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EVALUATION OF FOREST-COVER DYNAMICS AND ITS DRIVERS IN OKELUSE FOREST RESERVE, ONDO STATE, NIGERIA

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ABSTRACT

This study x-rays the prevailing situation in the Okeluse Forest Reserve (OFR) for necessary interventions. The study assessed the effects of anthropogenic activities on land-use changes in OFR between 1984 and 2020 using Landsat TM, ETM+ and OLI images of 1984, 1990, 2001, 2010 and 2020. The images were acquired from USGS Earth Resources Observation and Science Center (EROS), processed, and classified using ArcGIS. Ground-truthing was achieved using GPS receiver. The images were pre-processed and classified using unsupervised iso-cluster classification method. The classified iso-cluster images were re-classified into forest, agricultural land, shrubland, built-up areas and water bodies. Normalized difference vegetation index (NDVI) was used for assessing vegetated areas and non-vegetated land within the reserve. The rates of changes and forest-cover losses within the 36-year-period were then analyzed. The result revealed losses in forest areas and water bodies within the period. Area coverage of forest reduced from 11,422 ha in 1984 to 5,706.2 ha in 2020, water bodies also contrasted by 80.8%, from 1,425.9 ha in 1984 to 273.6 ha in 2020. Consequently, agricultural land increased by 832.4% from 702.7 ha in 1984 to 5,849.6 ha in 2020. Shrubland, a resultant effect of deforestation and eventual degradation, increased from 647.8 ha in 1984 to 2,196.1 ha (339%) in 2020. Built-up areas increased from 225.2 ha in 1984 to 398.1 ha in 2020 due to increases in farm settlements and other infrastructure. The results further showed that the reserve was far more vegetated in 1984 (NDVI = 0.67), and less vegetated in subsequent years. The major drivers of changes in the forest reserves were unsustainable timber exploitation, and unpermitted land clearing for agricultural activities. It is projected that there would be a substantial increase in agricultural land, shrubland, and built-up areas, if deforestation persists at the current pace. However, there would be continued contractions in forest areas and water bodies.

Keywords: Land-use changes; degradation; deforestation; drivers of change; simulation

INTRODUCTION

Land-related activities as consumptive such as mining, forest exploitation, hunting, fishing and clearing for agriculture cum non-consumptive uses like tourism, among others are classified as land uses (Maelle and Oghenerobor, 2012). However, unsustainable practices and handling of such resources of land would ultimately result in the losses of forest resources, and may change the affected landscapes, sometimes beyond repair (Hadi *et al*., 2013). Most times, these anthropogenic activities may accelerate the exploitation of forests to meet human needs and demands in the face of no-readily-available alternatives. Consequently, it leads to reduction in global forest estates (Laurance *et al*., 2014). Between 1990 and 2014, it was estimated that some 420 million hectares of forest were lost, and between 2015 and 2020, the rate of deforestation was estimated at 10 million hectares a year (FAO, 2020). Within these periods, many flora and fauna species have become endangered due to forest degradation and eventual habitat losses (IUCN, 2010).

Expectedly, and resulting from the rising global population, considering the falling standard of living in most developing countries, exploitations of forest for commercial and non-commercial purposes take place (Adubofour, 2011). As of 2012, the Federal Department of Forestry in Nigeria argued that deforestation due to anthropogenic activities would progress at 3.5%. This loss in forest lands would come from an increase in socio-economic development and the necessity to meet the ever-increasing demands for forest products the as population increases. Urbanization and economic activities, which involves road construction, shifting cultivation, fuel-wood harvesting, construction of residential building and industrialization have left most indelible marks on tropical forests. Most of these activities have had and will continue to have dangerous impacts on the forest resources and the environment as a whole (Akingbogun *et al.*, 2012). Remote sensing offers the possibility of locating changes in forest areas using various analyzing techniques, ranging from the purely visual interpretation to the implementation of a fully automated algorithm (Violini, 2013).

Okeluse Forest Reserve was established to serve as repositories of the primary habitats of the forest, and to ensure sustainable wood production, apart from provision of vital economic, social and environmental benefits. Other objectives of constituting the reserve were the supply of wood and non-wood forest products, support human livelihoods, act as watershed, among other things. Just as every other tropical forest, it serves as site for present and future biodiversity conservation and to safeguard the genetic diversity of species for continued evolution (FAO, 2018; Fasona *et al*., 2018).

Due to increase in human population, there has been high dependence on the forest and its resources for survival. Salami and Akinyele (2018) noted that degradation, fragmentation and conversion of forest to other land uses are progressing at alarming rates. There is a severe threat to the forest due to unrelenting human activities. The removal or destruction of significant of forest covers has resulted in a degraded environment with reduced biodiversity, shaping climate and geography (Packiam, 2015). Establishment of forest reserves and other protected areas in similar category is one of the core strategies of conservation. A measure often adopted to combat the problem of degradation of forest resources (King and Peralvo, 2010; Sims, 2010; Maelle and Oghenerobor, 2012). But most of these protected areas have not been spared from exploitation and encroachment. Nevertheless, specific extents of the areas affected are often obscured with little to no documentation.

In the western parts of Nigeria, forest reserves have been converted and exploited unsustainably. However, the extent of the damages caused by these anthropogenic incursions and its impact on forest resources in Okeluse Forest Reserve are yet unknown. Meanwhile developing a quality management plan to monitor and address issues concerning deforestation and forest degradation will be difficult, if not impossible, without adequate knowledge of status and changes in the reserve. Therefore, it is expedient to provide relevant information on the prevailing situation in the reserve for necessary management and conservation interventions. Thus, the main objective of the study is to assess the effects of anthropogenic activities on forest cover changes in Okeluse Forest Reserve in Ondo State.

