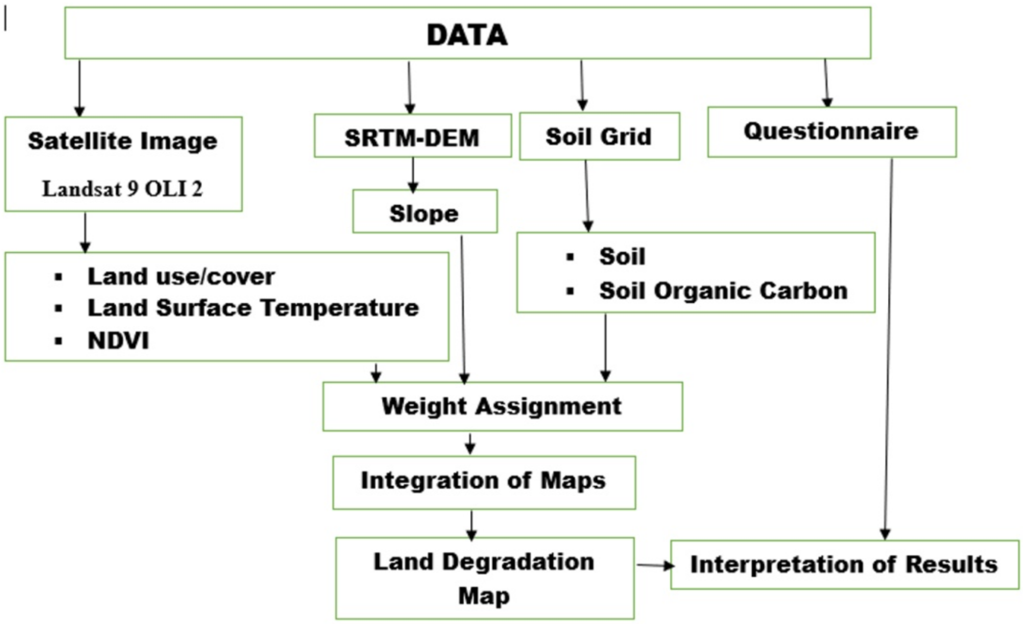

Figure 2: Methodology workflow

Information Centre (ISRIC) website (https://www.isric.org/explore/soilgrids). The base map and DEM of the study area were clipped out of the Nigeria shape file and SRTM-DEM of Nigeria. The DEM data was projected with the coordinate system of other datasets to ensure consistency and reduced errors and anomalies. Radiometric and atmospheric corrections were carried out on the satellite imagery to enhance the image quality. Maximum Likelihood algorithm was used to classify the Landsat image into five land use/cover classes, with the aid of training samples collected from the study area. The accuracy of the classified land use/cover map was validated by comparing it with the ground truth data. The atmospheric effects on the Landsat 8 thermal infrared band were corrected. The land surface temperature (LST) was calculated from the brightness temperature values using the Planck's law equation as shown in equation 1, considering atmospheric emissivity and other relevant factors, to obtain accurate LST values.

T = K2/K1 Bi (Ts) + 1---------- Equ. 1

where Bi (Ts) is the black body radiance value in the thermal infrared band while K1 and K2 were obtained from the image header file, as well as the K1 and K2 values, 774.89 W/m^2 sr µm and 1321.08 W/m^2 sr µm, respectively.

The LST values were further validated with ground truth measurements. The normalized difference vegetation index (NDVI) of the study area was derived with the aid of a raster calculator by using the near-infrared (band 5) and red (band 4) using the formular:

NDVI = (NIR - RED) / (NIR + RED) ……. Equ. 2

The soil organic carbon was imported into the GIS software, georeferenced and resampled to 30m resolution, to align with the coordinate system and projection of the study area. The DEM data was imported into the ArcGIS software environment, where the Spatial Analyst Slope tool was used to calculate the slope values in degrees. Inverse distance weighted interpolation analysis was performed on the soil organic carbon data to get the variations and distributions of soil organic carbon content across the study area, delineated into areas with high or low soil organic carbon content. Finally, the slope, land use/cover, land surface temperature, soil, soil organic carbon, and NDVI, were ranked using the analytical hierarchical process multi-criteria decision analysis (AHP MCDA) and their weights calculated using the online AHP priority calculator. Weighted overlay procedure was performed to generate the land degradation index of the study area. While the extent of the degraded lands was measured with a tape, the types of land degradation were identified and documented through field observations and photographs. To validate how mining activities affect local livelihoods, a structured questionnaire was developed, and purposive sampling method was used to carve out the sampling population as the communities directly bordering the mining activity areas. Out of the 50 questionnaires that were administered, 30 were recovered, which formed the sampling size for the analysis. Majority of the affected settlements are rural and of small populations. The questionnaire was randomly administered on heads of the households in the selected communities. The questionnaire derived information about the socioeconomic and environmental impacts of the artisanal mining operations on the quality of life within the selected communities. The methodology workflow is shown in Figure 2.

