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GEOSPATIAL MODELING OF FOREST LANDSCAPE ASSESSMENT: A CASE STUDY FROM IKERE FOREST RESERVE

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ABSTRACT

This study set out to assess the dynamic characteristics of the Ikere forest reserve landscape between 1985 and 2017 using remote sensing data and spatial metrics. Landscape of the study area maintained complex patterns of spatial heterogeneity over the years. Forest cover loss to other land cover types results in new large non-forest area at increasing rate. As at the year 2017, the changes in land cover types were not yet at equilibrium, thus the need to determine the future forest cover extent using a three-way markov Chain model. The decrease in number of patches of forest land (NumP) with increase in its mean patch size (MPS) shows that the forest is becoming a single unit probably due to clearing of existing patches of forest trees. The decrease in class diversity and evenness (SDI and SEI) of the general landscape over the years strengthens this assertion. The findings of this study would be very helpful to government and other stakeholders responsible for ensuring sustainable forest and general environment.

Keyword: Landscape, Spatial metrics, sustainable forest and Environment.

INTRODUCTION

Forests provide us with a range of goods and services (FAO, 2011). We need them for their products such as timber, paper, medical plants, fruits etc. and the services that include wildlife habitat, hydrological functions and carbon storage (FAO, 2011). Considering the substantial roles of forests to man's well-being, it is important to know the status of our forests. Assessing the forests will reveal if they are being degraded and the possible causes of the degradation so that appropriate measures can be taken to stop the process. Good information on forest condition and the extent of forest degradation will enable the prioritization of human and financial resources to prevent further degradation and to restore and rehabilitate degraded forests. The increase in forest loss in the tropics, Africa in particular, is as a result of unrestrained tree felling, and other human activities such as farming and grazing (Isaac *et al.* 2018). These are factors that can lead to increase in population growth, human movement, cost of energy, fire outbreaks, and other forest death factors (Isaac *et al*., 2018).

Several human activities have modified the landscapes and this development has had a deep effect on the natural surroundings (Yang, 2001). To avert forest mortality and enhance the services of a forest, it becomes inevitable to monitor the forest to track its status for adequate and effective management (Soraya, 2013). Remote sensing data have been so useful recently to detect changing patterns of ecological landscape (Rajesh, *et al*, (2009). Change detection, according to Ramachandra, *et al*, **(**2004), quantifies the changes which are associated with land cover in the landscape using time series remote sensing data. These satellite remote sensing data provide a synoptic view of the landscape type (Lillesand *et al*, 1987). One important aspect of remote sensing data is that they support the evaluation of forest landscape over a large area, revealing the heterogeneity of ecological landscape (Lillesand *et al*, 1987).The availability of reliable remote sensing data with systematic processing and inventive analytical techniques, will help to monitor and analyze forest cover and landscape metrics of large areas in a timely and cost-effective way (Li *et al*, 2004).

Landscape metrics, also known as spatial metrics are vital for understanding and characterizing the landscape changes and their consequences (Li and Wu 2004). Landscape metrics are indicators that are used to determine numerous aspects of landscape structure in space and time (Li and Wu 2004). The application of spatial metrics models in analyzing landscape dynamics of our changing ecosystem has increased in recent times. (Dietzel *et al*., 2005 and Porter *et al*., 2007). Various metrics models have been used to assess landscape characteristics of individual class and general landscape (Li and Wu, 2004 and Uuemaa *et al*., 2009). These are very important tools employed by ecologists to better understand and depict ecological processes and resultant effects (Bharath *et al*, 2012). Multi-spatial satellite data explains the changes in landscape pattern at different scales (Saura *et al* 2007). Landscape metrics aids in categorizing diversity and differences in diversity of landscape within forest estate.

The main focus of this study therefore, was to assess: the forest cover and landscape pattern of the study area with the following specific objectives: (i) to examine the forest cover dynamics within the study area for the period between 1985 and 2017; (i) to estimate equilibrium state and future forest cover, and (iii) to examine the forest landscape characterization using metric models, within the study area

MATERIALS AND METHODS

Study Area

Ikere Forest Reserve is located in the southern part of Ekiti State, southwest Nigeria. The forest estate covers an area of $19.66km^{2.}$ It is located between longitude735147.15 E and 740015.956, E and latitude 823910.15 N and 828196.4 N. It experiences dry and rainy seasons. The annual rainfall ranged from 1,200mm to 1,500mm. Temperature ranges from 21^0C to 32^0C throughout the year. Annual average relative humidity is about 90 % at 7.00 am and 65 % at 4.00 pm. The topography is hilly and the vegetation type is rain forest the study area.