Reliable and timely information about the status and trends of changes in forest resources are required for effective sustainable forest management. Also, forest is considered very important to the sustainability of forest resources. Unfortunately, this is hardly done for most forest reserves in South-west Nigeria. Consequently, many forest reserves known to exist only appear on paper. Meanwhile, new technologies have provided opportunities for adequate quantification of forest-cover extents for effective management. Nevertheless, suitability of such method has rarely been tested in evaluating land-use changes in OFR. With the use of a more reliable approaches like remote sensing, relevant information can be gotten, and actions can then be taken to address possible mismanagement and unsustainable use. Result-oriented and evidence-based awareness needs to be created to the public and exploiters in order to understand the damage these activities have caused and are still being caused to the forest and environment. Nevertheless, this would be impossible without having sufficient knowledge of the current situation in the forest reserve.

MATERIALS AND METHODS

The Study Area

The study was carried out in Okeluse Forest Reserve in Ose Local Government Area of Ondo State, south-west Nigeria. The reserve is 14,400 ha in size, and it is located between latitudes 6º43'0'' and 6º50'0''N, and between longitudes 5º33'30'' and 5º47'30''E (Figure 1). Okeluse is about 5 km southwest of Ifon. It is bordered in the north by Ute and in the south by Ogbesse. The reserve is one of the twelve (12) forest reserves in Ondo State. The climate of the forest reserve is tropical with an average annual rainfall of about 1500 mm while the mean relative humidity is estimated to be 94%. The wind speed of the reserve is 00 m/s with a mean temperature of about 23ºC (with values ranging between 22 and 29.4ºC). The study area is located within the rainforest zone as it is characterized with tall trees and dense undergrowth during the rainy season.

Data Collection Procedures

Since the assessment requires images of different periods and change detection analysis is carried out most-effectively with not less than 3 image-datasets of the study areas, Landsat imageries of moderate spatial resolutions of 1984, 1990, 2001, 2010 and 2020 were acquired from USGS for processing and analyses (Table 1). The acquired images' dates were irregular due to non-availabilities of quality (cloud-free) images in definite periodic intervals. The characteristics of these LULC types are described in Table 2.

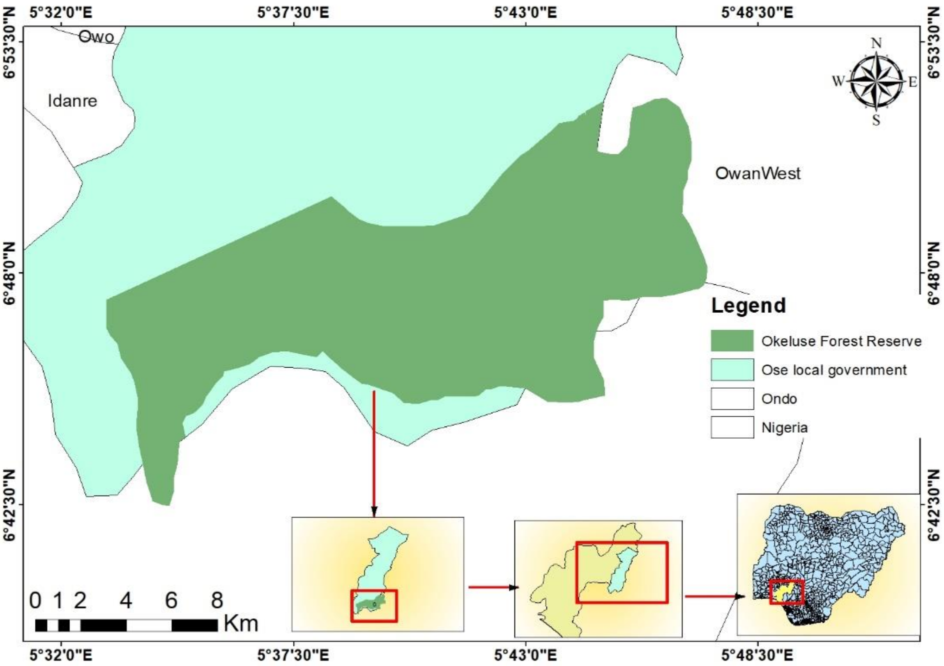


Figure 1: Map of the study area

Table 1: Satellite imageries used

S/N	Satellite Data	Date
1	Landsat 5 (TM)	27/06/1984
2	Landsat 4 (TM)	12/02/1990
3	Landsat 7 (ETM+)	09/01/2001
4	Landsat 7 (ETM+)	18/01/2010
5	Landsat 8 (OLI)	14/02/2020

Table 2: Description of the LULC classes in the area

LULC	Description
Forest	Dense forest with closed canopies
Agricultural land	Lands used for the cultivation of crops, either subsistence or commercial agriculture, and excluding non-cultivated areas within the reserve
Shrubland	Comprises of woody vegetation less than 2 m in heights and include tall grasses
Built-up areas	Including bare soil, roads infrastructure and buildings inhabited by humans
Water bodies	Areas occupied by marshes, rivers, streams and other water resources

Image Acquisition and Processing Methods

ArcGIS 10.5 was used for image processing while pre-processing was done using Landsat Toolbox. Landsat TM, ETM+ and OLI satellite images of five age series for the study area were acquired from the United States Geological Survey (USGS). Acquisition dates of the multi-temporal satellite data of different sensors TM, ETM+ and OLI scenes in the change detection process fell within acceptable anniversary windows of the same seasons.

Field Data Collection

Hand-held GPS receiver was used to obtain the geographic coordinate of the study site. Readings were taken and the locations were indicated on the OLI image. Landsat OLI image, topographic map and Global Positioning System were used to verify the location of the GCPs in the field during ground-truthing.

