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Assessment of Spatio-Temporal of the Oyimo Forest Reserve Degradation in Ondo State, Nigeria Towards the Development of Applicable Guidelines

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Abstract:
This work assessed the Spatio-Temporal of the Oyimo Forest Reserve Degradation in Ondo State, Nigeria towards the development of applicable guidelines. Forest degradation is a changing process that impacts the values of a forest, reducing its ability to provide products and services. Information derived from land use, land cover change and forest degradation are important to land conservation, sustainable development, and management of forest reserve. To identify land use, land cover changes and degradation; remote sensing data from satellite imagery and image processing techniques was done within three dates of 1998, 2011 and 2021 using Landsat images of 30 m resolution. ERDAS Imagine, IDRISI Selva, QGIS and ArcGIS software were used to classify, identify the changes and degraded area. The classification was done using five land cover classes (forest, settlement, water body, farmland and bare surface). Preprocessing and classification of the images were analyzed carefully and accuracy assessment was tested separately using the kappa coefficient. The results showed that Oyimo forest area was 35,257.22ha in 1998, 22,708.04ha in 2011 and 23, 903.2ha in 2021. Prediction analysis showed that if measures are not put in place in the forest reserves will be seriously degraded and if this happen there would be serious climate change as more carbon are releasing to the atmosphere. The highest carbon loss for this period was 27,660 tons, and the lowest carbon loss was 687 tons in year 2017 and 2003. Land area improved was 11, 978.02184, land area stable was 29,032.919, Land area degraded was 18,727.849 and land area with no data was 19.21016 the correlation between carbon emission and loss of forest is r2 0.8506 and organic carbon and loss of forest is r2 0.9959, which was highly correlated. It was concluded that there was degradation in the Oyimo forest reserve between 1998 and 2011, between 2011 and 2021 there was significant improvement in the forest. In order to address particular problems like carbon loss, habitat degradation, and soil productivity, as well as to propose pathways for improving forest quality, remote sensing and GIS can be used as space quantification tools for forest conservation.

Keywords: forest degradation, LULCC, Trend. Earth, guideline, remote sensing and GIS.

INTRODUCTION

Forest degradation is a changing process that impacts the values of a forest, reducing its ability to provide products and services. These changes are the result of disturbances that vary in size, frequency, origin, quality, and severity. Disturbance can be natural, caused by humans, or a combination of the two. Human-induced disturbance might be purposeful (direct), such as logging or grazing, or unintentional (indirect), such as the spread of an invasive alien species (FAO, 2009).

Deforestation is a major environmental, social, and economic issue. However, quantifying the scope of the problem is challenging since forest degradation has numerous causes, manifests itself in various forms and with varying intensity, and is viewed differently by different stakeholders (ITTO, 2002). To serve different reasons, forest degradation may need to be measured at different scales. Assessment at the scale of a stand or site, for example, is frequently required for effective local-scale corrective intervention. Larger scale assessments, on the other hand, are required for national and international reporting and other objectives. Given the importance of forests to human well-being, the state of the forests is a concern for all of us. We need to know if forests are degrading and, if so, what is causing it so that we can take efforts to stop and reverse the process. Good information on forest condition and the amount of forest degradation would allow for the prioritising of human and financial resources to prevent further degradation, restore and protect the forest.

Restoration goals are increasingly being framed in the context of complex ecosystems with contingent and stochastic dynamics. Precise forest restoration targets are thus rarely achievable, especially in environmental futures with no recent precedents (Hiers et al., 2016). Alternative trajectories driven by process-based dynamics responding to changing environmental conditions are more likely results of restoration initiatives, according to (Hughes et al. 2012).

Statement of the Research Problem

By steadily diminishing the Oyimo forests, we endanger our quality of life, jeopardise climate stability and local weather, endanger the existence of other species, and undermine the vital services supplied by biological diversity. Deforestation can cause tropical diseases to arise, and outbreaks of novel diseases, particularly deadly hemorrhagic fevers like Ebola and Lassa fever, are a subtle but important consequence of forest degradation. Nonetheless, the primary goal of this research is to identify and mitigate the causes of forest degradation in the Oyimo forest reserve. Understanding distinct degradation processes is essential for developing appropriate ways for measuring and monitoring. Various types of degradation will have varying effects on forest carbon storage, and the outcome is determined by the indicators used to measure the degradation, which can be in-situ or by remote sensing approaches. Through the REDD-plus scheme (Reducing Emissions from Deforestation and Forest Degradation in Developing Countries), great work has been made on climate change mitigation measures. Estimating above-ground biomass (AGB) in tropical and subtropical countries with a biophysical environment remains difficult (Lu, & Weng, 2007). As a result, forest conservation strategies based on spatial monitoring that address specific risks such as carbon loss, soil productivity, and habitat degradation may present avenues for improving forest quality. As a result, the ecosystem must be built in a planned manner, and GIS may help with this planning process as a decision support system. Remote sensing satellites are also a good instrument for studying historical land use land cover change (LULCC) and providing data in inaccessible places.

Justification

Accurate estimates of terrestrial carbon storage over an area are essential to address the growing threat to the local climate posed by rising concentrations of greenhouse gases in the Oyimo community's environment. The remote sensing and geographic information system (GIS) provide a more flexible and powerful tool than traditional data processing systems, as it allows for the manipulation and combination of large volumes of different types of data sets into new data sets that can be displayed in the form of thematic maps. The use of GIS permits the creation of models from which a new thematic map (for example, a forest degradation map) can be created from a collection of thematic maps (Harasheh, 1994).

The study objectives are:

1. Detection and prediction of changes in land use/land cover in the Oyimo forest reserve.
2. Estimation of Oyimo forest reserve total carbon stores for biomass and restoration.
3. Estimation of Oyimo forest soil organic matter for ecological services.
4. To ascertain the relationship between forest loss and carbon emissions in Oyimo forest.

STUDY AREA AND METHODOLOGY

Study Area

Oyimo forest reserve in Supare, Akoko South West Local Government Area of Ondo State, Nigeria is geographical located in Latitude: 7° 22' 17" N to 7° 54' 28" N and 5° 43' 40" E to5° 51' 19" E as in figure 1 It has an area of 226 km^2 and a population of 239,486 at the 2006 census.