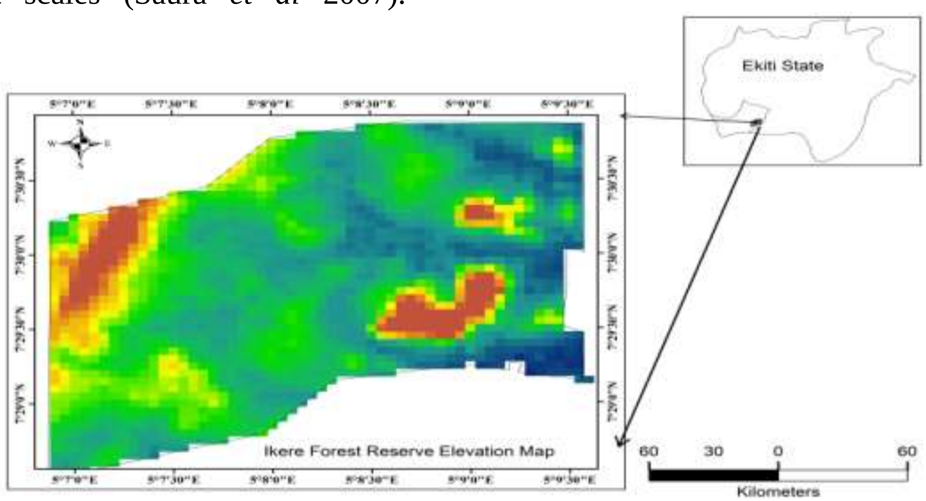

Figure 1: Map of the Study area

Data Collection

To assess the forest cover and landscape pattern of the study area in the study area, Landsat images of 1985, 2001 and 2017) were downloaded from the official website of US Geological Survey (USGS). The study area is within the Landsat path 190 and row 55. Table 1 shows the specifications of Landsat TM, ETM+ and OLI images used.

Table1. Data used for the analysis

Satellite Sensor	Spatial resolution	Acquisition years	Path	Row
Landsat 5, 7 & 8	30m x 30m	1985, 2001 and 2017	190	55
Reference Data	*100 horizontal distance randomly generated for image classification accuracy assessment			

Forest Cover Dynamics

Figure 2 shows the steps that were followed to achieve the specific objectives of this study. The raw remote sensing data have digital numbers which corresponds to a raw measure required by the sensor (Giannini *et al*, 2015). To derive Forest cover changes from these images, the digital numbers were converted to reflectance values. The images in their reflectance values were combined to give false composites that were classified into three different land cover types. This study utilized Maximum Likelihood classification algorithm to group the pixels in Idrisi Selva environment. The accuracy and the confidence level of the classification operations were carried out using sample points and area proportion.

Image Classification Accuracy Assessment

Classification accuracy of 1985, 2001 and 2017 images was assessed to determine the quality and reliability of information obtained from the data. If the derived information is useful in analyzing detected changes, it is important to carry out accuracy assessment for each classification (Butt, . *et al.*, 2015.

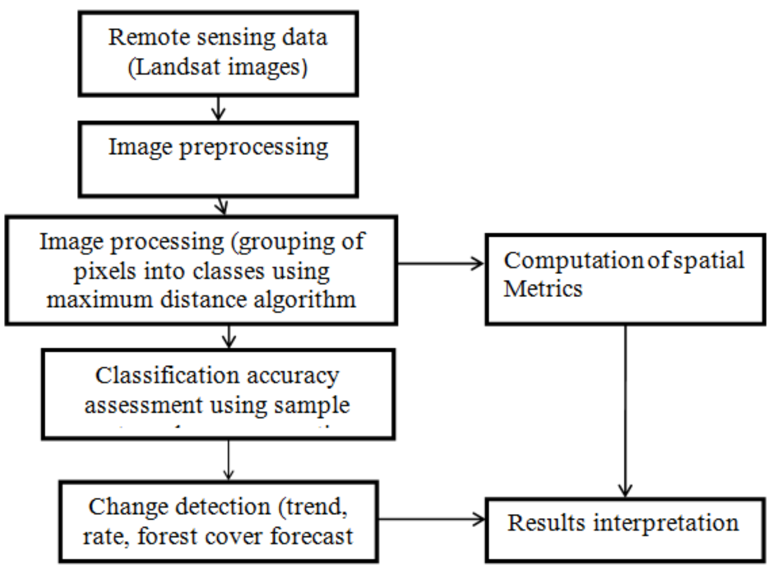

Figure 2: Method used to assess the forest cover and landscape dynamics

Sampling Design

Simple random sampling was applied to determine the reference points. (Pontus, 2013). To determine the sample size the study employed the 'binomial principle where the population is used as a basis for determining the minimum sample size needed for any serious analysis. (Udofia, 2011):