Image Classification

The main aim of image classification was to categorize all pixels in an image into respective and appropriate land-cover/land-use classes. Unsupervised (Iso-cluster) classification was performed with 25 classes. These were later reclassified into 5 classes after ascertaining the correctness of classes during classification procedures. Using the Landsat image bands combinations for periodic images, preliminary land-cover maps were produced, and land-cover classes were distinguished for each of the study years. Following this technique, images of different dates were classified, and land-use/land-cover maps were produced. Images were further re-classified as forest, shrubland, water bodies, agricultural land and built-up areas.

Data Analysis

Classification of the land use and land cover of each year was analyzed using spatial statistics, as follows:

$$Area = Count \times 0.09 \quad (1)$$

$$Percentage = \frac{Count}{Sum\ of\ count} \times 100 \quad (2)$$

$$\Delta\ \text{LULC} = L_2 - L_1 \quad (3)$$

$$\text{Percentage Change (trend)} = \frac{L_2 - L_1}{L_1} \times 100 \quad (4)$$

$$R_t = \left((L_2 - L_1) \times \frac{1}{t} \right) \quad (5)$$

Where:
L_2 (ha) = land-use/land cover (final year),
L_1 (ha) = land-use/land cover (initial year).
t (year) = periodic interval
R_t = rate of change

$$\text{Annual rate of change (\%)} = \frac{Trend}{Number\ of\ Study\ Years} \times 100 \quad (6)$$

Normalized Difference Vegetation Index (NDVI)

The NDVI was calculated by a sensor system with values ranging from -1 to +1. Healthy vegetation is represented by NDVI values between 0.1 and 1, while non-vegetated surfaces (e.g., water bodies, yielded negative values), and bare soil yields value closest to 0. The NDVI was extracted as:

$$\text{NDVI} = \frac{TM4 - TM3}{TM4 + TM3} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (7)$$

Where:
TM4 = near infrared band,
TM3 = red band.

Accuracy Assessment

The accuracy of the classification was evaluated using ground-reference data. An error matrix that contains information about actual and predicted land-use/land-cover classes by a classification system was adopted. The classified pixels from the images were compared to the same site on the ground. The overall accuracy was estimated, using:

$$\text{Overall Accuracy} = \frac{\text{total number of correct samples}}{\text{total umber of all samples}} \times 100 \ldots \ldots \ldots \ldots (8)$$

$$\text{Sensitivity (producer's accuracy)} = \frac{\text{a}}{\text{a} + \text{b}} \ldots \ldots \ldots \ldots \ldots \ldots \ldots (9)$$

$$\text{Comission} = 1 - \text{specificity} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (10)$$

$$\text{Omission} = 1 - \text{sensitivity}$$

$$\text{Positive predictive power(User's accuracy)} = \frac{\text{a}}{\text{a} + \text{b}} \ldots \ldots \ldots \ldots (11)$$

$$\text{Negative predictive power} = \frac{\text{d}}{\text{c} + \text{d}} \ldots \ldots \ldots \ldots \ldots \ldots \ldots (12)$$

Where:
a = number of times a classification agreed with the observed value,
b = number of times a point was classified as “a” when it was observed to not be “a”.
c = number of times a point was not classified as “a” when it was observed to be “a”.
d = number of times a point was not classified as “a” when it was not observed to be “a”

Kappa coefficient was computed for accuracy assessment as:

$$(K) = \frac{N \sum_{i=1}^{r} xii - \sum_{i=1}^{r} (xi + X_{XI+1})}{N^2 - \sum_{i=1}^{r} (xi + X_{XI+1})} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (13)$$

Where:
r = number of rows and columns in the confusion matrix,
N = total number of ground truth points (pixels),
Xii = observation in row i and column i,
Xi+ = marginal total of row i, and X+i = marginal total of column i,

A Kappa coefficient equal to 1 means perfect agreement whereas a value close to zero means that the agreement is no better than would be expected by chance

Simulation

Markov chain analysis is an application of change detection that can be used to predict future changes in one area based on the rates of past change in the area. The method is based on probability that a given piece of land will change from one mutually LULC to another. These probabilities are generated from past changes and then applied to predict future change. The future change scenarios were predicted, using:

$$Future\ Projection\ = (\Delta A\ \times A_i + A_o) \dots \dots \dots \dots . . \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (14)$$

Where:
ΔA = annual rate of change,
A_i = future years,
A_o = magnitude in current year.

The future projection was made for 2030 to 2100.

RESULTS

Current Land-use/Land-cover Pattern in Okeluse Forest Reserve

Land-cover maps of the study area were produced from the classification of the five (5) images. Five (5) LULC classes (i.e., forest, agricultural land, shrubland, built-up areas and water bodies) were identified.

In 1984, forest occupied the highest extent with 11,422 ha (79.2%) of the reserve land, followed by water bodies with 1,425.9 ha (9.9%). Agricultural land was 702.7 ha (4.9%) at the time with shrubland having 647.8 ha, (4.5%). Built-up areas had the least coverage of 225.2 ha (1.56%) in total. In 1990, forest decreased to10,283.8 ha (71.3%). Water bodies, however, increased to 1,589 ha (11%). In the same vein, agricultural land, shrubland and built-up areas increased to 1,273 ha (8.8%), 831.2 ha (5.8%) and 446.7 ha (3.1%), respectively. By 2001, forest area had decreased to 8,581.6 ha (59.5%) of the reserve area. Meanwhile, agricultural land, shrubland and built-up areas increased to 2,365.5 ha (16.4%), 1,697.5 ha (11.8%) and 842.7 ha (5.8 %), respectively. Nevertheless, water bodies began to shrink in size to 936.4 ha (6.5%) of the forest reserve (Table 3).

In 2010, forest cover, water bodies and built-up areas further shrank to 7,187.2 ha (49.8%), 545.1 ha (3.8%) and 479.3 ha (3.3%), respectively. However, agricultural land and shrubland increased to 29.3% (4,218.8 ha) and 1,993.1 ha (13.8%) of the total land area, respectively. By 2020, agricultural land and shrubland had occupied over 50% of the forest reserve covering 5,849.6ha (40.6%) and 2,196.1 ha (15.3%), respectively. Meanwhile, forest, built-up areas and water bodies decreased within the period. In that year, forest, built-up areas and water bodies occupied 5,706.2 ha (39.6%), 398.1 ha (2.8%) and 273.6 ha (1.89%) of the forest reserve, respectively. Details of the serial changes in LULC are shown in Figures 2, 3 and 4.