Results and Discussion

Factors responsible for land degradation

The slope of the study area ranges from 0^0 - 90^0 (Fig. 3). The slope was grouped into five classes viz: 0^0 - 18^0 (flat), 18^0 - 36^0 (gentle), 36^0 - 54^0 (moderate), 54^0 - 72^0 (steep), 72^0 - 90^0 (very steep). The very steep slope class covers about three-quarter of the study area, while nearly flat to gentle terrain occupies one-quarter. Steeper slopes are more likely to experience soil erosion owing to detachment and runoff, thereby leading to more land degradation (Nabiollahi *et al.*, 2018; Tolche *et al.*, 2021). Very steeply sloping classes received higher weights, whereas flat areas received lower weights.

The result shows that the study area is characterized by two dominant soils namely ferric luvisols and eutric nitosols (Fig. 4). Luvisols is highly adaptable for farming because of it can be easily cultivated but greatly affected by water erosion. Therefore, it easily loses fertility and hence, is potentially degraded. However, nitosols is one of the best and most fertile tropical soils which only gets eroded when the

Table 1: Pair-wise comparison matrix of land degradation factors used for AHP

S/N	Slope	Soil	Land use	NDVI	SOC	LST	Weight (%)
Slope	1	2	3	4	5	6	38.2
Soil	0.5	1	2	3	4	5	25.0
Land use	0.33	0.5	1	2	3	4	16.0
NDVI	0.25	0.33	0.5	1	2	3	10.1
SOC	0.2	0.25	0.33	0.5	1	2	6.4
LST	0.17	0.2	0.25	0.33	0.5	1	4.3

