



Research Article

Assessment of Land Degradation Vulnerability in Atakumosa Area of Osun State, Nigeria

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Abstract

Land degradation poses a significant threat to environmental sustainability, agricultural productivity, and socio-economic stability, particularly in cities and villages where mining activities are very rampant. This study aims to assess land degradation vulnerability in Atakumosa Area, Osun State using Geospatial techniques. By leveraging multi-temporal satellite imagery and spatial analysis techniques, the study identifies and maps degradation-prone areas based on a combination of biophysical and anthropogenic indicators, including land use/land cover (LULC), slope, modified soil adjusted vegetation indices (MSAVI), topographic wetness index (TWI), geology, soil types, soil acidity, soil texture, soil depth and drainage density. The SRTM DEM, Landsat 8 OLI, soil map, and geology map were used to create these thematic maps. Each class of these parameters was given appropriate weighting factors. Using the analytical hierarchical process, weighting factors were assigned to the different themes according to their influence to land degradation. GIS tools were utilized to integrate these spatial layers using weighted overlay analysis to produce the Land Degradation Vulnerability Index (LDVI) for the study area. The results indicated that 36.6 % (297.19 km²) of the total area was prone to high degradation risks, 17.1% (138.85 km²) was prone to moderate risks, 14.2% (115.30 km²) was prone to low risks, while 32.1% (260.65 km²) was prone to very low risks. The consistency ratio (CR) for the study was less than 0.1, which is an indication of the acceptability of the pairwise comparison. The study highlights the critical role of geospatial technologies in environmental assessment and decision-making processes.

Keywords

Land Degradation, Vulnerability, Multi-Temporal, Atakumosa, GIS

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1. Introduction

Land degradation defined as the long-term decline in ecosystem productivity and ecological functions is a pressing global concern, particularly in sub-Saharan Africa, where it threatens agricultural productivity, biodiversity, and livelihoods [3, 6, 15, 19]. Nigeria faces pervasive degradation driven by rapid deforestation, unsustainable farming, overgrazing, bush burning, mining and urban expansion [14]. Manifestations include soil erosion, declining fertility, gully formation and diminishing vegetation, with estimated losses of up to 350,000 ha/year in northern Nigeria alone.

Within Osun State, southwestern Nigeria, peri-urban expansion and agricultural encroachment have resulted in large scale land cover change [8, 12, 20]. Studies in Oba Hills Forest Reserve and Shasha Forest Reserve confirm substantial forest loss (42.7% over 36 years) and conversion to farmland and built environment [1, 2]. Meanwhile, economic analysis of farming practices in Osun report prevalent use of tillage, fertilizer and fallow systems, yet highlight constraints in adoption of conservation techniques [7, 5].

Remote sensing and GIS approaches have become indispensable tools in quantifying land degradation and assessing vulnerability through land use/land cover (LULC) dynamics [4, 10, 18]. Recently, machine learning approaches such as artificial neural network, random forests, and deep learning have been applied to LULC classification for effective land use planning and environmental monitoring [12, 14]. While studies specifically labelled “land degradation” using AHP in Nigeria are limited, several researchers have demonstrated the use of AHP in erosion vulnerability and soil risk assessments, which are direct aspects of land degradation research and relevant for contextualizing multi-criteria decision methods in the Nigerian setting. [11] applied Analytic Hierarchy Process (AHP) within a GIS framework to model and map erosion vulnerability in the coastal areas of Rivers State, Nigeria, identifying zones with varying susceptibility to erosion and thereby addressing land degradation issues using weighted criteria and expert-derived factor importance. [17] employed AHP coupled with the Universal Soil Loss Equation (USLE) to assess soil erosion risk in Ondo State, showing how multi-criteria weighting and expert judgments can integrate spatial and environmental variables to classify erosion susceptibility—a key component of broader land degradation analysis. State-of-the-art studies integrate RUSLE/USLE erosion models, vegetation indices like NDVI, LAI, and multi-criteria decision analysis (MCA/AHP) to map vulnerable zones [10, 16, 18]. Systematic reviews of LULC classification methods in Nigeria indicate that while Landsat and Sentinel imagery are widely

used, there remains a need for high-resolution and deep-learning-based classifiers, and national LULC data repositories [4].

Despite this rich body of research, few studies have explicitly focused on land degradation vulnerability—which considers exposure, sensitivity, and adaptive capacity—at fine spatial scales such as Local Government Areas. Specifically, there is a knowledge gap for the Atakumosa area (East and West LGAs) in Osun State, where mining activities, pressure from farming, fuelwood harvesting, rapid urbanization and topographic variation likely increases vulnerability. This study seeks to fill that gap by conducting a geospatially explicit vulnerability assessment in Atakumosa area. It employs multi-temporal remote sensing, field surveys, and MCA techniques to identify key drivers/factors contributing to vulnerability and map vulnerability index.

2. Materials and Methods

2.1. Study Area

Atakunmosa area is located in the south eastern part of Osun State, Nigeria (Figure 1). The study area is one of the areas noted for the mining of gold and other valuable minerals with notable towns such as Itaganmodi, Ibodi, Iperindo, Osu. It consists of Atakunmosa East and Atakunmosa West local government areas. Atakunmosa East with its headquarters in the town of Iperindo and lies between Latitude 6°5'05" and 6°12'35"N and Longitude 14°20'00" and 14°27'35"E with an area of 238 km² and a population of 76,197 at the 2006 census. Atakunmosa West with its headquarters in the town of Osu and lies between Latitude 6°5'05" and 6°12'35"N and Longitude 14°20'00" and 14°27'35"E with an area of 577 km² and a population of 68,643 at the 2006 census. It is characterized by undulating terrains with flat to steep slopes, seasonal rainfall (1,200–1,500 mm/year), and lateritic soils prone to erosion. The elevation ranges from 900 m to 1500 m. The climate is tropical, with two major seasons, the rainy and the dry season. The area is predominantly agrarian, with activities including cocoa farming, subsistence agriculture, and small-scale mining. It lies within the Ilesha Schist Belt, one of the prominent schist belts in the Nigerian Basement Complex. The geology of Atakunmosa area comprises three main lithological groups: Migmatite-Gneiss Complex, Schist Belt Rocks and Intrusive Igneous rocks.