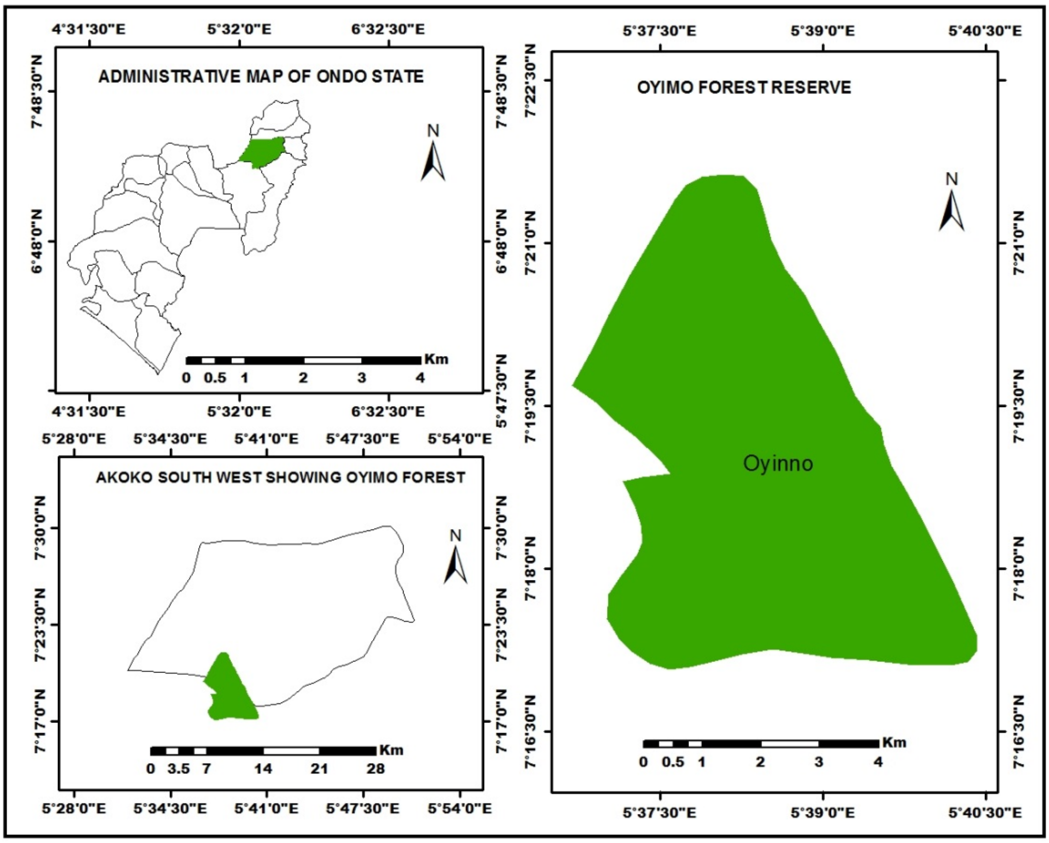

Figure 1: Study area Map

Vegetation

The Oyimo Forest Reserve, is covered an area of 59, 758 hectares at inception (Ezealor, et al, 2013). Their crowns touch one another thus forming a complete cover over the layers below. Their crowns were also draped by various climbers, which tended to bind crowns of many trees together. Some characteristics of the trees observed included tall large trunks, light thin barks (peeling off in some species), buttress roots, stilt roots, leaves with drip tips and some leaves with epiphyllous algae. These characteristics are typical for forest trees and they have been observed elsewhere.

Climate

The climate of the Oyimo forest reserve, Akoko South west, Ondo states in the southwestern part of Nigeria is that of tropical rain forest type, with distinct wet and dry seasons. The tropical climate of the area is broadly divided into two seasons: the dry season and the rainy season. The dry season comprises the Harmattan season and heat period, while the wet season begins in March, ending in early April, and the wet season ends in October or occasionally early November. The annual average rainfall ranges between 1480 mm and 2500 mm, the relative humidity of 60 to 85%, and the temperature of the area is between 24°C and 32°C (degree Celsius) according to (Ajayi, 2008).

METHODOLOGY

Data Acquisition and Source

Reconnaissance:

The purpose of the survey and ground truth campaign was to verify the classified signatures of the satellite images in Oyimo Forest Reserve and to monitor the rapid changing of the landscapes. A reconnaissance study was conducted to determine the sample points, taking into consideration remote sensing and geographic information system (GIS) work. This was done to help the researcher have an overview of the area under study and to assist in the feasibility and logistics plans for the fieldwork. Fieldwork/Data Collection: One fieldwork project was conducted at the Oyimo Forest Reserve on December 22, 2021. During the field work, the coordinates of land use samples were collected. Some of these samples were used as training sites for the supervised classification and also to interpret the clusters derived during the unsupervised classification. The second set of samples was used for conducting accuracy assessments (user's and producer's accuracies) to test the consistency and reliability of the supervised classification.

Remote Sensing Image:

The Landsat data was acquired from the global land-cover website at the University of Maryland, USA (URL; http://glcfapp.umiacs.umd.edu:8080/esdi/index.jsp). The acquired images were Enhanced thematic mapper (ETM) of 1998, Enhance Thematic Mapper plus (ETM^+) image of 2011 and the Operational land imager (OLI) of 2021 respectively, as shown in Table 1. The satellite data has 30m spatial resolutions, the ETM Plus images have a spectral range of 0.45-2.35 micrometers with bands 1,2,3,4,5,6,7 and 8 while the Operational Land Imager (OLI) extends to band 12.

Table 1: the Characteristics of Landsat Imagery

S/N	Data Type	Year	Spatial Resolution
1	Landsat Enhanced Thematic mapper (TM)	8/4/1998	30 meters
2	Landsat Enhanced Thematic mapper (ETM^+)	8/4/2011	30 meters
3	Landsat Operational Land Imager (OLI)	84/2021	30 meters

Data Pre-Processing:

The satellite images were preprocessed to correct errors that occurred during data scanning, transmission, and recording. The pre-processing steps used were:

- Radiometric correction to compensate for the effects of the atmosphere;
- Geometric correction, i.e., registration of the image to make it usable with other maps or images of the applied reference system; and
- Noise removal to remove any type of unwanted noise due to the limitation of transmission and recording processes.

Data Post Processing

Image Compositing:

A false Colour Composite operation was performed using the ERDARS Imaging software and the Landsat bands were combined in the order of band 4, band 3 and band 2 for Landsat ETM and ETM^+ while Landsat OLI was composited in the order of band 5,4 and 3 due to change in sensor.

Image Classification:

The false colour composite was further classified using the maximum likelihood classification technique. A supervised classification was performed by creating a training sample, and based on the spectral signature curve, various land use classes were created, namely, high-density Forested area; low-density forested area; farmland; water body; settlement; and bare surface The classified map was generated for the years 1998, 2011, and 2021, respectively. Ground truthing was carried out to verify the results of the classified maps.

Accuracy Assessment:

Accuracy assessment is essential for individual classifications if the classification data is to be useful in change detection (Owojori and Xie, 2005). For the accuracy assessment of land cover maps extracted from satellite images, a stratified random method was used to represent different land cover classes in the area. The accuracy was assessed using 120 points based on ground truth data and visual interpretation. The comparison of classification results and reference data was carried out statistically using error matrices. In addition, a nonparametric Kappa test was also performed to measure the extent of classification accuracy, as it not only accounts for diagonal elements but for all the elements in the confusion matrix.

Land Use/Land Covers Change Detection and Prediction:

The post-classification change detection technique, performed in Idrisi-Selva, was employed by the study. Post-classification in urban environments has been effectively used by various researchers due to its efficiency in detecting the location, nature, and rate of change (Hardin et al. 2007). Another technique used to obtain the changes in land cover and use during the specified time period was the overlay procedure. For all these tasks, Land Change Modeller (LCM) used the LULC maps generated for the years 1998, 2011, and 2021. The change analysis was performed for two separate periods, one from 1998 to 2011 and another from 2011 to 2021. A two-way cross-matrix obtained by the application of this was used to describe the key change types in the study area. Cross-tabulation analysis was conducted in order to determine the quantitative conversions from a particular category to another land cover category and their corresponding area over the evaluated period on a pixel-by-pixel basis. Thus, a new thematic layer was also produced from the two five-class maps, containing different combinations of ‘‘from and to’’ change classes. The transition probability between 1998 and 2021 was calculated in Markov chain analysis.

Quantification of Carbon Stock and Soil Organic Carbon

The IPCC 2000 embedded in the plugin QGIS was adopted for the analysis of carbon stock and soil organic carbon.

Sustainable Development Goal 15.3 intends to combat desertification, restore degraded land and soil, including land affected by desertification, drought, and floods, and strive to achieve a land degradation-neutral world by 2030. In order to assess the progress towards this goal, the agreed-upon indicator for SDG 15.3 (proportion of land area degraded) is a combination of three sub-indicators: change in land productivity, change in land cover, and change in soil organic carbon.

All these indicators are performed in QGIS. Moreover, soil organic carbon has three sub-indicators: productivity trajectory, productivity state, and productivity performance.

Productivity Trajectory:

A Mann-Kendall non-parametric significance test is then applied, considering only significant changes that show a p-value ≤ 0.05. Positively significant trends in NDVI would indicate potential improvement in land condition, and negatively significant trends would indicate potential degradation.

Productivity State:

For each pixel, use the annual integrals of NDVI for the baseline period to compute a frequency distribution. That expanded frequency distribution curve is then used to define the cut-off values of the 10 percentile classes. Possible values range from 1 (lowest class) to 10 (highest class); assign to the mean NDVI for the comparison period the number corresponding to that percentile class. Determine the difference in class number between the comparison and the baseline period (comparison minus baseline). If the difference in class between the baseline and the comparison period is ≤ 2, then that pixel could potentially be degraded. If the difference is ≥ 2, that pixel would indicate a recent improvement in terms of primary productivity. Pixels with small changes are considered stable.