Table 3: Land-use/land-cover statistics for 1984, 1990, 2001, 2010 and 2020

LULC	1984		1990		2001		2010		2020	
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
Forest	11,422	79.2	10,283.7	71.3	8,581.6	59.5	7,187.2	49.8	5,706.2	39.6
Agric. land	702.7	4.9	1,273	8.8	2,365.4	16.4	4,218.8	29.3	5,849.6	40.6
Shrubland	647.8	4.5	831.2	5.8	1,697.5	11.8	1993.1	13.8	2,196.1	15.2
Builtup area	225.2	1.6	446.7	3.1	842.7	5.8	479.3	3.3	398.1	2.8
Water bodies	1,425.9	9.9	1,589	11	936.4	6.5	545.1	3.8	273.6	1.9
Total	14,423.6	100	14,423.6	100	14,423.6	100	14,423.6	100	14,423.6	100

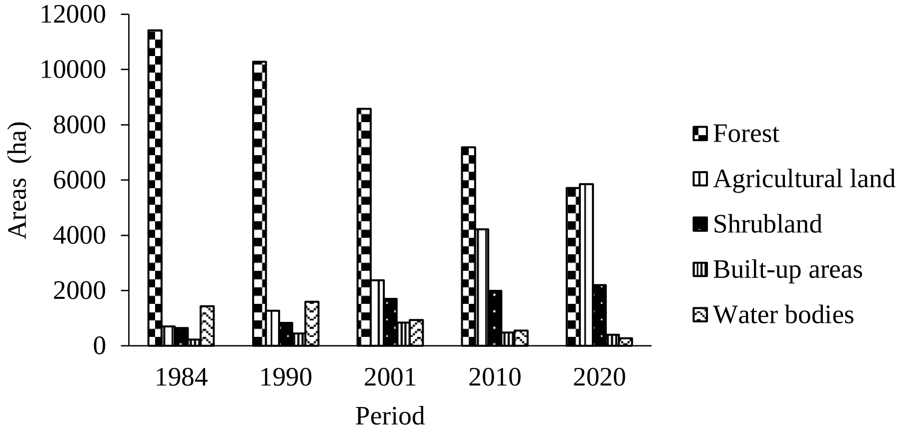


Figure 2: Coverage of the land-use/land-cover in Okeluse Forest Reserve within the period

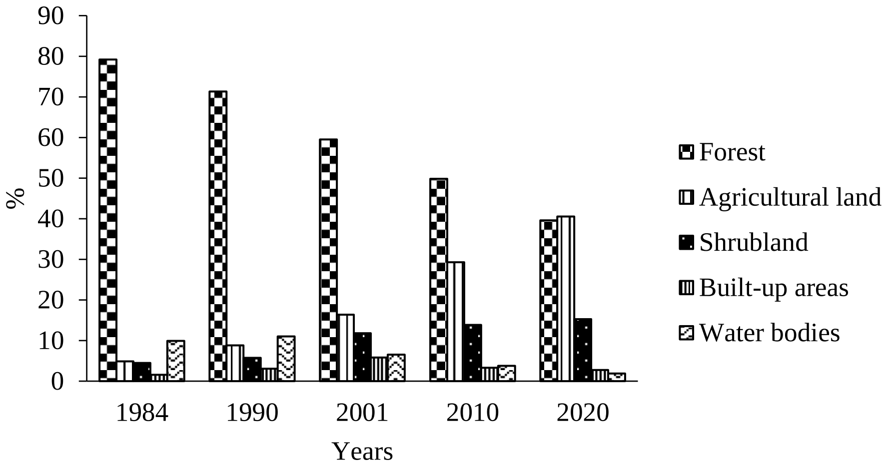


Figure 3: Percentage covers of LULC types in Okeluse Forest Reserve within the period