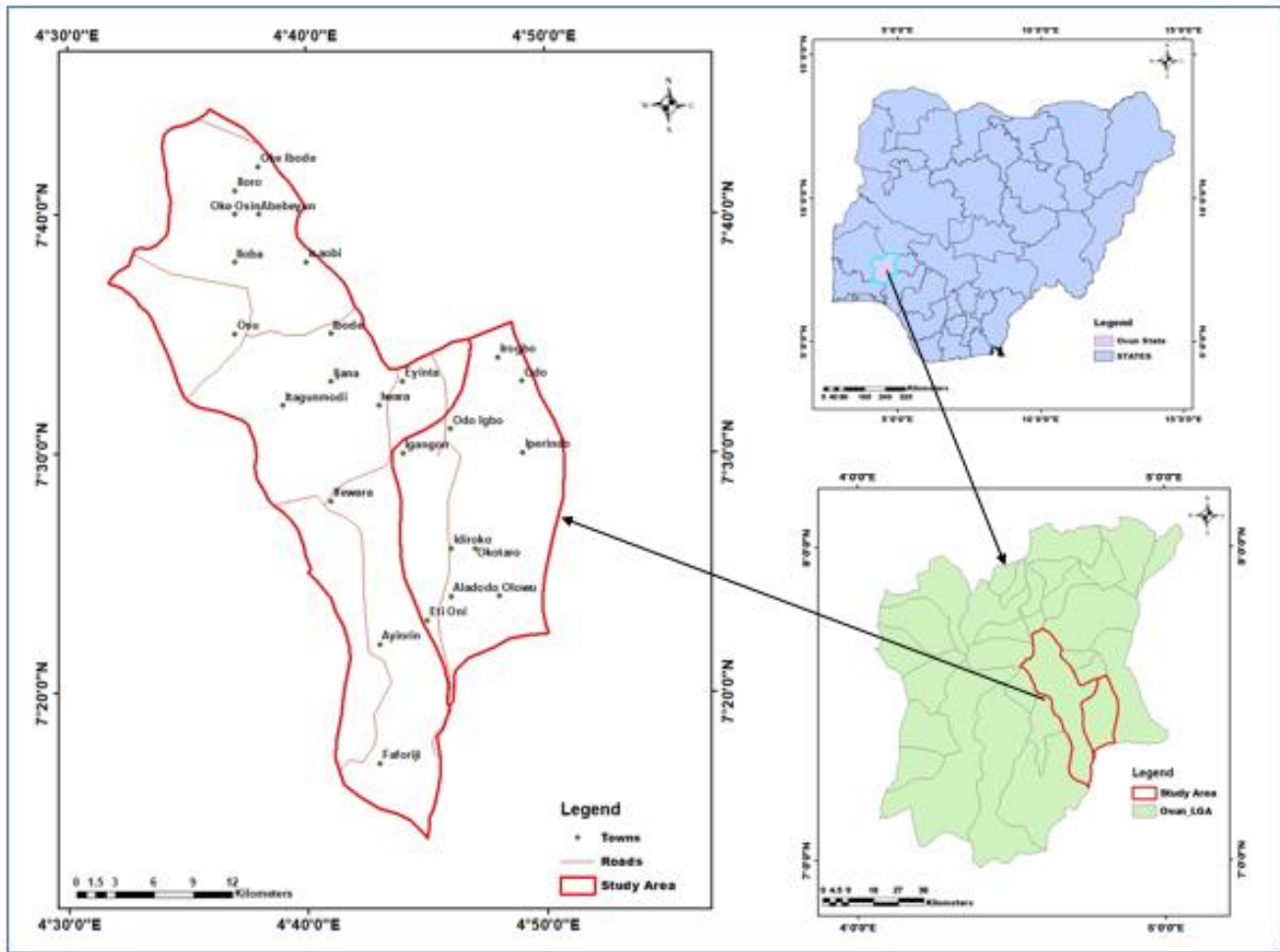


Figure 1. Study Area.

2.2. Methodology

Both primary and secondary data were used for this study. The data include SRTM DEM, satellite imagery such as Landsat 8 OLI/TIRS (2024); ancillary data such as soil map, topographic map, and geological map. The primary datasets which include the GPS coordinates of various mining sites and their images were acquired during the field work. Secondary data such as Nigeria shapefile which was used to generate the location map of the study area was sourced from ARCSSTE-E; SRTM DEM and Landsat 8 OLI were downloaded from USGS and Copernicus websites; geology map was derived from Nigeria Geological Survey Agency (NGSA) Rocks and Mineral map; and soil map from FAO websites. Landsat 8 OLI/TIRS images of Path/Row 190/055 of December, 2024 were pre-processed using radiometric and geometric correction, atmospheric correction and image enhancement techniques. Then the study area imagery were clipped out, Bands 543 were combine and supervised classification was carried

out using the maximum likelihood algorithm to analyse land use/land cover (LULC). Accuracy assessment was carried out using confusion matrix and kappa statistics. MSAVI was derived using the formula: $MSAVI = \frac{2NIR+1-((2NIR+1)^2-8(NIR-RED)^2)^{0.5}}{2}$. The slope, drainage density, and topographic wetness index were derived from the Digital Elevation Models (DEMs) using the Spatial Analyst tools. Soil texture, soil types, soil acidity, and soil depth of the study area were clipped out from the soil map of Nigeria. The geological map and soil map were rasterised to a grid size of 30×30m to give a uniform spatial resolution of 30m with SRTM and Landsat 8. All the thematic factors were reclassified, normalized and Analytical Hierarchical Process (AHP) was used to assign weight to each factor based on their contribution to land degradation. ArcGIS Spatial Analysis tools weighted overlay was used to integrate the thematic factors and classified into low, moderate, high and very high vulnerability zones. The methodology workflow is shown in Figure 2.