Productivity Performance:

The indicator is computed as follows:

1. Define the analysis period, and use the time series of the NDVI to compute the mean of the NDVI for each pixel.
2. Define similar ecologically similar units as the unique intersection of land cover and soil type.

For each unit, extract all the mean NDVI values computed in step 1 and create a frequency distribution. From this distribution, determine the value that represents the 90th percentile (we don't recommend using the absolute maximum NDVI value to avoid possible errors due to the presence of outliers). The value representing the 90th percentile will be considered the maximum productivity for that unit. Compute the ratio of the mean NDVI and maximum productivity (in each case, compare the mean observed value to the maximum for its corresponding unit). If the observed mean NDVI is lower than 50% of the maximum productivity, that pixel is considered potentially degraded.

Statistical Analysis of Variable

Linear regression analysis was used in Excel software to carry out correlations between forest loss and carbon stock to determine the level of confidence. As this formula imply,

$$y = ax+b+\mathcal{E} \quad (1)$$

Where,

- Y = dependent variable
- X = independent variable (explanatory)
- A = intercept
- B = slope
- Ɛ = residual (error)

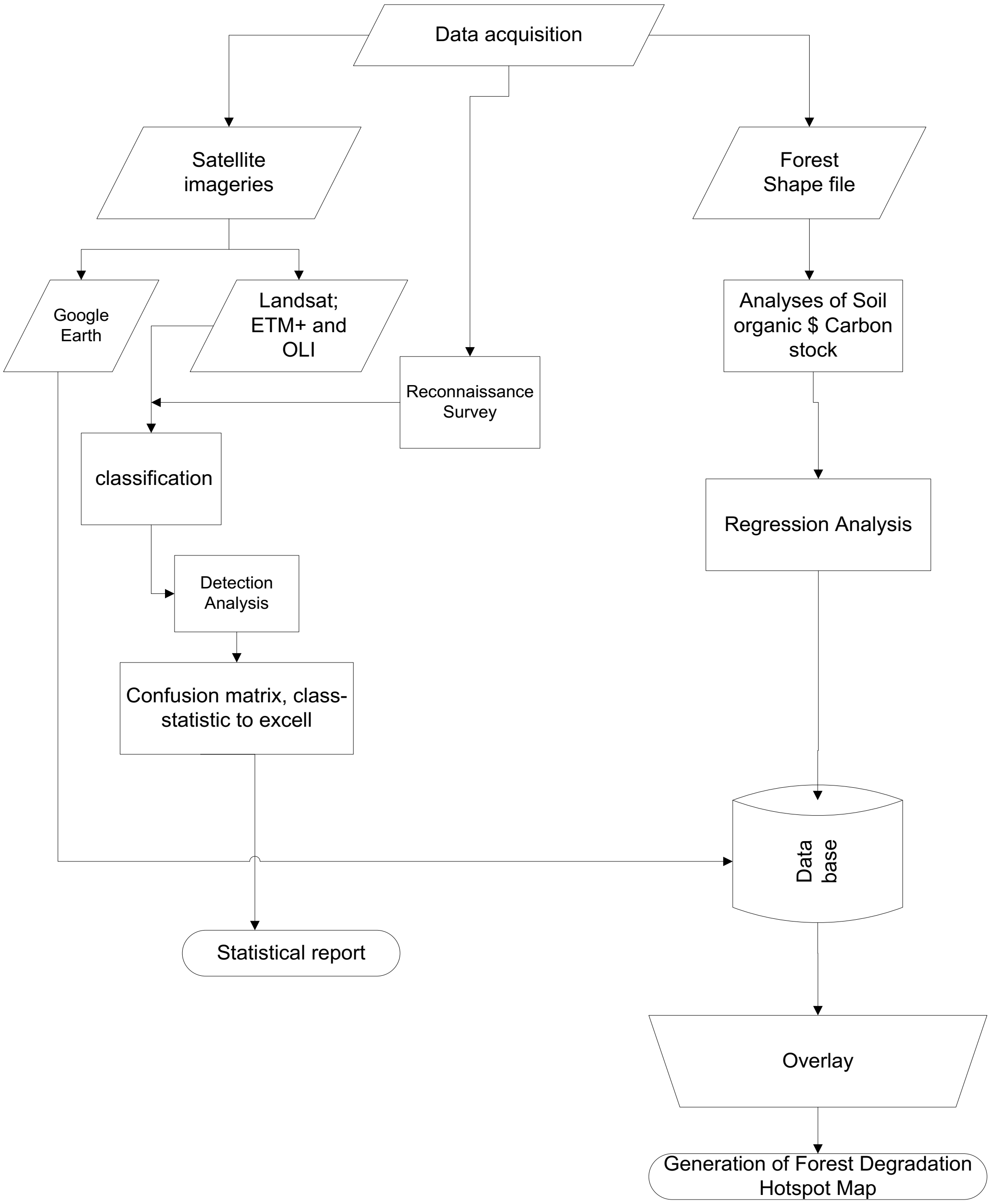

Figure 2: Flowchart methodology

RESULTS AND DISCUSSION

Results

Analysis of Land Use and Land Cover in the Oyimo Forest Reserve From 1998 To 2021:

The results of the image classification of the Oyimo forest reserve in 1998 in Figure 3 showed that the total land area of the Oyimo forest reserve was 59,758 hectares (ha). The accuracy of the assessment of land use and land cover is summarised in Table 2. The forest area is 59%, the settlement is 9%, the water body is 4%, the farmland is 27%, and the bare surface is 1%, respectively. Total accuracy for the 1998 classified image was 82.98%, and Kappa statistics were 0.8725.

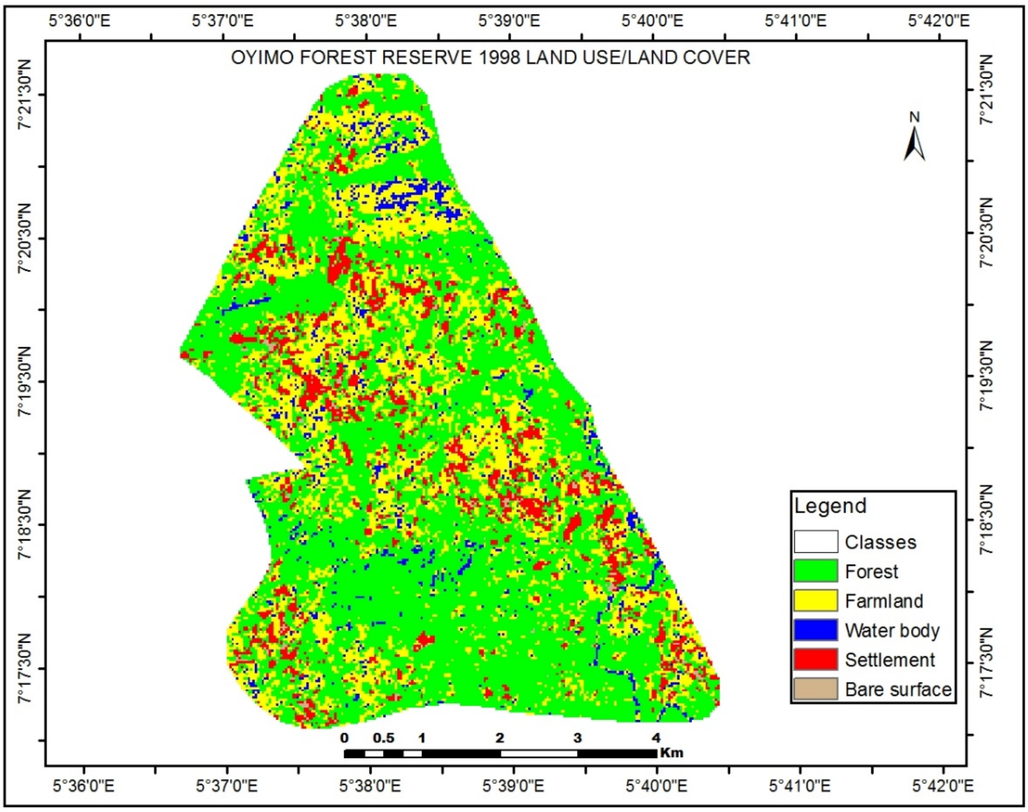

Figure 3: 1998 land use/land cover of Oyimo forest reserve
(Source: fieldwork 2021)