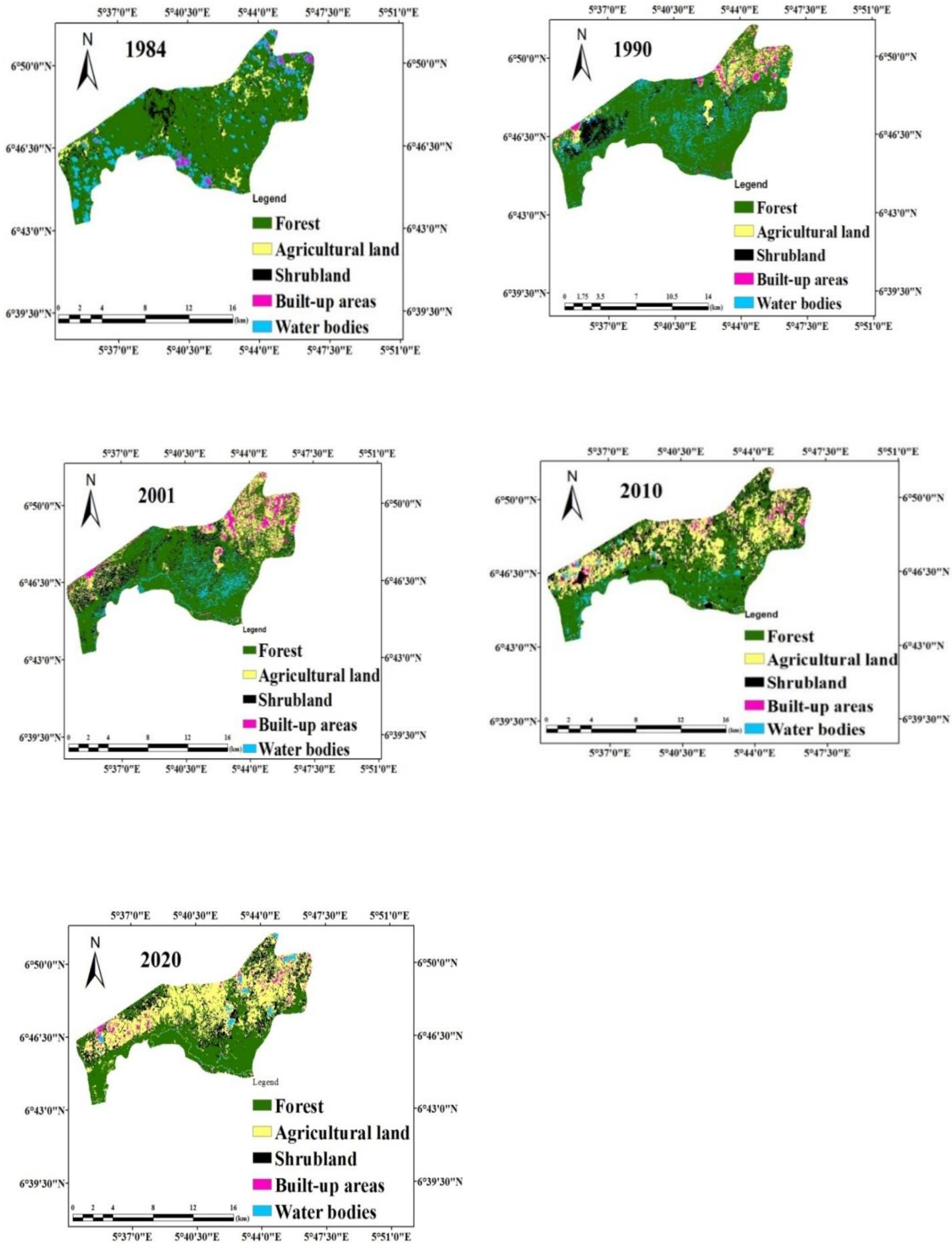


Figure 4: Land-use/land-cover maps of Okeluse Forest Reserve between 1984 and 2020

Land-use/Land-cover Changes in Okeluse Forest Reserve between 1984 and 2020

The results showed that there were continual losses in forest cover in the reserve. For instance, 16.6% (-1,702.2 ha) was lost between 1990 and 2001. In 36 years studied, there were depletions of the forest to the tune of 5,715.8 ha (50.2% of the original forest cover), whereas agricultural land had increased by 5,146.9 ha (732.4%). Due to the degradation of the forest, shrubland increased by 1,548.3 ha (239%). In the same vein, there was an overall increase in built-up areas by 76.8% (172.9 ha) within the period. Nevertheless, water bodies shrank by 80.8% (1,152.3 ha) in 36 years. Details of the changes are shown in Tables 4, 5 and Figure 5.

Table 4: Land-use/land-cover changes in Okeluse Forest Reserve between 1984 and 2020

Period	LULC (ha)				
	Forest	Agric. land	Shrubland	Built-up areas	Water bodies
1984-1990	-1,138.2	570.2	183.4.	221.5	163.1
1990-2001	1,702.2	1,092.5	866.3	396	-652.6
2001-2010	-1,394.4	1,853.4	295.7	-363.4	-391.2
2010-2020	-1,481	1,630.8	203	-81.2	-271.5
1984-2020	-5,715.8	5,146.9	1,548.3	172.9	-1,152.3

N.B.: Negative sign (-) implies a decline or loss in LULC

Table 5: Percentage change in LULC of Okeluse Forest Reserve between 1984 and 2020

Period	LULC (%)				
	Forest	Agricultural land	Shrubland	Built-up areas	Water bodies
1984-1990	-10	81.2	28.3	98.4	11.4
1990-2001	-16.6	85.8	104.2	88.7	-41.1
2001-2010	-16.2	78.4	17.4	-43.1	-41.8
2010-2020	-20.6	38.7	10.2	-16.9	-49.8
1984-2020	-50.2	732.4	239	76.8	-80.8

N.B.: Negative sign (-) implies a decline or loss in LULC

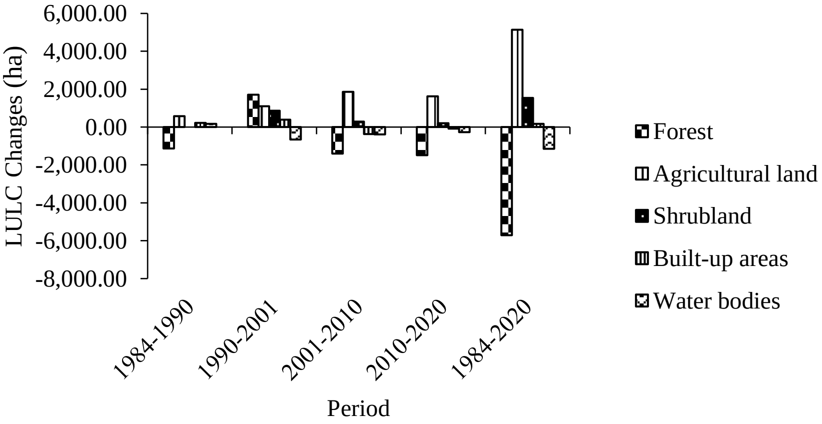


Figure 5: LULC changes in hectares

Table 6 presents the annual rate of change in land covers of Okeluse Forest Reserve within the period. The average rate of change in forest area was -226.9 hayr^{-1} (-1.8%), indicating a net loss forest area. Agricultural land had a mean net gain of 147 hayr^{-1} (8.5%). Similarly, shrubland gained 64.4 hayr^{-1} (4.2%). With respect to built-up areas, there was an annual gain of 7.2 ha (4.5%). In 36 years, water bodies lost 48 hayr^{-1} (-2.8%).