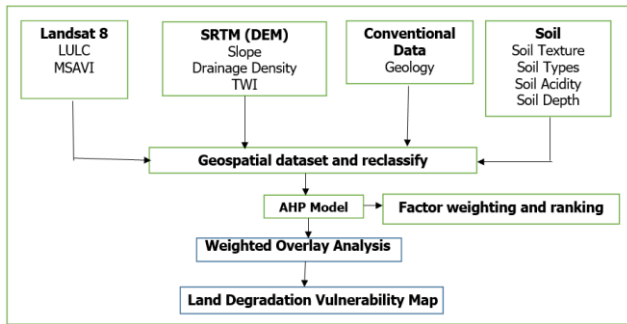


Figure 2. Methodology workflow.

3. Results and Discussion

3.1. Factors Influencing Land Degradation Vulnerability

3.1.1. Slope

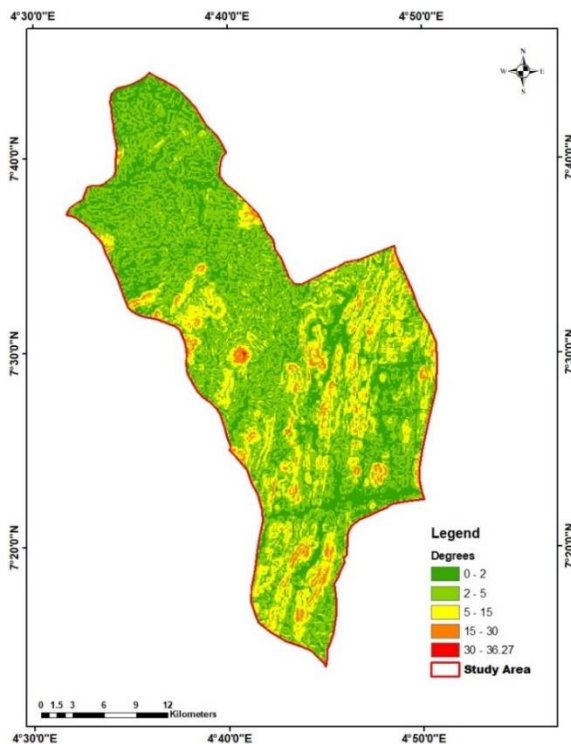


Figure 3. Slope.

Slope is a crucial determinant of land degradation vulnerability since it directly affects soil erosion risk, water infiltration, vegetation challenges and land use and mismanagement. Steeper slope classes generally correlate with greater vulnerability to land degradation, especially in the absence of proper soil conservation practices. This makes slope an important factor in land suitability analysis, erosion modelling, and land use planning. The slope of the study area ranges from 0° to

36.27° (Figure 3). Based on its possible effect on land degradation vulnerability, the slope was divided into five classes: flat ($0^\circ - 2^\circ$), gentle ($2^\circ - 5^\circ$), moderate ($5^\circ - 15^\circ$), steep ($15^\circ - 30^\circ$), and very steep ($30^\circ - 36.27^\circ$). Flat to gentle slopes are less vulnerable to degradation, while moderate, steep and very steep slopes are moderately and highly vulnerable to degradation and ranked as such [9, 12].

3.1.2. Geology

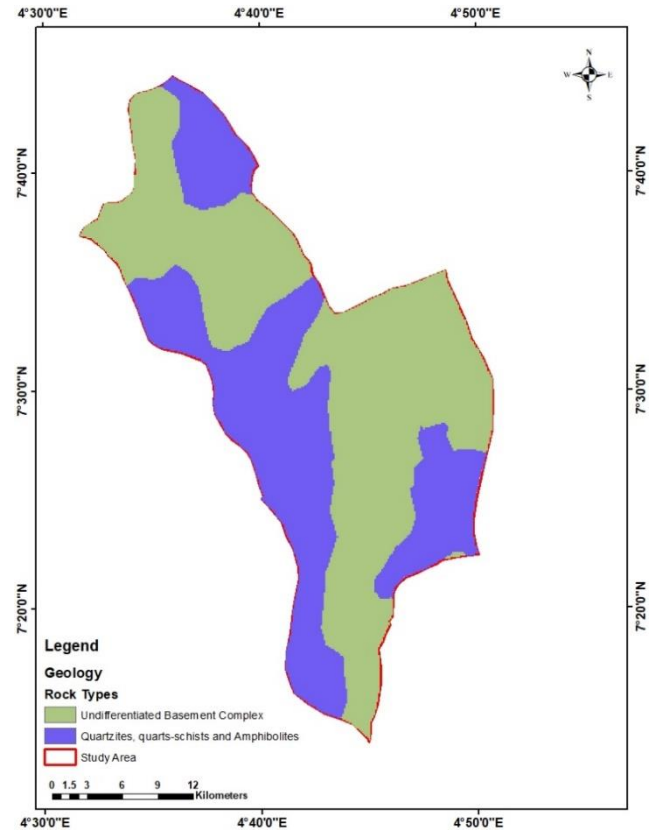


Figure 4. Geology.