Table 2: Accuracy assessment of 1998 land use/land cover of Oyimo forest

CLASS	Forest	Settlement	Water body	Farmland	Bare surface	Row Total	User Accuracy
Forest	83	14	4	0	0	101	82.18 %
Settlement		87	9	3	0	99	87.77 %
Water body		0	1	0	0	1	63.45 %
Farmland	0	0	6	28	0	34	82.35 %
Bare surface	0	0	0	5	16	21	76.19 %
Total	83	101	20	36	16	256	
Producer Accuracy	84.00 %	86.14 %	65.00 %	77.78 %	86.00 %		Total Accuracy = 82.98 %

Overall Kappa Statistics = 0.8725 (Source: fieldwork 2021)

It was drawn from Table 3 and Figure 4 of the 2011 classification that the forest area is the largest in the study area. The forest area was 22,708.04 ha, or 38%; settlement 9,261.28 ha, or 16%; water body 11,354.02 ha, or 19%; farmland 15,537.08 ha, or 26%; and bare surface 596.58 ha, or 1%, respectively. Its accuracy assessment was 81.14% and Kappa statistics were 0.9000.

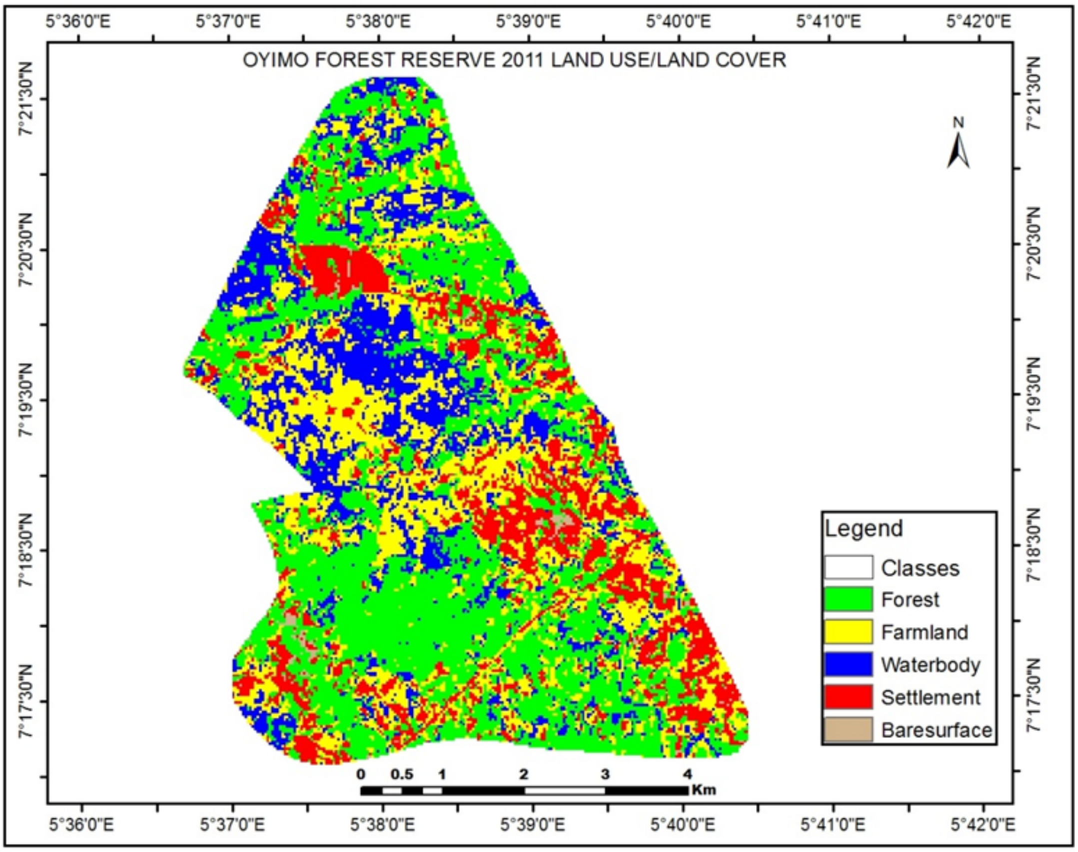

Figure 4 2011 land use/land cover of Oyimo forest reserve
(Source: fieldwork 2021)

Table 3: Accuracy assessment of 2011 land use land cover of Oyimo forest

CLASS	Forest	Built-up	Water body	Rock outcrop	Bare surface	Row Total	User Accuracy
Forest	79	5	2	2	2	90	87.78 %
Settlement	1	4	0	0	0	5	80.00 %
Water body	0	0	1	0	0	1	68.00 %
Farmland	1	1	3	28	3	36	77.78 %
Bare surface	2	2	2	3	31	40	67.50 %
Total	86	12	8	33	36	172	
Producer Accuracy	95.58 %	63.33 %	52.50 %	85.84 %	86.11 %		Total Accuracy = 81.14 %

Kappa Statistics = 0.9000 (Source: fieldwork 2021)

The results of the image classification for 2021 in Figure 5 showed that the total land area of the Oyimo forest reserve was 59,758 hectares (ha). The accuracy of the assessment of land use and land cover is summarised in Table 4. The forest area was 35257.22 ha, the settlement was 597.58 ha, the water body was 3585.48 ha, the farmland was 10159.03 ha, and the bare surface was 4780.64 ha, respectively. Total accuracy for the 2021 image was 84.35%, and Kappa statistics were 0.8375.

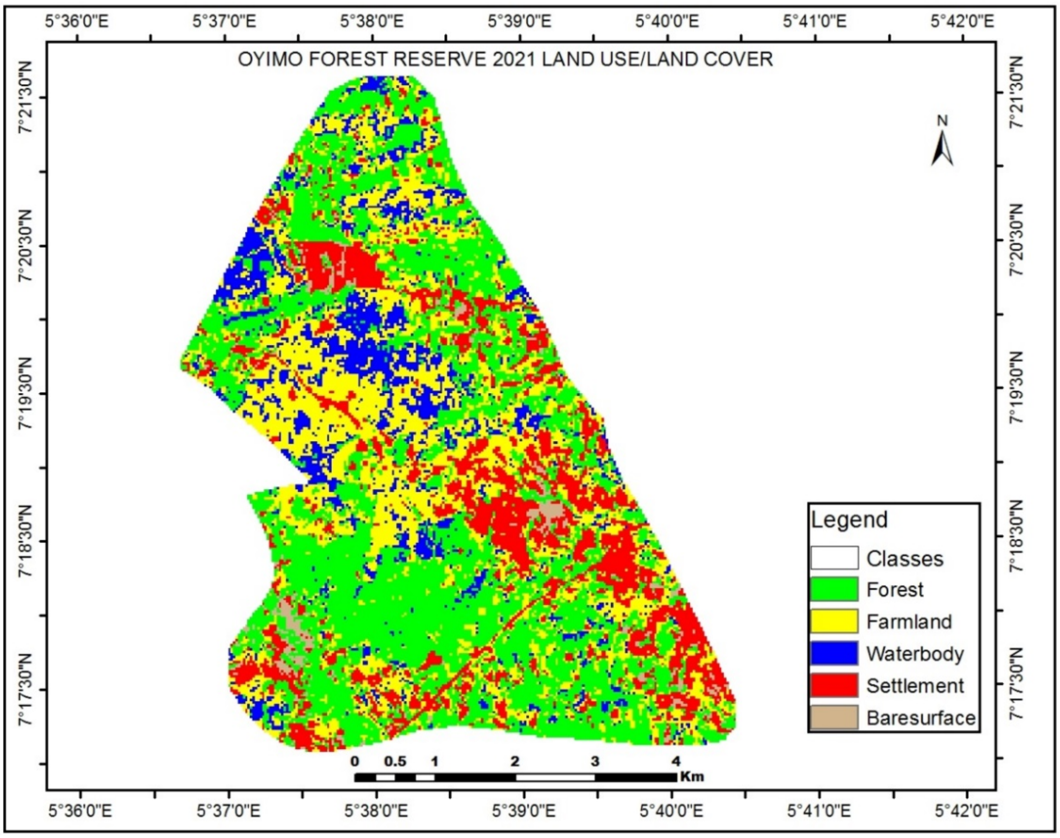

Figure 5: 2021 land use/land cover of Oyimo forest reserve (Source: fieldwork 2021)