Consistency Ratio (CR) = 2.0%

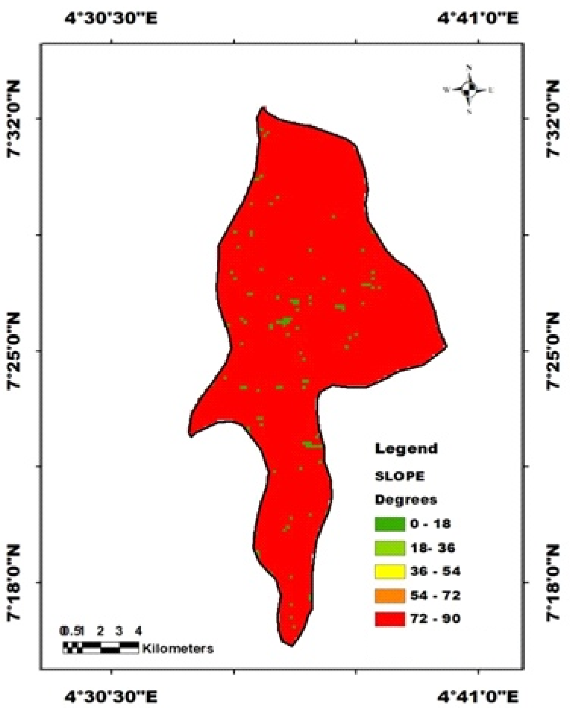

Figure 3: Slope

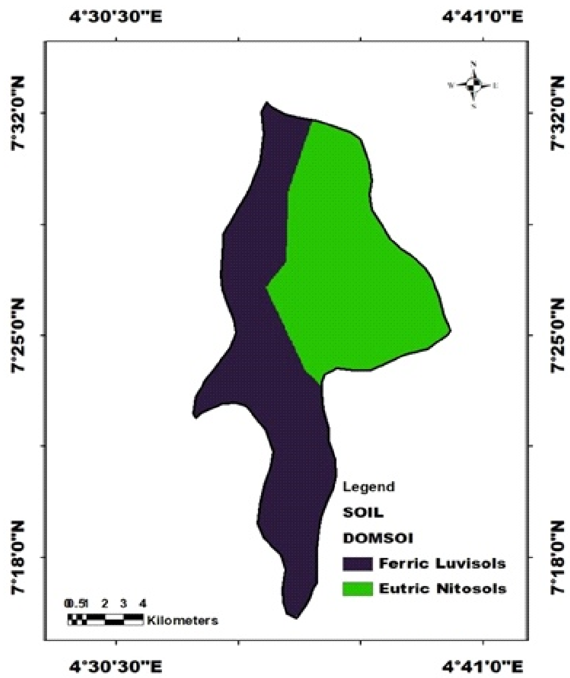

Figure 4: Soil

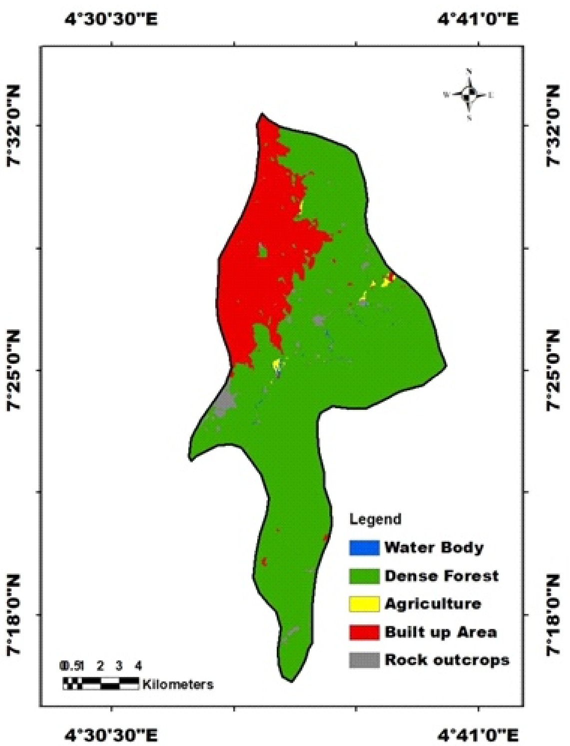

Figure 5: Land use/cove

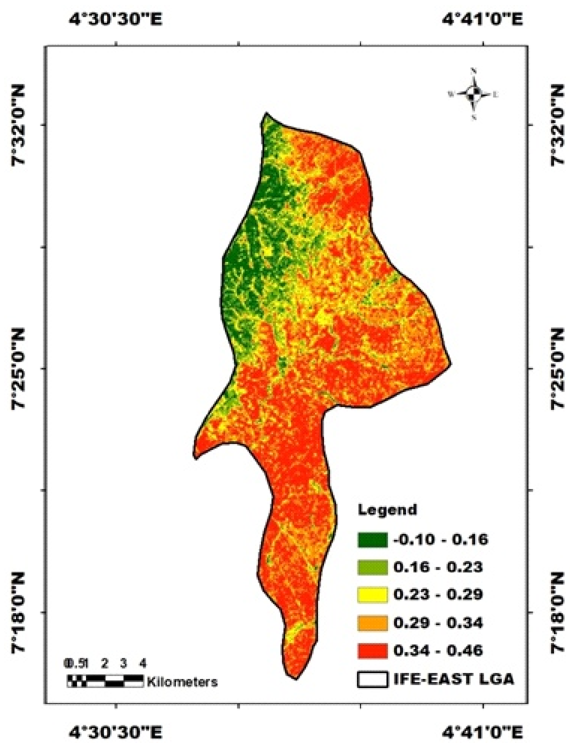

Figure 6: NDVI

organic carbon content decreases. Therefore, it shows better resilience to degradation than luvisols. Consequently, higher weight was assigned to luvisols while lower weight was assigned to nitosols.

The Land use/land cover of the study area was divided into five classes viz: water body, built up area, agriculture, rock outcrops and dense forest (Fig. 5). Forested areas dramatically lessen the impact of rainfall and reduces land degradation. The greatest weight was given to agricultural land since it is more susceptible to erosion and deterioration than other land use/cover types.