The geology of the study area (Figure 4) is divided into two major group: undifferentiated basement complex and quartzites, quartz-schists and amphibolite. The resistance of the rock to weathering and soil formation characteristics strongly influence land degradation vulnerability. The undifferentiated basement complex is a mixed, undifferentiated group, and vulnerability varies widely. However, in many cases, soils are thin and fragile, increasing susceptibility to erosion and degradation, especially when vegetation is removed or land use is intensive. Hard, resistant rocks like quartzites tend to form thin soils that degrade easily once disturbed. Rocks like amphibolites can support better soils and vegetation, reducing vulnerability. Undifferentiated Basement Complex is the predominant rock type in the study area, accounting for roughly 470.93km^2 (58%), while Quartzites, quartz-schists and Amphibolite occupy 341.99km^2 (42%) of the study area. The un-

differentiated basement complex was given 4 due to its variable nature and low risk to degradation, while 3 was assigned to quartzites, quartz schists and amphibolite rock type which is at moderate-high risk due to thin soil and vegetation disturbance.

3.1.3. Land Use/Land Cover

The study area is characterised by five Land use/land cover classes: water body, forest, vegetation, built up, and bare soil (Figure 5). These classes occupied 1.1580, 753.4013, 39.7605, 22.8607, and 0.0478 km², which represented 0.14%, 92.19%, 4.87%, 2.80%, and 0.01% of the total area, respectively. The classes were reclassified based on the critical role they play in determining the area's vulnerability to degradation. Bare soil are prone to erosion, very high vulnerability level and direct indicator of degradation and ranked very low, built up causes runoff and erosion, high vulnerability level and indirect degradation driver and was ranked low. Vegetation though protects soil and retains moisture but exhibit moderate to low vulnerability level and was given moderate ranking; water body can cause or prevent degradation and has neutral to low vulnerability to degradation and are ranked high, while forest offers the strongest defense against degradation and portrays a very low vulnerability level and are ranked as very high.

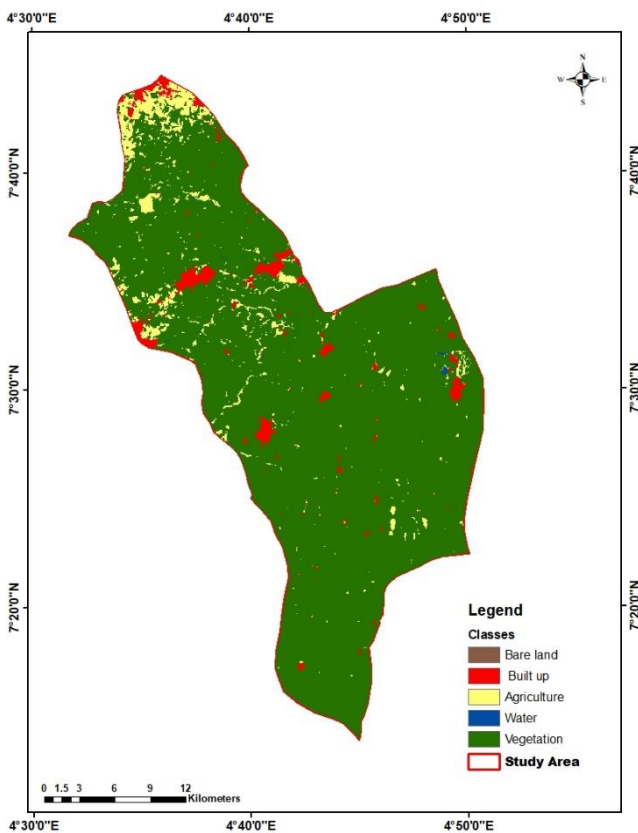


Figure 5. Land use/Land cover.

3.1.4. Soil Types

The soil of the study area (Figure 6) was classified into four of orthic luvisol, orthic acrisol, lithosols and chromic luvisol. The orthic luvisol is the predominant soil with an area of 449.107 km² (73.54%), chromic luvisol occupies 120.883 km² (14.89 %), orthic acrisol with an area of 65.252 km² and the least is lithosols with an area of 28.643 km² (3.53%). The chromic luvisol is generally fertile and well-drained, but can degrade under overuse and thus have a moderate land degradation vulnerability, orthic luvisol has a moderate to high vulnerability to degradation, orthic acrisol has a high and lithosols are highly vulnerable to degradation due to poor fertility, shallow depth, and susceptibility to erosion and nutrient loss.

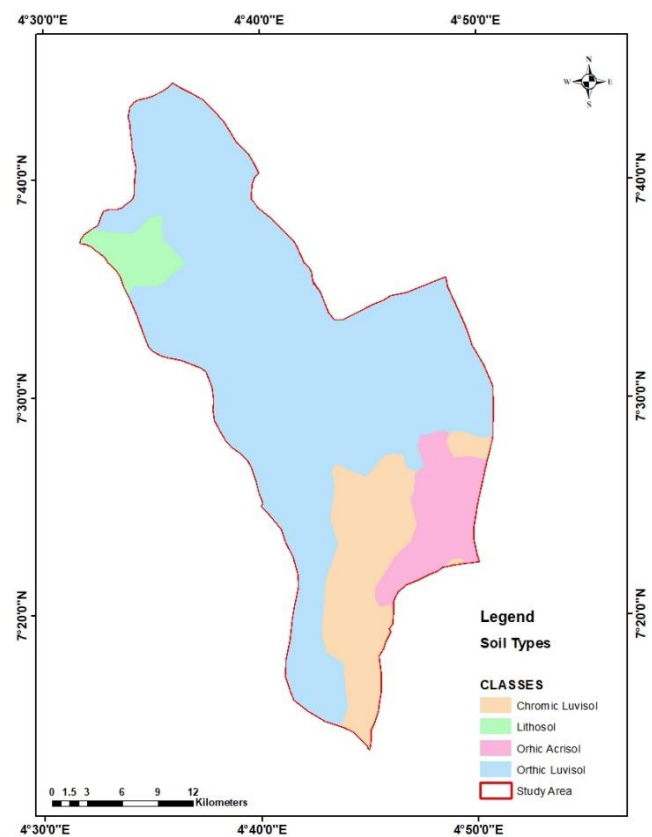


Figure 6. Soil types.