Table 4: Accuracy assessment of 2021 land use/land cover of Oyimo forest

CLASS	Forest	Built-up	Water body	Rock outcrop	Bare surface	Row Total	User Accuracy
Forest	21	0	0	0	0	21	91.30%
Settlement	0	18	0	0	0	18	78.26%
Water body	0	0	19	0	0	19	82.61%
Farmland	0	0	0	19	0	19	82.61%
Bare surface	0	0	0	0	20	20	86.96%
Total	21	18	19	19	20	97	
Producer Accuracy	87.50%	90.00%	79.17%	86.36%	83.33%		Total Accuracy = 84.35%

Overall Kappa Statistics = 0.8375 (Source: fieldwork 2021)

Table 5 shows the land mass and percentage of each class from 1998 to 2021

Table 5: Year wise area covered and percent

Land use Land cover class	1998		2011		2021	
	Hectares	(%)	Hectares	(%)	Hectares	(%)
Forest	35,257.22	59	22,708.04	38	23,903.2	40
Settlement	5,378.22	9	9,561.28	16	10.756.44	18
Water body	2,390.32	4	11,354.02	19	6,573.38	11
Farmland	16,134.66	27	15,537.08	23	17,329.82	29
Bare surfaces	597.58	1	597.58	1	1,195.16	2

Land Use Land Cover Change Detection and Prediction

It shows in figure 6 that other classes gain from forests, but water bodies gain more area than the rest of the classes, and water bodies gain close to 600 hectares. The least gained from the forest among the classes was the bare surface, which was about 10 hectares. Similarly, forest loss was approximately -900 hectares, the highest loss class among all classes. Bare surface had the least loss among all the classes, losing about 5 hectares of land.

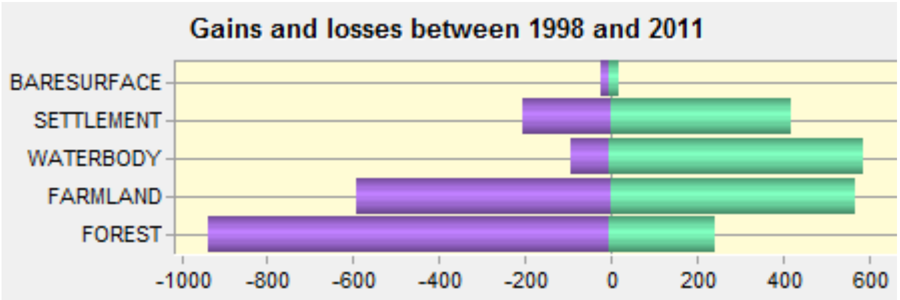

Figure 6: Gains and Losses between 1998 and 2011 Land use/land cover

(Source: Fieldwork 2021)

Analysis in Figure 7 shows that all other classes gain from forest, but farmland gains more area than the rest of the classes, and its gains were close to 280 hectares. The water body, which covered about 10 hectares, benefited the least from the forest. Similarly, water bodies lose about -270 hectares, the highest reduction class among all classes, and farmland loses about -180 hectares. Bare Surface did not lose any classes between 2011 and 2021.

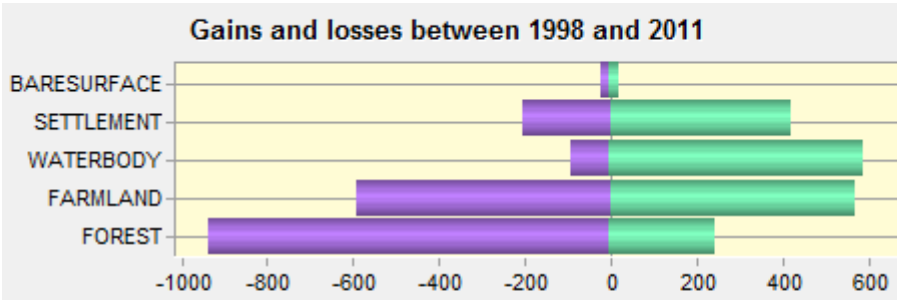

Figure 8: Gains and Losses between 2011 and 2021 Land use/land cover

(Source: Fieldwork 2021)

Predictions of Future Land Use and Land Cover Dynamics

In this work, the Markov chain analysis was implemented over one period: 1998–2021. Thus, the land use area transfer matrix and transition probability matrix were obtained. From Tables 7 and 8, the forest area will change in 2021 and 2030 from 1351.2600000 ha to 1199.1600000 ha. What this means is that if there is further reduction of forest by degradation, it will reduce to 152.1 hectares in the 2030 projection. Table 9 shows various stages of prediction for 2030 land use and land cover change in the Oyimo forest reserve due to forest degradation.

Table 7: Area covered by Oyimo forest 2021 land use land cover before Prediction

Category	Hectares	Legend
0	2411.1900000	Unclassified
1	1351.2600000	FOREST
2	1004.1300000	FARMLAND
3	393.6600000	WATERBODY

4	603.2700000	SETTLEMENT
5	78.4800000	BARESURFACE

Table 8: Area covered by Oyimo forest land use land cover by 2030 Prediction

Category	Hectares	Legend
0	2411.1900000	Unclassified
1	1199.1600000	FOREST
2	1052.7300000	FARMLAND
3	430.5600000	WATERBODY
4	659.0700000	SETTLEMENT
5	89.2800000	BARESURFACE

Table 4.9: Oyimo Forest Probability change of classes from 2021 to 2030

Probability	Cl .1	Cl .2	Cl .3	Cl .4	Cl .5
Class 1	0.6929	0.1616	0.0541	0.0838	0.0104
Class 2	0.1424	0.4777	0.1981	0.1677	0.0140
Class 3	0.2344	0.3844	0.3632	0.0147	0.0033
Class 4	0.0355	0.3116	0.0317	0.5429	0.0783
Class 5	0.0897	0.1915	0.0000	0.5613	0.1575

Analysis of Forest Organic Carbon Stock of Oyimo Forest Reserve

The result of forest organic carbon showed that there was significant forest loss from 2000 to 2020, as observed in Table 9. Estimates show that forests are losing acreage every year between 2001 and 2020. From 2000 to 2020, the forest loss was 1,858 ha; the carbon loss was 127,703 tonnes of CO_2e; and the total carbon emissions were 468,669 tonnes of CO_2e. The highest forest loss was 419 ha in 2017, and the lowest loss during the years was 10 ha, which occurred in 2003 (Salami et al., 2022). The highest carbon loss for this period was 27,660 tonnes, and the lowest carbon loss was 687 tonnes in 2017 and 2003. The lowest carbon emission during the year was 2,521 and the highest was 101,513 (tonnes of CO_2e); this happened in 2003 and 2017, respectively.