Table 6: Rate of change (ha/year) and rate of change (%)

Period	LULC				
	Forest	Agric. land	Shrubland	Built-up areas	Water bodies
1984-1990	-189.7 (-1.7%)	95 (13.5%)	30.6(4.7%)	36.9(16.4%)	27.2 (1.9%)
1990-2001	-238.7(-1.5%)	182.1(7.8%)	144.4(9.5%)	66(8.1%)	-108.8(-3.7%)
2001-2010	-232.4(-1.8%)	308.9(8.7%)	49.3(1.9%)	-60.6(-4.8%)	-65.2 (-4.6%)
2010-2020	-246.8(-2.1%)	271.8(3.9%)	33.8(1%)	-13.53(-1.7%)	-45.3(-4.9%)
Mean	-226.9(-1.8%)	147(8.5%)	64.4(4.2%)	7.2(4.5%)	-48.0(-2.8)

N.B.: Negative sign (-) implies a decline or loss in value

Table 7 shows the confusion matrix for the LULC classifications. The overall classification accuracy was 86.8%. Producer's accuracy ranged between 0.77 and 0.90 with an average of 0.85. User's accuracy ranged between 0.78 and 1 with a mean of 0.90. According to Rwanga and Ndambuki (2017), user's accuracy is the most relevant measure of the classification's actual utility in the field, and it reflects the reliability of the classification to the user (e.g., Adeyemi and Ibrahim, 2020; Adeyemi and Oyeleye, 2021; Adeyemi and Ayinde, 2022). The average commission and omission errors were 0.10 and 0.15, respectively. The overall Kappa coefficient for the LULC classification was 0.80 (Table 7).

Table 7: Confusion matrix of LULC map for the year 2020

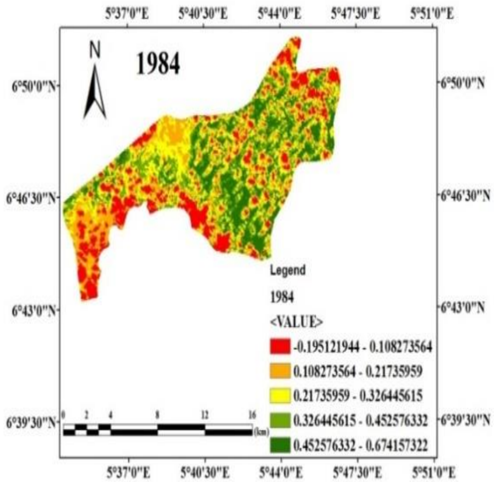
LULC	Forest	Agric. land	Shrubland	Built-up	Water bodies	Column Total	UA	OE
Forest	105	6	8	0	1	120	0.88	0.11
Agric. Land	11	153	5	5	0	174	0.88	0.11
Shrub land	2	11	47	0	0	60	0.78	0.22
Built-up	0	1	0	17	0	18	0.94	0.23
Water Bodies	0	0	0	0	8	8	1	0.11
Row Total	118	171	60	22	9	380		
PA	0.89	0.90	0.78	0.77	0.89	OA = 86.8%		
CE	0.13	0.12	0.22	0.56	0			

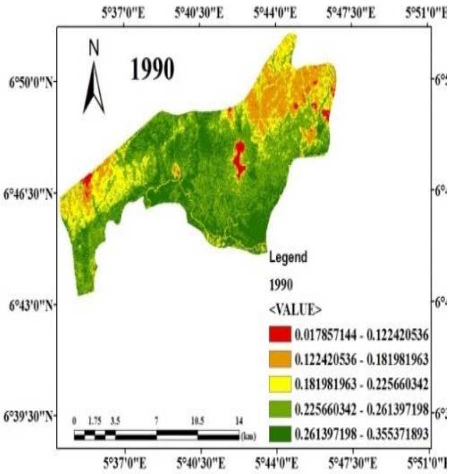
N.B.: PA - Producers Accuracy; CE - Commission Error; UA - User's accuracy; OE - Omission Error; OA - Overall Accuracy

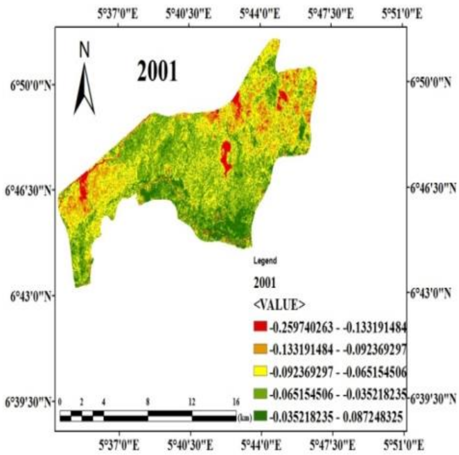
The NDVI results revealed that the reserve was most vegetated in 1984 with continuous contractions in the later years, as the vegetation was healthier than the rest of the periods having a value of 0.67. Details of the NDVI results are shown in Table 8 and Figure 6.