3.1.5. Soil Depth

Soil depth plays a critical control on land degradation vulnerability. The deeper the soil, the more resilient it is to degradation. Shallow soils, especially on slopes or under poor land use practices, are extremely prone to erosion and fertility loss. Soil depth of the study area (Figure 7) was classified into deep and very deep soils. The deep soils occupy 517.81km² (63.77%), while the very deep soils occupy 294.179 km² (36.23%). Deep soils promote stronger vegetation cover that can resist erosion and has a moderate vulnerability and ranked as 3, while very deep soils supports productive and resilient vegetation and hence are low vulnerable and ranked as 4.

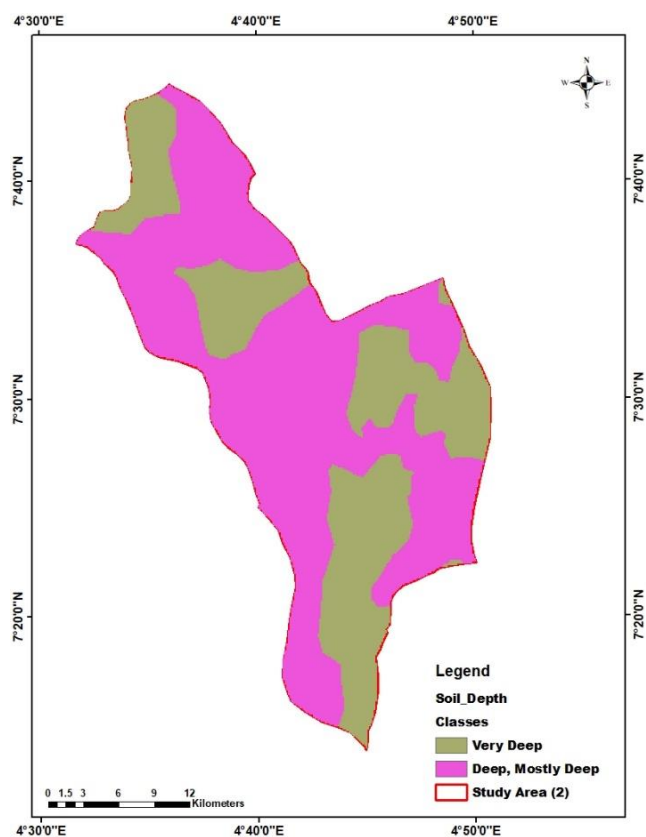


Figure 7. Soil Depth.

3.1.6. Soil Texture

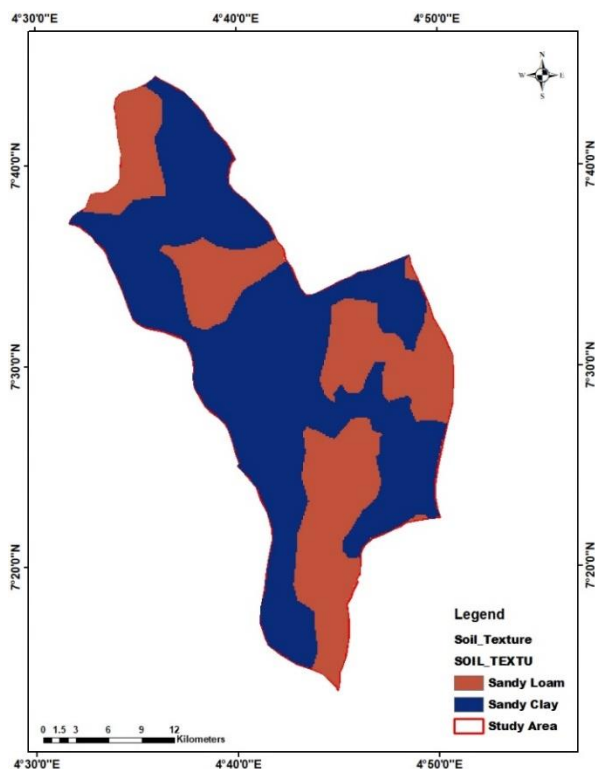


Figure 8. Soil Texture.

Soil texture is significant to land degradation vulnerability assessment because texture determines key soil properties like water retention, infiltration, aeration, erodibility, and nutrient availability. These factors directly affect how resilient or fragile a soil is under stress from land use or climate. The soil texture of the study area (Figure 8) was divided into two classes: sandy clay with an area of 517.813 km² (63.77%) and sandy loam occupies 294.179 km² (36.23%). Sandy loam are more resilient to degradation as compared to sandy clay and are ranked as 4 and sandy clay 3.

3.1.7. Soil Acidity

Soil acidity significantly contributes to land degradation vulnerability by reducing soil fertility and biological activity, promoting erosion and runoff, limiting land use flexibility and interacting with other degradation drivers. The soil acidity (Figure 9) is classified into four with slightly acidic occupying 116.078 km² (14.30 %), moderately acidic with an area of 173.296 km² (21.34 %), strongly acidic occupies 148.106 km² (18.24 %), and very strongly acidic occupies 28.643 km² (3.53 %). Slightly acidic soils was ranked highest due to its least contribution to degradation since acidity is mild and generally favourable for most plants and microbial activity, followed by moderately acidic soils due to increasing aluminium toxicity and nutrient availability issues. Strongly acidic soils have a high contribution to degradation and was ranked low, while very strongly acidic soils have the highest contribution to land degradation vulnerability and was given the lowest value.