NDVI values ranged from -0.10 to 0.46 and was categorized into 5 classes viz: < 0.16, 0.16 – 0.23, 0.23 – 0.29, 0.29 – 0.34 and 0.34 – 0.46 (Fig. 6). Lower values were observed in the N-NW part of the study area, which shows that these areas have less vegetation and have undergone more land degradation, compared to other parts (Stellmes *et al.,* 2015; Rukhovich *et al.*, 2021). Higher weights were assigned to lower NDVI values.

The soil organic carbon (SOC) was classified into 5 classes viz: 0 – 11.8, 11.8 – 23.6, 23.6 – 35.4, 35.4–47.2 and 47.2 - 59 g/kg (Fig. 7). SOC plays an important role in assessing the land degradation of an area because a higher soil organic carbon values is an indication of a soil that is of better quality. Results from the analysis of soil organic carbon content show a reduction in soil organic matter levels, indicating the soil of the area has been degraded. Reduced soil organic carbon impacts negatively on the soil structure, nutrient cycling, and soil water retention capacity, leading to increased vulnerability to erosion and reduced agricultural productivity. Lower weights were assigned to higher SOC as they are least potentially degraded and vice versa.

Results of the assessment of land surface temperature (LST) show elevated temperatures in the mining areas. Increased land surface temperature will lead to increased evapo-transpiration, land desiccation and disappearance of surface water, which can significantly alter the microclimatic conditions of the study area, with multidimensional socio-economic and environmental consequences. The high LST in the study area (Fig. 8), ranges from 70.03°C to 79.71°C. The high LST values which may be connected to the removal of vegetal cover by artisanal miners has been implicated as a cause of land degradation (Malav *et al.,* 2022). Also, land surfaces in the built-up areas tend to lose soil moisture due to evaporation as a result of their direct exposure to sunlight and activities of the miners, while biomass addition under a forest is substantially higher, resulting in soil organic carbon buildup and less soil degradation (Mzuri *et al*. 2021). Higher land surface temperatures (LST) locations have higher levels of land degradation. Higher weights were assigned to higher temperature values, and vice versa.

Delineation of the areas degraded by mining

The AHP MCDA was used to combine factors such as slope, soil types, land use, soil organic carbon, NDVI, and LST. This was to enable a systematic and structured approach to prioritize these factors, and to identify the most critical factors contributing to land degradation in the study area. The weight of each factor was generated (Table 1) and the subclasses of each factor were ranked (Table 2) and combined. Using the weighted overlay, the land degradation map was generated. According to the AHP results, slope (38.2 %) was the most significant factor, followed by soil (25 %), land use/land cover (16 %), NDVI (10.1), SOC (6.4 %) and LST (3 %). The consistency ratio (CR) is 2 %, which indicates that the pairwise comparison is acceptable.

Although, the findings by Sandeep *et al*. (2021) disagreed that slope has the highest contribution, other studies (Mzuri *et al.* 2021; Torabi *et al.* 2021; Abuzaid *et al.* 2021) largely implicated slope as a principal factor in mapping land deterioration.

Table 2: Parameters subclasses and ranks

S/N	LST	Weight (%)
Slope	0° – 18°	1
	18° – 36°	2
	36° – 54°	3
	54° – 72°	4
	72° – 90°	5
Soil	Eutric Nitosols	4
	Ferric Luvisols	5
Land use	Built up area	1
	Water body	2
	Rock outcrops	3
	Agriculture	4
	Dense forest	5
NDVI	0.34 – 0.46	1
	0.29 – 0.34	2
	0.23 – 0.29	3
	0.16 – 0.23	4
	< 0.16	5
SOC	47.2 – 59	1
	35.4 – 47.2	2
	23.6 – 35.4	3
	11.8 – 23.6	4
	0 – 11.8	5
LST (°C)	70.03 – 72.69	1
	72.69 – 73.79	2
	73.79 – 75.34	3
	75.34 – 77.01	4
	77.01 – 79.71	5