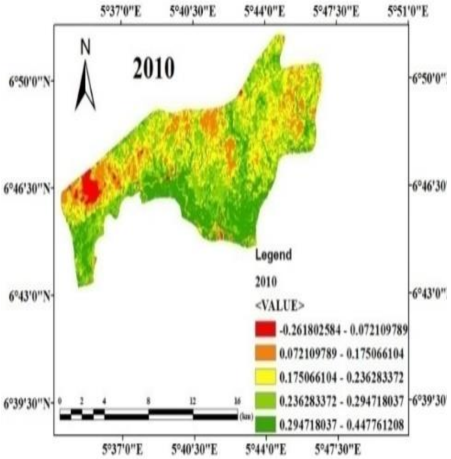
Table 8: NDVI Values

Year	Maximum	Minimum
1984	0.67	-0.20
1990	0.36	0.02
2001	0.09	-0.26
2010	0.45	-0.26
2020	0.40	0.09









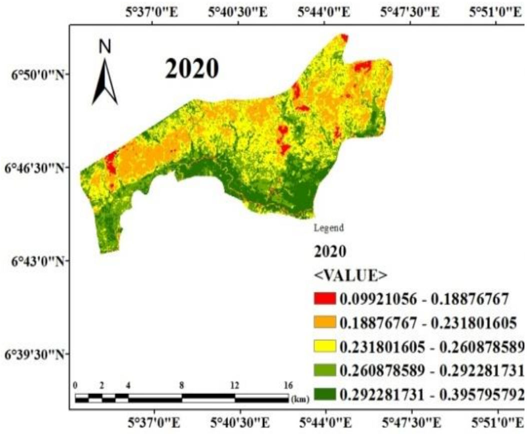


Figure 6: NDVI maps for Okeluse Forest Reserve between 1984 and 2020

Land-use/land-cover Projection for Okeluse Forest Reserve

The future projection results showed that there would be continuous increase in agricultural land, shrubland and built-up areas, resulting in increased degradation and damage to the forest reserve (Table 9 and Figure 7). While forest areas and water bodies would decline in areas amounting to more losses in associated forest resources, especially biodiversity.

Table 7: LULC prediction for 2030-2100

Year	Projected LULC (ha)				
	Forest	Agricultural land	Shrubland	Built-up areas	Water bodies
2030	4,118.5	7,279.3	2,626.2	446.1	-46.5
2040	2,530.7	8,709	3,056.2	494.1	-366.6
2050	943.01	10,138.7	3,486.3	542.1	-686.6
2060	-644.7	11,568.4	3,916.4	590.2	-1,006.7
2070	-2,232.4	12,998.1	4,346.5	638.2	-1,326.8
2080	-3,820.2	14,427.8	4,776.5	686.2	-1,646.9
2090	-5,407.9	15,857.5	5,206.6	734.2	-1,966.9
2100	-6,995.6	17,287.2	5,636.7	782.3	-2,287

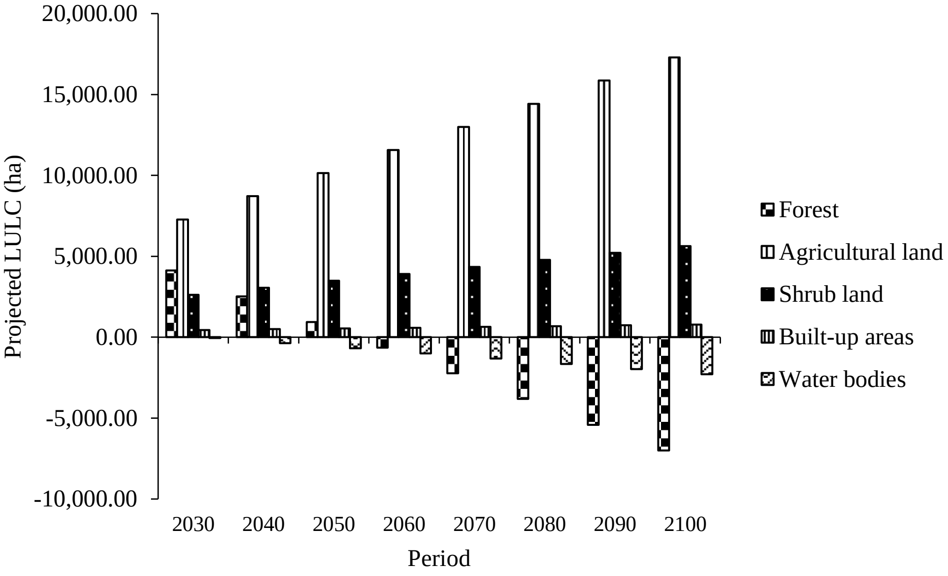


Figure 7: Land-use/land cover change predictions for 2030-2100

DISCUSSION

The analyses of LULC in the reserve showed that forest areas and water bodies within the reserve land decreased substantially in 36 years. Consequently, forest cover density in the reserve experienced a downward trend in recent years due to forest degradation, conversion and eventual deforestation. Dwellers in settlements established within the forest reserve were identified to be majorly cocoa and plantain farmers, who engaged in large-scale commercial production. The finding is in consonance with the findings of Gbiri and Adeoye (2019), who reported a decline in forested land due to conversion for agriculture and other life-supporting activities. Similarly, Acheampong *et al*. (2019) noted that agricultural expansion has direct debilitating impacts on forest resources causing forest degradation and deforestation in the tropics. One of the resultant negative effects of forest conversion in the area was the increase in shrubland throughout the entire 36 years. Most of well-stocked areas of forest as of 1984 were fast being replaced by shrubs and young regenerations of valuable tree species. This corroborates the reports by Acharya *et al*. (2011), who described shrubland as nothing but a degraded forest area, where tree stems have been removed but still contains some woody vegetation cover arising from unsustainable forest exploitation.

The expansion of settlements within the reserve was probably necessitated by desire to meet their housing needs during the farming seasons. This was by agricultural intensification in the area. Most of the people farming in the reserve are migrant farmers, who left their states (especially Delta, Edo, Osun, and Benue) to cultivate cocoa and plantain on perennial basis while living within the reserves. The disastrous effects of converting forest land to incompatible agricultural practices by increasing population of migrant farmers have been described by Tchatchou *et al*. (2015), who observed that increasing population is a major factor responsible for changes in forest lands. Ineffective implementation of the state forest policies, which encourage deforestation, may also be one of the driving forces of loss in forest cover within Okeluse Forest Reserve. It was observed that extensive areas of degraded forest areas were recently cleared for ethanol production project. Unfortunately, this had not seen the light of day as at the time of the study. This is in line with the observation of Packiam (2015) and Kissinger (2020), who independently noted that unintentional deforestation may be orchestrated by weak state policies, which supports unrealistic development projects, and approving incentives for enterprises investing in agriculture and rural areas without due considerations.