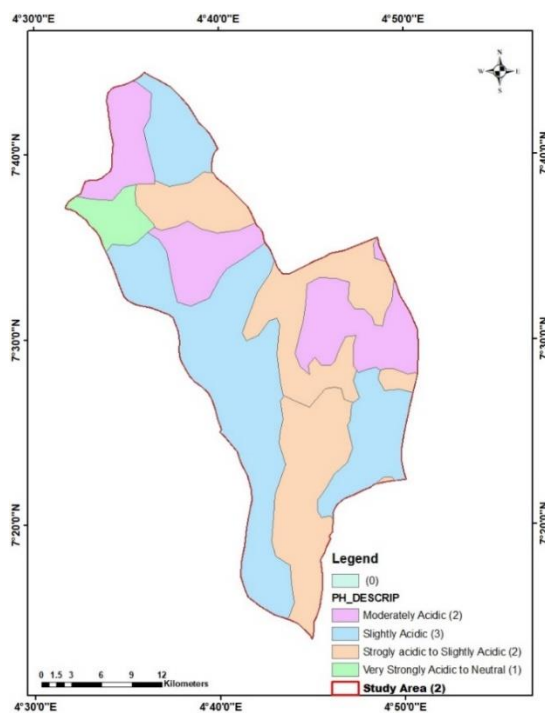


Figure 9. Soil acidity.

3.1.8. Drainage Density

Drainage density is the total length of streams and rivers in a drainage basin divided by the total area of the basin (km/km^2). It reflects how well or poorly a landscape is dissected by channels. The drainage density is classified into five classes which ranges from 0-77.1, 77.1-201.8, 201.8-337.6, 337.6-499.0 and 499.0-935.6 respectively (Figure 10). High drainage density is generally associated with increased land degradation, particular through water-induced erosion, while low drainage density may indicate either stable land or hidden degradation depending on regional climate and soil conditions. The drainage density classes was ranked based on their contribution to land degradation vulnerability.

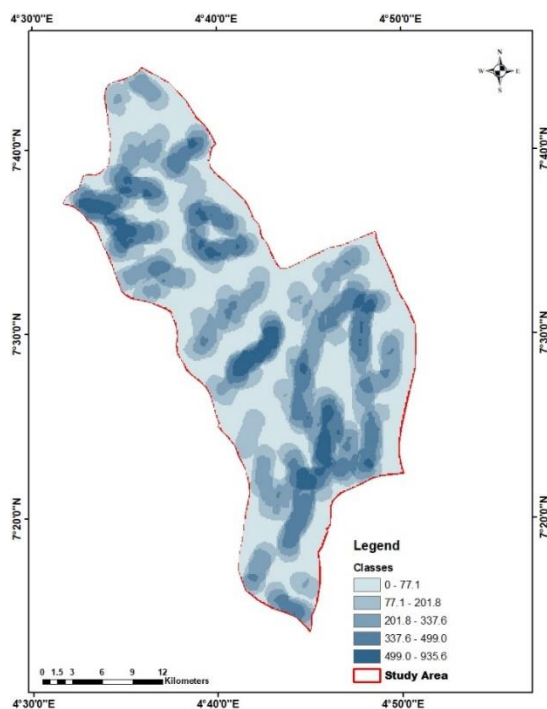


Figure 10. Drainage Density.

3.1.9. TWI

The Topographic Wetness Index (TWI) plays an important role in understanding land degradation vulnerability, especially regarding erosion, soil saturation, and vegetation stress. High TWI values indicate areas prone to water accumulation, potential saturation, and higher erosion risk, while low TWI values indicate well-drained areas with low moisture accumulation potential. The TWI (Figure 11) ranged from -5.110 to 9.425 and was classified into five (5) classes of -5.110 to -2.203, -2.203 to -0.607, -0.607 to 1.502, 1.502 to 4.181 and 4.181 to 9.425 respectively. Low TWI values show a steep slope, with little accumulation, are high erosion risk areas; moderate TWI values is an indication of gentle slopes with moderate drainage with typically lowest degradation vulnerability and high TWI values indicate flat land, large upslope

area with low degradation risk. The different classes were ranked according to their degradation vulnerability with low values ranked as 1 and progressive in like manner.

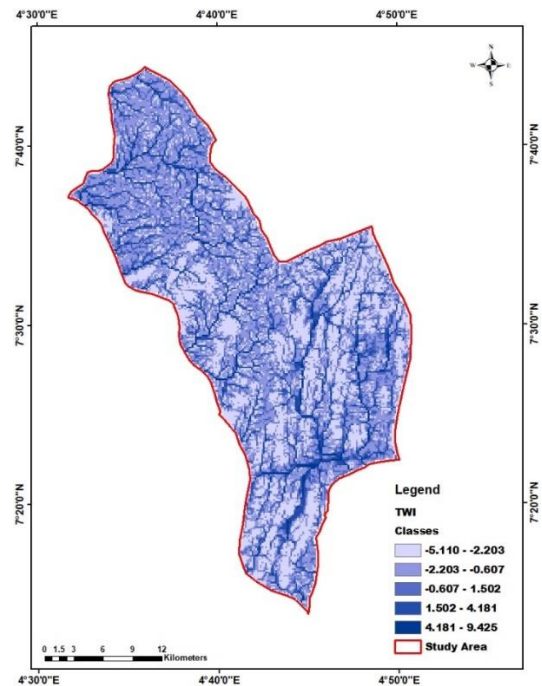


Figure 11. TWI.

3.1.10. MSAVI

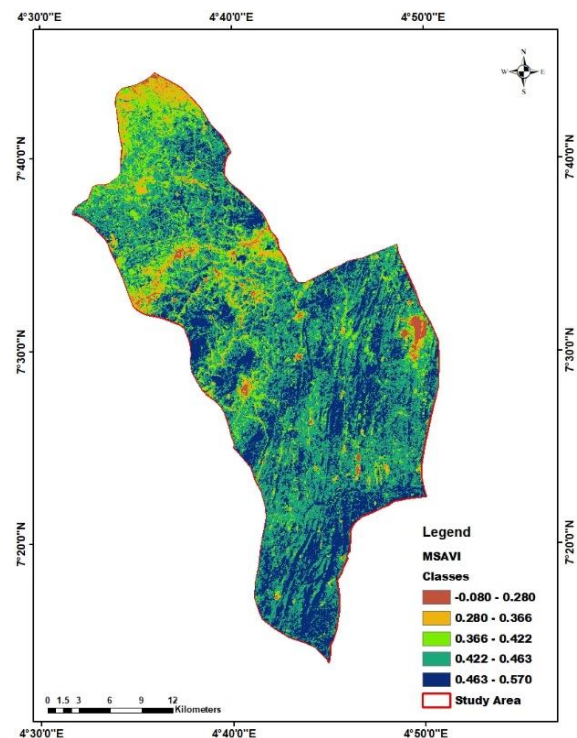


Figure 12. MSAVI.