Table 4.10 Summary of Oyimo carbon loss due to degradation

Summary of carbon loss due to degradation*					
Baseline land cover					
		Area (hectares)	**Percent of total area**	**Total biomass (tonnes of C):**	
	Initial forest area:	**59,413**	99.4%	3,535,543	
	Initial non-forest land area:	345	0.6%		
	Water area:	0	0.0%		
	Missing data:	0	0.0%		
	Total:	**59,758**	**100.0%**		
Land cover change summary					
		Baseline year:	2000		
		Final year:	2020		
		Forest loss over period (hectares):	**1,858**		
		Loss of carbon over period (tonnes of C)	**127,703**		
		Total carbon emissions over period (tonnes of CO2e):	**468,669**		
Carbon loss by year*					
Year	**Forest Loss During Year (ha)**	**Forest Cover at End of Year (ha)**	**Loss of Carbon During Year (tonnes of C)**	**Total Biomass at End of Year (tonnes of C)**	**Carbon Emissions During Year (tonnes of CO2e)**
2001	93	59,320	7,326	3,528,217	26,886
2002	65	59,255	4,890	3,523,327	17,945
2003	10	59,245	687	3,522,640	2,521
2004	32	59,213	2,442	3,520,198	8,962
2005	39	59,174	2,895	3,517,303	10,626
2006	27	59,147	2,051	3,515,252	7,526
2007	34	59,114	2,487	3,512,765	9,128
2008	50	59,064	3,780	3,508,985	13,873
2009	83	58,981	6,195	3,502,790	22,735
2010	75	58,907	5,546	3,497,243	20,355
2011	53	58,854	3,917	3,493,327	14,374
2012	30	58,824	2,133	3,491,194	7,827
2013	160	58,664	9,772	3,481,422	35,863
2014	109	58,554	7,286	3,474,136	26,738
2015	204	58,351	13,023	3,461,114	47,793
2016	102	58,249	6,978	3,454,136	25,609
2017	419	57,830	27,660	3,426,476	101,513
2018	183	57,647	12,506	3,413,970	45,896
2019	92	57,555	6,130	3,407,840	22,498
2020	0	57,555	0	3,407,840	0

Table 10 shows the change in biomass with restoration for above-ground biomass and below-ground biomass. This analysis revealed the initial biomass, total biomass, and biomass change in the study area compared to pre-restoration levels. The Eucalyptus plantation had the highest level of biomass restoration among the others, with pre-restoration levels of 37883296 and a final total biomass of 48620525 (tonnes of CO_2). Agroforestry had the least amount of biomass restoration, with pre-restoration levels of 3748068 and a total biomass of 14485297 (tonnes CO_2e).

Table 10: Change in biomass of above and below ground in Oyimo forest

Potential carbon removals from restoration summary table		
	Value	**Units**
Total area of polygon:	59,758	hectares
Time since initiation of restoration:	20	years
Initial biomass:	10,737,229	tonnes CO2e
Change in biomass with restoration		
Restoration approach	**Change in biomass compared to pre-restoration levels (tonnes CO2e)**	**Final total biomass (tonnes CO2e)**
Natural regeneration	10,228,039	20,965,269
Agroforestry	3,748,068	14,485,298
Teak plantation	25,854,827	36,592,056
Eucalyptus plantation	37,883,296	48,620,525
Oak plantation	11,167,998	21,905,227
Other broadleaf plantation	19,321,640	30,058,869
Pine plantation	14,241,579	24,978,808
Conifer plantation	15,362,000	26,099,230

Figures 9, 10, and 11 show the results of soil productivity state degradation, soil productivity performance degradation, and soil productivity trajectory degradation, respectively. The output soil productivity state degradation map generated in Figure 9 is sliced into four density classes and their color ramp: area with no data, improvement, stable, and degradation. Areas with no data mean no information has been acquired from these areas. Improvement areas mean there is recovery from degradation in the area. In stable areas, that is, degradation has not taken place in these areas, and degradation area indicates the area is actually degraded. For soil productivity performance degradation output, the three classes are: no data, no degradation, that is, the areas have never experienced degradation. The degradation area shows there is significant degradation, as shown in Figure 10. Productivity trajectory degradation shows four classes from map output in figure 11, which include: no data; degradation ($P<0.05$), which indicates there is significant degradation; stability, which means degradation has not taken place at all; and improvement ($P<0.05$), which means there is significant improvement in some degraded areas.