Shrinkages in water bodies within the forest reserve may be due to significant losses in forest cover leading to an increase in evapotranspiration and exposing the land to soil erosion and siltation of water bodies. This is supported by the findings of Zemp *et al*. (2017), that deforestation may likely lead to strong rainfall reduction and increasing evapotranspiration, since reduction in forest cover would lessen the landscape's capacity to intercept, retain and transport precipitation (Packiam, 2015). Shrinkage in forest cover may also result from inappropriate conducts and negligence on the part of authorities concerned, as it was observed that there is general apathy about the activities of the illegal operators in the forest reserve. Rademaekers *et al*. (2010) noted that poor governance and inadequate natural resource monitoring can be some of the important underlying factors of deforestation and forest degradation. These is also supported by the findings of Arima *et al*. (2014) and Asuncao *et al*. (2015), that the implementation of policies by the government to protect forest lands combined with the prominent roles played by the law enforcement agents would provide a significant positive contribution to reducing deforestation. According to Adeyemi and Ibrahim (2020), Adeyemi and Adeleke (2020), proper monitoring and appropriate management practices can tackle illegal operations within and around protected areas. Thus, non-supervision from concerned authorities may lead to encroachment in the forest reserve, resulting in continued illegal activities in the forest reserve.

Forest and water bodies are projected to experience further decline until 2100. However, agricultural land, shrubland and built-up areas would continue to increase in the future as a result of persistent intensive agricultural uses. This agrees with Padonou *et al*. (2017), who reported a continuous deforestation to give room for other land uses. With gradual losses in fertility of cultivated areas, new areas of forest are being converted into farmlands while the depleted and degraded were seen abandoned, resulting to increase in shrubland in the long run. This has had a diminishing effect on the productive potential of the forest with associated losses of livelihoods and important biodiversity. This corroborates the report of Brink *et al*. (2014), which stated that continued vegetation losses are detrimental to flora and fauna diversity, just at it worsens local climate and expose humans to untold hardship. It agrees with the findings of Lawrence and Vandecar (2015), Saputra and Lee (2019), that one of the future impacts of continuous forest land conversion and degradation is loss of forest biodiversity. The forest reserve is now at the verge of becoming an example of state-owned forest reserves, which only exist on papers but with little or no substance, but replaced with cocoa, plantain, and other agricultural plantations.

According to Bradley and O'Sullivan (2011), forest degradation has potential negative effects on climate, soil conditions (loss in soil nutrient) and geomorphology of the area, increasing runoff and sedimentation of the river system. Logging operations, especially poor logging practices may result in higher nutrient concentrations, higher water temperatures and increased light availability in water bodies. This may alter the habitat for aquatic organisms useful to man. The effect of deforestation and forest degradation on water bodies have been described by Packiam (2015), who concluded that the water bodies available for irrigation, drinking and economic use are subjected to extreme fluctuations due to losses in forest covers.

The forest reserve has become a source of carbon emissions due to massive deforestation and forest degradation, and it has the potential to become even greater source of carbon emissions as noted by Archana (2013). However, deforestation releases carbon originally held in forests to the atmosphere as CO_2, either immediately, if the trees are burned, or more slowly as un-burned organic matter decays. The bulk of carbon emissions in the forest reserve from deforestation arise, when forest is converted for agricultural activities, particularly if the forests are cleared by burning, which is the usual practice in the forest reserve as observed during ground-truthing. This constitutes a negative effect to the micro-climate. Adnan *et al*. (2011), Ali *et al*. (2014) and Yuksel (2014) noted that continuous emission of greenhouse gases would result in unsavory hydro-meteorological events, sea-level rise, and seasonal unpredictability. The immediate and long-term impacts of forest degradation on social aspect are one-too-many, including loss in ecological services and balance.

CONCLUSION

This study examined the past, current and future land-use/land-cover changes in Okeluse Forest Reserve. The study has shown that there were significant reductions in forest covers and water bodies due to several anthropogenic activities, such as agricultural intensification, illegal timber extractions, construction of roads and building infrastructures. It further showed that the reserve has been badly degraded in the last 36 years. If these continue, there will be little or no forest cover left for protection or conservation, and it could worsen the environmental, social and even economic conditions of people in the area. Though, some efforts were made in the past to regenerate some illegally logged areas with teak, and to meet the increasing demand for wood, the project failed, and the young trees are now being cleared to increase lands for farming due to poor management.

Increased efforts in forest rejuvenation can bring about a healthy forest that is required and sought after. This, alongside sustainable use of forest resources, would prevent further loss and degradation in the forest reserve. To reduce the effect of human activities in the reserve, available areas occupied by agricultural land need to be converted into plantation of fast-growing indigenous tree species, and further forest degradation should be prevented. With the imposition of penalties requiring heavy fine or prosecution, illegal encroachment can be discouraged in the area. More attention should be given to the promotion of non-timber product trades by the government. Consequently, heavy dependence of the rural populace on timber can be shifted, thereby reducing the pressure on forest trees being felled. As part of sustainable forest management strategies in the reserve, all extant laws and policies that ensure forest protection and restoration should be resuscitated and strictly adhered to. Proper awareness or education that provides adequate information on the current state of things in the forest reserve should be available to the communities around and outside the reserve, with proper understanding and commitment. To achieve this, effective community-centered participation can be encouraged to help restore sanity in the forest reserve. Lastly, with the use of remote sensing, important and accurate databanks and information on the existing land-use/land-cover of the forest reserve can be built for subsequent monitoring and management. Also, effective conservation of the remaining areas of forest in the reserve can be ensured through participatory mapping, involving all stakeholders.

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