The Modified Soil-Adjusted Vegetation Index (MSAVI) is closely related to land degradation vulnerability because it provides a more accurate measure of vegetation health in areas where soil exposure can distort vegetation indices like NDVI. Understanding this relationship helps in monitoring, assessing, and predicting land degradation. MSAVI is a sensitive indicator of land degradation vulnerability, especially in areas with sparse vegetation. Low MSAVI values can be used as a proxy for degradation hotspots, while increasing values over time can indicate ecosystem recovery. MSAVI of the study area (Figure 12) ranged from -0.080 to 0.570 and divided into five classes: -0.080 - 0.280, 0.280 - 0.366, 0.366 - 0.422, 0.422 - 0.463 and 0.463 - 0.570. High MSAVI is an indication of dense, healthy vegetation which is an implication of low vulnerability, moderate values indicate a partial vegetation cover and an implication of moderate vulnerability and low MSAVI indicate sparse vegetation and an implication of high vulnera-

bility. The MSAVI values were ranked based on the contribution to degradation vulnerability.

3.2. Assignment of weights

Ten factors such as slope, soil types, soil texture, soil depth, land use/land cover, drainage density, topographic wetness index, geology, MSAVI and soil acidity were selected over other factors to assess the land degradation vulnerability due to their impacts, literature search and experts opinion. Weights were assigned based on the reviewed literature, the professionals in the field and the Saaty's scale [13]. Slope had a great influence on the land degradation vulnerability due to preliminary analysis and expert opinion and was assigned the highest weight of 25.9 %, while TWI has a least contribution given the weight of 1.5%. The pairwise comparison matrix and the relative weights are shown in Table 1 and Table 2.

Table 1. Pair-wise comparison matrix for land degradation vulnerability.

	Slope	SD	ST	DD	GEO	LULC	MSAVI	Soil types	Soil acidity	TWI	Weightage
Slope	1	2	2	3	4	5	6	7	8	9	0.259
SD	0.50	1	2	3	4	5	6	7	8	9	0.225
ST	0.50	0.50	1	2	3	4	5	6	7	8	0.165
DD	0.33	0.33	0.50	1	2	3	4	5	6	7	0.116
GG	0.25	0.25	0.33	0.50	1	2	3	4	5	6	0.081
LULC	0.20	0.20	0.25	0.33	0.50	1	2	2	3	4	0.051
MSAVI	0.17	0.17	0.20	0.25	0.33	0.50	1	2	3	4	0.040
Soil types	0.14	0.14	0.17	0.20	0.25	0.50	0.50	1	2	3	0.029
Soil acid- ity	0.12	0.12	0.14	0.17	0.20	0.33	0.33	0.50	1	2	0.021
TWI	0.11	0.11	0.12	0.14	0.17	0.25	0.25	0.33	0.50	1	0.016
Total	3.33	4.83	6.72	10.59	15.45	21.58	28.08	34.83	43.50	53.00	1.003

Table 2. Rating and Weightage of the sub classes and factors influencing land degradation vulnerability.

Factors	Sub-classes	Rating	Weightage
Slope	0° – 2°	1	25.9
	2° – 5°	2	
	5° – 15°	3	
	15° – 30°	4	
	30° – 36.27°	5	
Soil Depth	Deep	3	22.5
	Very Deep	4	
Soil Texture	Sandy clay	3	16.5

Factors	Sub-classes	Rating	Weightage
Drainage Density	Sandy loam	4	11.6
	499.0 – 935.6	1	
	337.6 – 499.0	2	
	201.8 – 337.6	3	
	77.1 – 201.8	4	
	0.0 – 77.1	5	
Geology	Quartzites, quartz-schists and Amphibolites	3	8.1
	Undifferentiated Basement Complex	4	
LULC	Bare soil	1	5.1
	Built up	2	
	Vegetation	3	
	Water body	4	
	Dense forest	5	
	-0.080 – 0.280	1	
MSAVI	0.280 – 0.366	2	4.0
	0.366 – 0.422	3	
	0.422 – 0.463	4	
	0.463 – 0.570	5	
Soil types	Lithosol	2	2.9
	Orthic acrisol	3	
	Orthic luvisol	4	
	Chromic luvisol	5	
	Very Strongly acidic	1	
Soil Acidity	Strongly acidic	2	2.1
	Moderately acidic	3	
	Slightly acidic	4	
	-5.110 - -2.203	1	
TWI	-2.203 - -0.607	2	1.6
	-0.607 – 1.502	3	
	1.502 – 4.181	4	
	4.181 – 9.425	5	

3.3. Matrix Consistency Assessment

The reliability of the approach employed in this study was verified by calculating the Consistency Ratio (CR). This ratio helps to find any discrepancies in the comparisons of each pair

of criteria and acts as an acceptance test for the weights given to the various factors. The Consistency Ratio (CR) is computed by $CR = CI/RI$

Where RI is the Random Index (Table 3). The RI for this study made of 10 factors is 1.49.

Table 3. Ratio index (RI) for various n scores.

N	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51

The pairwise comparison matrix (Table 1) was calculated, normalise and the primary eigenvalue (λ max) by dividing the priority vector by the original matrix and averaging the resultant values.