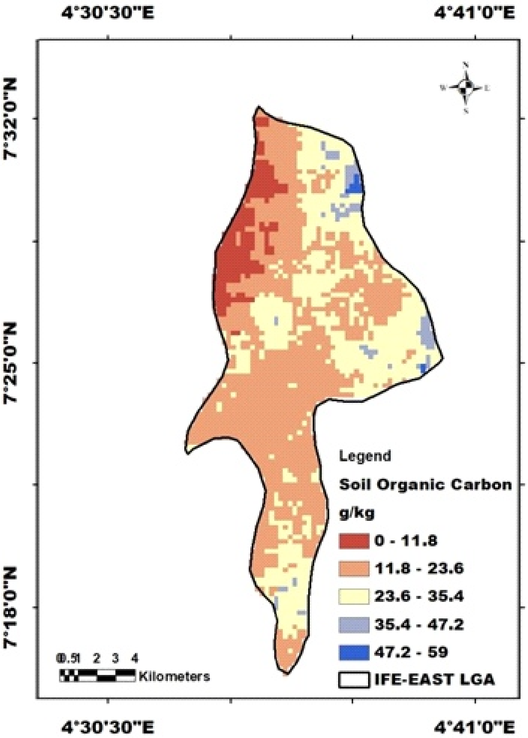

Figure 7: Soil Organic Carbon

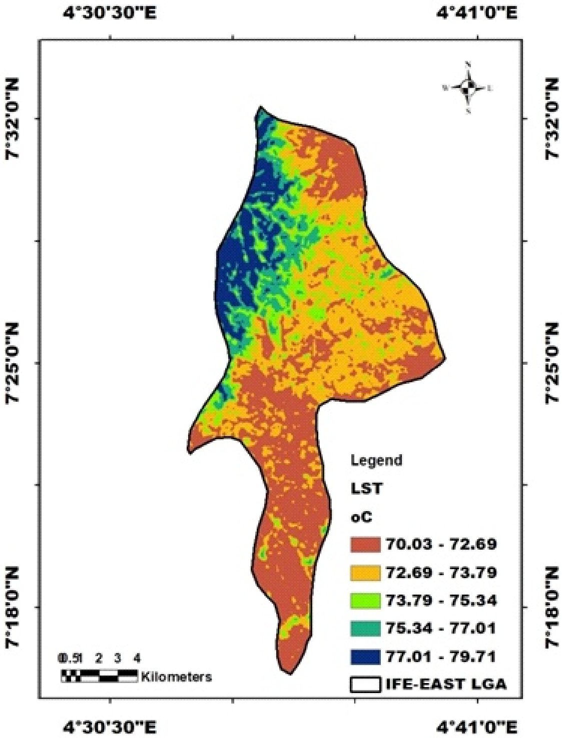

Figure 8: Land Surface Temperature

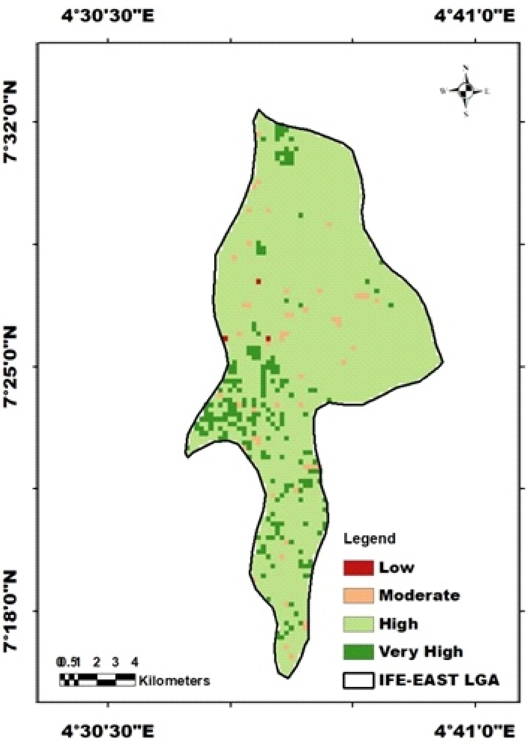

Figure 9: Land Degradation map

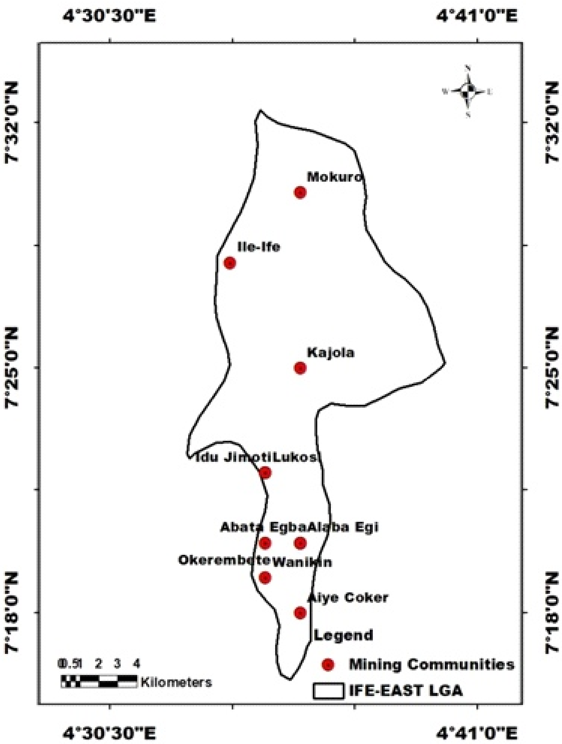

Figure 10: Location of mining sites in the study area

Land degradation

The land degradation map (Figure 9) shows the level of degradation in the study area. The land degradation was divided into four classes: low, moderate, high, and very high; and the percentage area occupied by each is shown in (Table 3). The result shows that 8.02 % falls under very high category and about 89.90 % of the study area has been highly degraded, while 2.09 % falls under low to moderate category. This result clearly indicates high degradation due to mining activities in the local communities.

Table 3: Land degradation percentage

Class	%
Low	0.11
Moderate	1.98
High	89.90
Very High	8.02

Table 4: Effects of mining activities

Effects	Frequency	%
Loss of farmlands	10	30
Loss of forest area	8	25
Water pollution	7	27
Health-related issues	5	18
Total	**30**	**100**

The effects of mining activities on the Local Communities

Figure 10 showed the mining communities, while Table 4 are the areas of the mining activities within the communities. Mining activities were observed mainly around farmlands, forested area and sometimes the settlements, which consequently led to the destruction of farmlands, vegetal cover, pollution of drinking water and land degradation. This evidence justified the claim of Ako *et al.* (2014), who reported that mining activity resulted into land degradation, destruction of vegetation, erosion of soils and pollution of water bodies.

Results of the survey presented in Table 4 showed that 72 % of men and 28 % of women who had lived in the community for more than 50 years said that mining activities had resulted to negative impacts on their land. Thirty percent (30 %) of the respondents said that mining activities had cost them a lot of farmlands, a major source of their livelihood. Plates 1, 2, 3, 4, 5, 6, 7 and 8 show the active and abandoned mining pits around the traditional farmlands of the rural communities. According to Olanipekun (2002) numerous farmlands in the rural communities had in substantial part