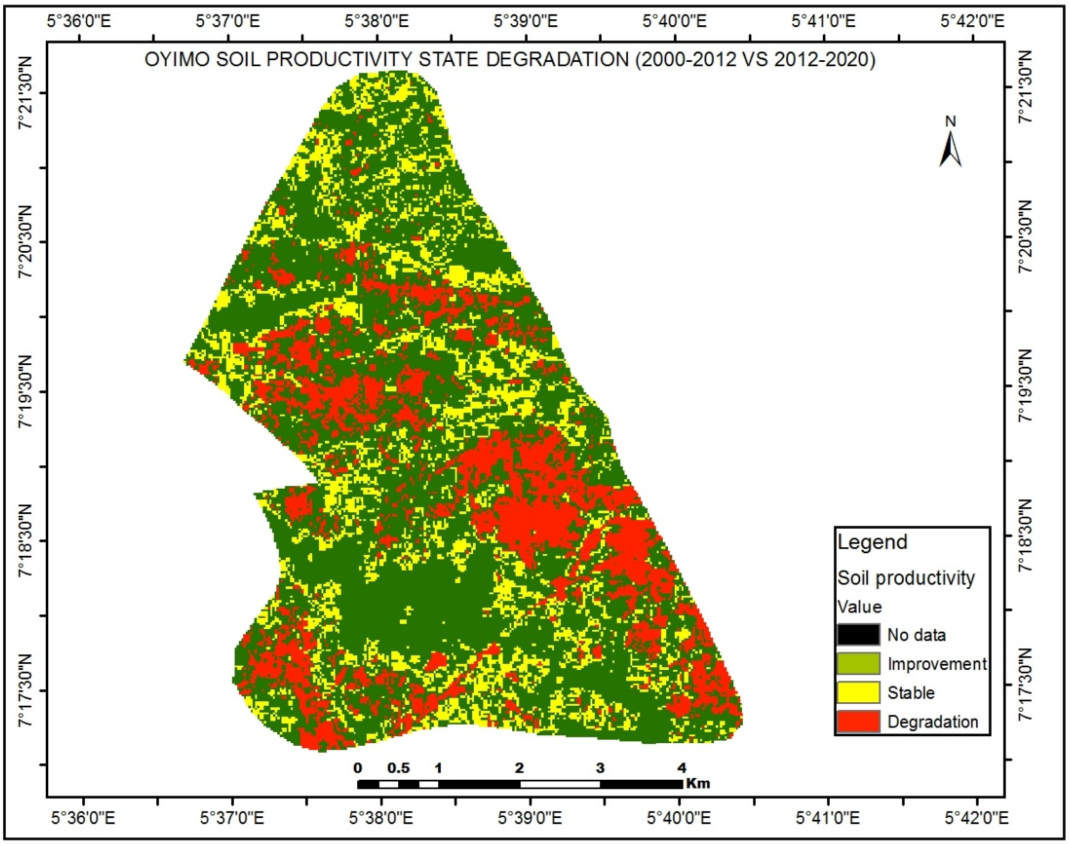

Figure 9: Soil productivity state degradation of Oyimo forest

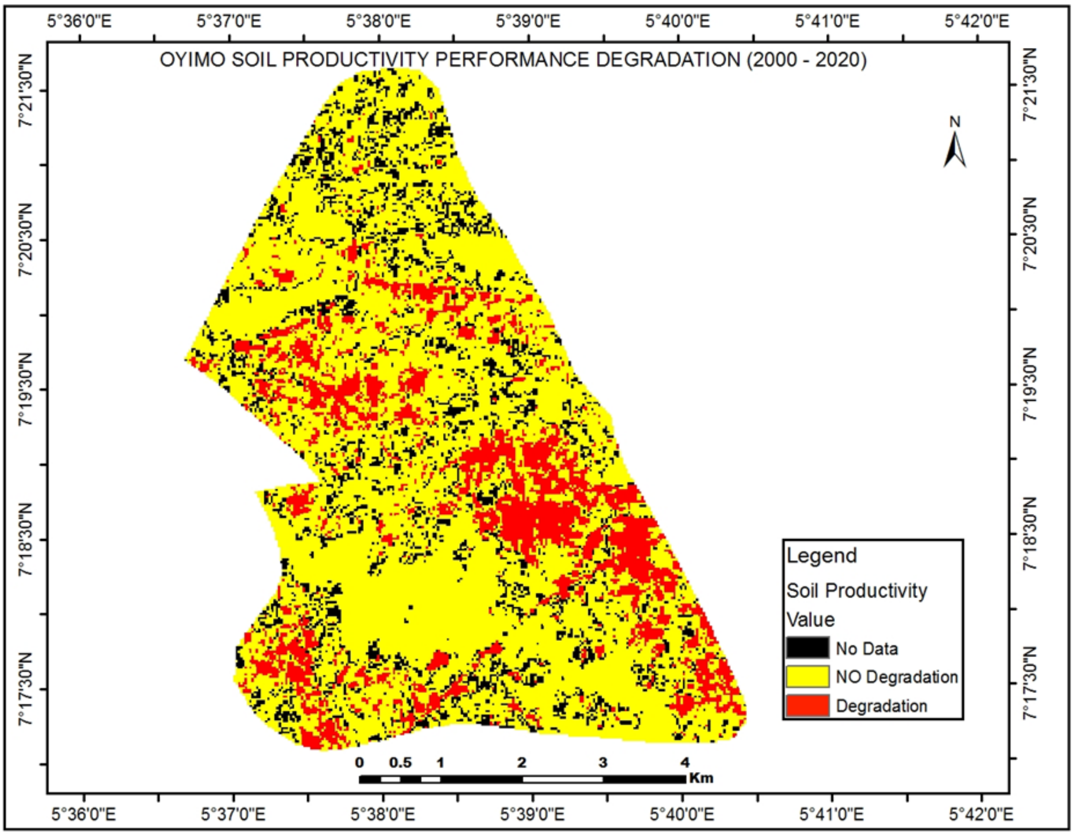

Figure 10: Soil productivity performance degradation of Oyimo forest

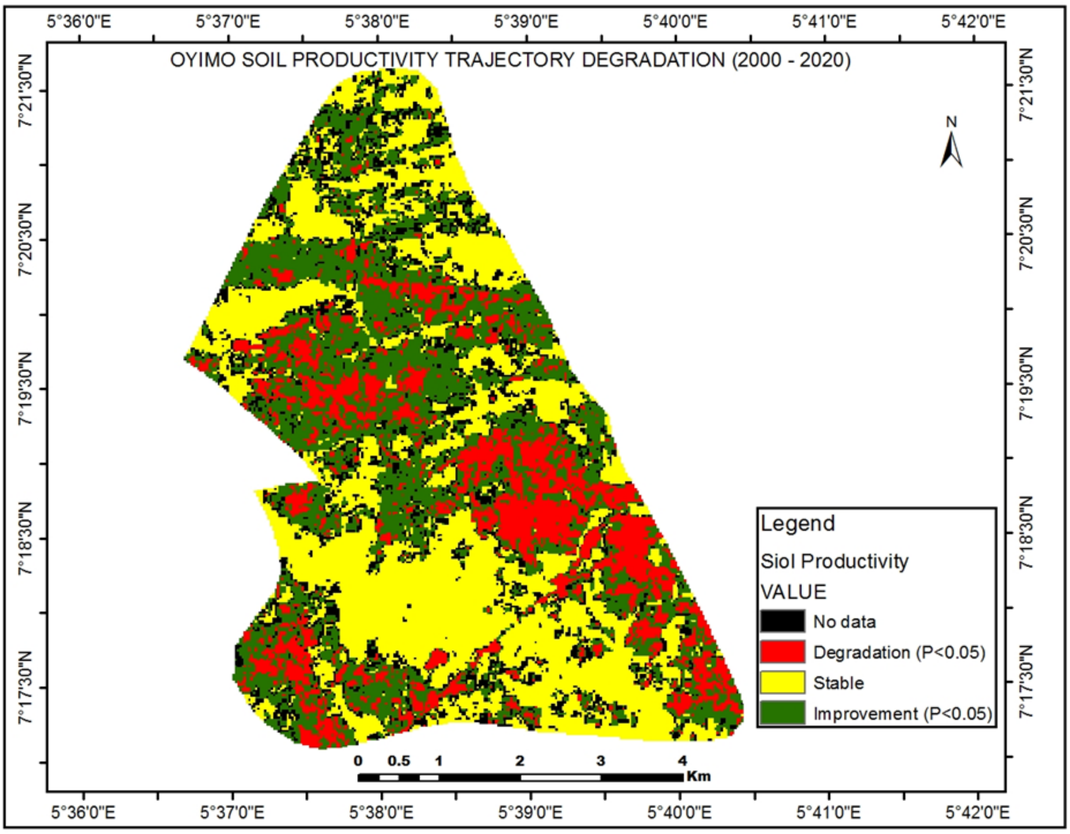

Figure 11: Soil productivity trajectory degradation of Oyimo forest

Table 11 shows the percentages and areas covered by soil productivity: degraded area, stable area, and improvement area. It is well known that organic matter is a key component of soil that affects its physical, chemical, and biological properties, contributing greatly to its proper functioning, on which human societies depend. Benefits of soil organic matter (SOM) include improvement of soil quality through increased retention of water and nutrients, resulting in greater productivity of plants in natural environments and agricultural settings. SOM improves soil structure and reduces erosion, leading to improved water quality in groundwater and surface waters and, ultimately, increased food security and decreased negative impacts on ecosystems.

Table 11: Summary table of soil organic carbon land use cover of Oyimo forest reserve

Summary of SDG 15.3.1 Indicator		
Area (hectares)		Percent of total land area
Total land area:	59,758	100.00%
Land area improved:	11,978.02184	20.045%
Land area stable:	29,032.919	48.584%
Land area degraded:	18,727.849	31.34%
Land area with no data:	19.21016	0.031%

Analysis of Relationship Between the Variables

Figures 12 and 13 showed the relationship between carbon emissions versus forest loss and carbon loss versus forest loss. It shows a positive correlation: as more forest is lost, the greater the increase in carbon emissions to the atmosphere, and the more the forest is lost, the more useful the carbon loss to the surrounding area. These correlation analyses describe the strength of an association between the two variables in figures 12 and 13 and are completely symmetrical; the correlation between carbon emission and loss of forest is the same as the correlation between loss of organic carbon and loss of forest. Although the first one, r^2, was 0.8506 and the latter was 0.9959, which was highly correlated,