Next, the following formula is used to calculate the Consistency Index (CI):

$$CI = (\lambda \text{ max} - n) / (n - 1)$$

Where n is the number of factors involved = 10, λ max = 10.459

$$\text{For this study, } CI = (10.459 - 10) / (10 - 1) = 0.051$$

$$CR = 0.051 / 1.49 = 0.034$$

The Consistency Ratio of 0.034 for this study is less than 0.1 which is an indication that the pairwise is acceptable.

3.4. Delineation of Land Degradation Vulnerability Index

were used to delineate the land degradation vulnerability index. Result of Land Degradation Vulnerability was grouped into 4 which are very low (32.1%), low (14.2%), moderate (17.1%), and high (36.6%) (Figure13). The very low area covers about 260.65 sq km and are noted for dense vegetation cover and stable soils, low area covers about 115.30 sq km and characterised by mixed farmland-vegetation areas with manageable erosion risks, moderate area covers 138.85 sq km and are noted with soil disturbance, poor vegetation or proximity to mining sites, and high covers 297.19 sq km and characterised by active mining clusters, steep terrains and heavily deforested regions. The very low zones cover some towns which are Eti Oni, Ayibirin, low zones are found in Iloba, Oke osin and Abebeyun communities, moderate zones are found in Iwara, Isaobi and Eyinta communities, while high zones are found in Itagunmodi, Faforiji, Ijana and Odo communities.

4. Conclusion

The combination of ten thematic parameters, including slope, geology, soil type, drainage density, soil acidity, soil texture, Soil depth, MSAVI, TWI, and land use/land cover with the use of Analytical Hierarchy Process (AHP) and spatial analysis techniques has aided the delineation of land degradation vulnerability index of the study area. The results from the analysis classified the study area into four vulnerability zones: very low 32.1% (260.65 km²), low 14.2% (115.30 km²), moderate 17.1% (138.85 km²), and high 36.6% (297.19 km²). These findings provide valuable insights for policymakers to develop and implement effective land degradation mitigation strategies. This study acknowledges certain limitations particularly lack of high-resolution satellite data because medium-resolution satellite data may not detect small-scale degradation features and exclusion of socio-economic drivers such as land tenure, poverty, policy enforcement and population pressure. It is hereby recommended that vegetation restoration and afforestation should be carried out and illegal mining activities should be prevented. A comprehensive vulnerability re-assessment is recommended at 3–5 years intervals to adequately capture environmental change while minimizing short-term variability.

Abbreviations

LULC	Land use Land cover
MSAVI	Modified Soil-Adjusted Vegetation Index

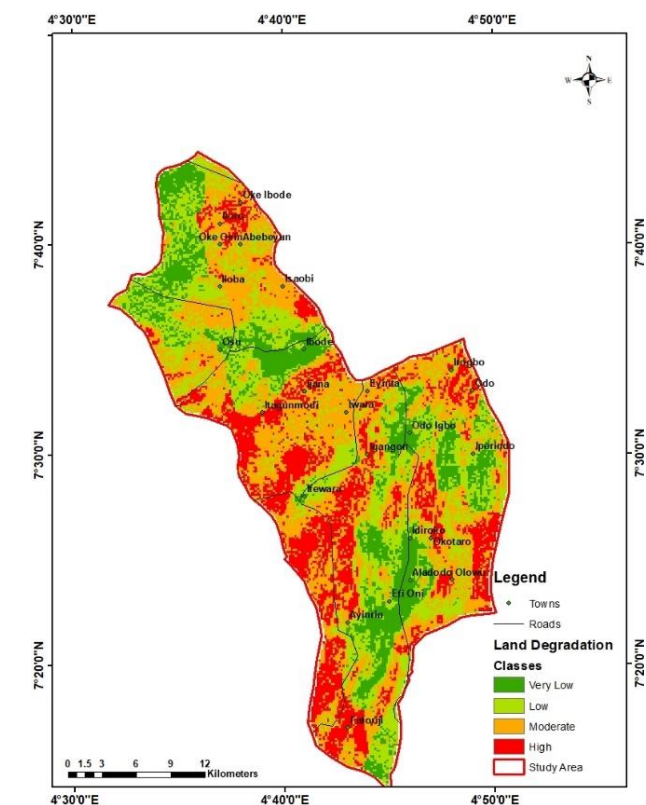


Figure 13. Land Degradation vulnerability Index map.

A total of ten thematic layers viz., slope, soil texture, soil acidity, land use/land cover, drainage density, topographic wetness index, soil types, geology, soil depth and MSAVI

TWI	Topographic Wetness Index
SRTM DEM	Shuttle Radar Topographic Mission Digital Elevation Model
GIS	Geographical Information System
LDVI	Land Degradation Vulnerability Index
CR	Consistency Ratio
FAO	Food and Agricultural Organization
ARCSSTE-E	African Regional Centre For Space Science and Technology Education-English
AHP	Analytical Hierarchical Process
USGS	United States Geological Survey

Author Contributions

Ojo Adebayo Gbenga: Project administration, Conceptualization, Supervision, Writing – review & editing

Ajayi Felicia Oluwatoyin: Supervision, Resources, Writing – review & editing

Ebeiyamba Okon Ekpo: Methodology, Software, Validation

Aluko Olaniran Emmanuel: Conceptualization, Methodology, Writing – original draft, Writing – review & editing

Fasote Oluwabunmi: Conceptualization, Methodology, Investigation, Writing – review & editing

Fatile Samuel: Data curation, Resources, Software

Ogah Okibe: Formal Analysis, Visualization, Validation

Elugoke Nicholas Olaniyi: Data curation, Formal Analysis, Validation

Ogunyemi Samson Akintunde: Data curation, Methodology, Software

Alage Isiaka Lukman: Conceptualization, Methodology, Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

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