been converted into mining pits; thereby confirming the observation of this study. Additional comments provided by respondents to the questionnaire, revealed that some of the local farmers and residents, yielded their lands to the miners in exchange for monetary compensation. This could explain the reason for large number of pits discovered in the study area (Makinde *et al.*, 2014; Adeoye 2015). 25 % of those surveyed concurred that mining operations in their neighborhoods truly destroyed their forest and land. Moreover, 27 % of the respondents believed mining activities destroyed the quality of their water bodies, which are mostly used as sources of drinking water and for other domestic purposes.

Conclusions

The assessment of mining-induced land degradation in this study, utilizing factors such as slope, soil types, land use land cover types, soil organic carbon, normalized difference vegetation index (NDVI), and land surface temperature (LST), has provided valuable insights into the environmental impacts of mining activities. The various pits dug, and the overburden dumps encountered in the study area revealed that mining activities have led to degradation of land in the region, which has affected the general livelihood of the mining neighborhood. These findings call for an urgent need for effective land management practices and land use planning strategies that balance economic development with environmental sustainability, to mitigate the negative impacts of mining-induced land degradation. Furthermore, the study underscores the urgent need for sustainable mining practices and effective environmental management strategies, specifically in Ile- Ife, Osun State, Nigeria. It is crucial to implement measures such as proper land reclamation, erosion control, soil conservation, and reforestation to restore degraded areas and mitigate further land degradation.

Plate 1: Mining pit in Mokuro

Plate 2: Mining pit in a farmland in Kajola

Plate 3: Mining pit in a farmland in Idujimoti Lukosi

Plate 4: Mining pit in a farmland in Okerembete

Plate 5: Mining pit in a forestland in Abata Egba

Plate 6: Mining pit in a farmland in Egi

Plate 7: Mining pit in a farmland in Abata Egba

Plate 8: Mining pit in a farmland in Egi

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