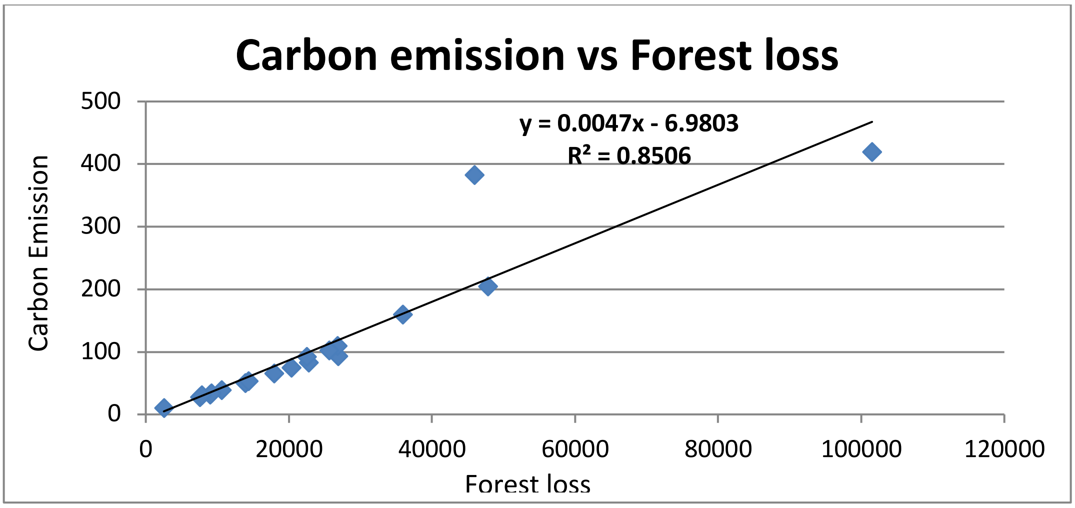

Figure 12: Relationship between Carbon Emission and Forest loss

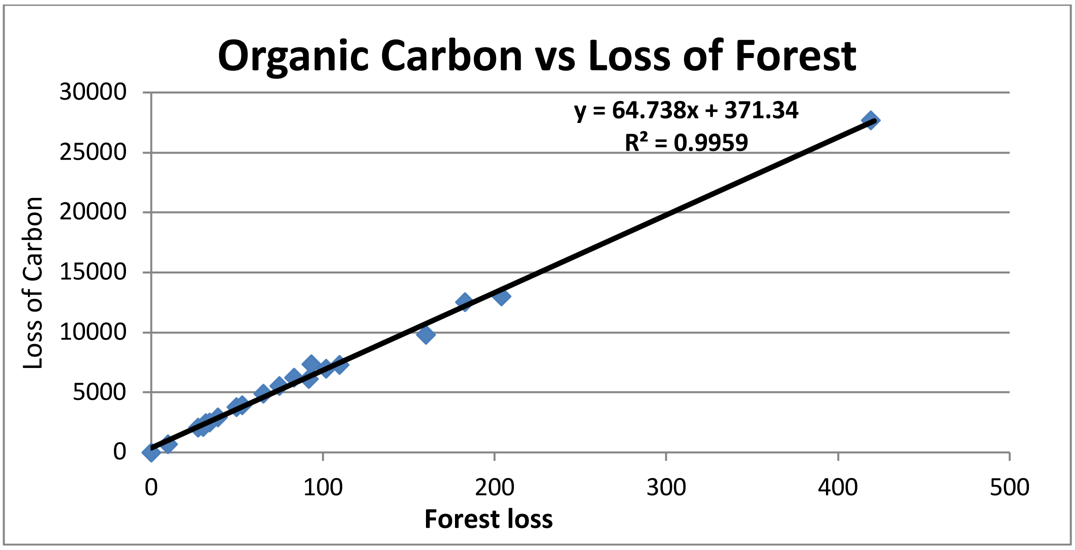

Figure 13: Relationship between Carbon loss and Forest loss

DISCUSSION

The total land use land cover (LULC) for the forest reserve was 59,758 ha. It was found that LULC for the forest between 1998, 2011, and 2021 varied among the various land cover types identified. LULC increased from 1999 to 2021 for bare surface area, settlement area, and areas covered by water. On the other hand, areas covered by cropland and forest decreased (Belay & Mengistu, 2019). What this mean is that there was loss of forest and cropland to settlement area, water, and bare surface area. Some croplands and forests were cleared for dwelling houses and thus changed into settlements. In the same vein, from 2011 to 2021, the forest class gained about 2% of other land as a result of replanting trees by the Ondo State Government programme.

According to Abate (2011), an important aspect of change detection is to determine what is actually changing to what category of land use land cover type (i.e., which LULC type is changed to the other type of LULC class). Forest cover experienced more varied changes than any other land cover type in the Oyimo Forest Reserve. Some of the areas covered by forest became bare surfaces through bush burning and construction activities. Parts of the forest were also cleared for housing projects, hence the change to a settlement area with an area of hectares (ha). Parts of the forest very close to water bodies were covered by water, including wetland. This was due to the advancement of these water bodies due to erosion and inundation.

The prediction identified the extent to which the land area has the propensity and the right criteria to be altered. While the prediction created only a single realisation of the future LULC status, the prediction was a comprehensive assessment of change potential. This is why the output detected areas with varying degrees of vulnerability instead of identifying what and how much of the LULC area would be changed. From the modelled output, it is evident that most of the southern portion of the Oyimo forest reserve is highly vulnerable to transition under the current set of driver variables and identified individual transitions from one type to another. This is reasonable as this part of Oyimo has a large area of settlement and bare surface, which has exhibited the most significant depletion during the study period. Reasons for this vulnerability may be attributed to the recent intensified logging activity in this area along with land use change derived from agricultural and farming activities. The result of forest organic carbon showed that there was forest and carbon loss during this period. Converting the natural vegetation to agricultural land is likely to change the radiation balance of the given unit of area. In principle, the albedo increases as land is without vegetation for at least part of the year, causing more solar energy to reflect back into space. Other environmental impacts include the decrease in soil water holding capacity. On the other hand, it shows that soil productivity degraded areas, stable areas, and improvement areas where the effort of humans was felt both positively and negatively. It is also well known that organic matter is a key component of soil that affects its physical, chemical, and biological properties, contributing greatly to the proper functioning on which human societies depend. Benefits of soil organic matter (SOM) include improvement of soil quality through increased retention of water and nutrients, resulting in greater productivity of plants in natural environments and agricultural settings.

In this correlation analysis, the magnitude of the correlation coefficient indicates the strength of the relationship. However, the correlation coefficients R^2 = 0.9959 and 0.8506 are strong enough for this study to make a generalisation about the forest degradation of the surrounding area. The positive correlation in this present study means that when forest loss values increase, emissions of carbon dioxide increase. And an increase in forest loss values is also reflected in a decrease in carbon pull. This finding is also consistent with a study conducted by Kundu et al. (2017).

DEVELOPMENT OF APPLICABLE GUIDELINES

Sustainable forest management is essential for reducing the vulnerability of forests to climate change. There is no universally applicable measure for adapting forests to climate change. Forest managers should, therefore, have sufficient flexibility to deploy the adaptation measures most appropriate for their local situations. Flexible approaches to policy design are needed that are sensitive to context and do not rely on a single, one-size-fits-all mechanism. New modes of governance are required that enable meaningful stakeholder participation, provide secure land tenure and forest user rights, and provide sufficient financial incentives.

More research is required to reduce current uncertainties about the impacts of climate change on forests and people and to improve knowledge about management and policy measures for adaptation. Nevertheless, despite the limitations of current knowledge, climate change is progressing too quickly to postpone adaptation action pending the outcomes of future studies. A broad suite of agro-ecology practices can be used to increase carbon in the soil, including agroforestry, fallows (resting soil for a year or more), and sustainable pasture management through managed herd mobility.

CONCLUSION

It was concluded that despite many factors, such as the availability of imagery for specific times of the year and the availability of recent land use land cover maps, that created hurdles in finding change in the study area. The present study proved very effective in fulfilling the objectives that were set for the study. The study rendered the following findings:

The area that is covered by forests first of all decreased and gradually increased. This can be attributed to the increase in planting more trees as directed by the Ondo State Government. It was noted that the increase in forest is almost entirely part of the study area. This is because of the availability of cultivable land in those parts of the study area. It was noted that settlement area increased the most in terms of its proportion to total area. This can be attributed to the increase in agricultural products, which in turn increase economic activities and ultimately human settlements and population in the study area.

The bare surfaces in the study area increased a little bit. This is because the area that was once occupied by the bare surfaces is now covered by vegetation and human settlements. Water bodies in the study area have increased at a very high speed and have decreased by only 0.8% in around 21 years. This is because the area has been experiencing dry spells in recent times. Thus, on the basis of the results rendered by this study, it reveals that the geographic information system is one of the best methods available today for identifying and measuring changes in land use and land cover in a specific area with remote sensing (RS). In order to address particular problems like carbon loss, habitat degradation, and soil productivity, as well as to propose pathways for improving forest quality, remote sensing and GIS can be used as space quantification tools for forest conservation.

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