$$n = \frac{N}{1+N(e)^2} \quad \ldots\ldots\ldots 1$$

Where

n=sample size

N=finite population (i.e. the size of the area = 161989.2)

e= level of significance (0.05)

1=unity

The sample points used for the accuracy assessment were 100 as determined using the binomial model. The error matrix is presented in terms of estimated area proportions instead of absolute sample. The estimated area proportions normalize the absolute sample counts by the map area and are used to calculate the users and producer's accuracy (FAO, 2016). The accuracy statistics provides producer's accuracy (Pa), user's accuracy (Ua), overall accuracy and error-adjusted area (Pontus *et al*., 2014). To determine error-adjusted area the standard error for each class at 85% confidence interval (Foody, 2008) was calculated from error area estimated matrix. This reveals pixels misclassification in hectares using equation 2.

$$S_e = \sqrt{\sum_{i-1}^{3} W^2 \frac{\frac{\text{nij}}{\text{ni}}\left(1-\frac{\text{nij}}{\text{ni}}\right)}{\text{ni}-1}} \ldots\ldots\ldots \mathbf{2}$$

To assess the spatio-temporal pattern of forest cover, the images were classified into bare land, grass land and forest land. The rate of change was determined using dynamic weight model (The land use/cover changes between 1985and 2017 were determined by simple percentage (equation 3) and dynamic weight model (equation 4) with data derived from cross classification (Liu *et al.*, 2011).

$$\frac{S_{i-j}}{t} \times 100. \ \ldots\ldots..3$$

$$S = \left(\sum_{IJ}^{N}(\Delta S_{I-J}/S_I\right) \times \left(\frac{1}{T}\right) \times 100 \ \ldots\ldots..4$$

where S_I is the area of land type i in the beginning of the period, ΔS_{I-J} is the total area of land cover type I converted into other types. T is the study period; and S is the land cover dynamic degree in the period of T.

Forest Cover Forecast and quilibrium Estimates.

To forecast land cover of the area, it was important to first establish the fact that the land cover change has not reached its equilibrium where land cover types remain unchanged. The estimation of equilibrium/steady state and forecast of the land cover: were determined using two-way and three-way matrices (equations 5 and 9) respectively. The year of equilibrium was projected by the rate of land cover change, which serves as a base of land cover forecast to validate calculated equilibrium values.

$$A = \begin{pmatrix} x_{a_{11}} & x_{a_{12}} \\ x_{a_{21}} & x_{a_{22}} \end{pmatrix}, B = \begin{pmatrix} x_{b_1} \\ x_{b_2} \end{pmatrix} \ and \ C = \begin{pmatrix} x_{c_1} \\ x_{c_2} \end{pmatrix} \ \ldots\ldots..5$$

To determine the point the study area will experience steady or no change, the land cover maps were reclassified to reduce the land cover types to forest and non-forest. Based on this a two-way matrix was employed to calculate forest cover at equilibrium. Equations 7 and 8 describe the relationship between forest and non-forest cover types. The sum of their probabilities equals 1.

$$f_e = P_f + P_n = 1 \ldots\ldots\ldots\ldots 6$$

and

$$P_f + P_n = P_f \ or \ P_n \ \ldots\ldots\ldots7$$

where f_e is the equilibrium or steady state, P_f is probability of forest cover and P_n is probability of non-forest area.

Then

$$P_f = 1 - P_n \ldots\ldots\ldots\ldots\ldots..8$$

Substituting equation 8 in equation 7 produces the point of equilibrium.

To project, the study used cellular automata markov change prediction module in Idrisi software (Agbor *et al*, 2012 and Bangladesh *et al*, 2013). This was also manually calculated using matrix model (equation 9). Both methods utilized the transition probability matrix generated from image cross classification

$$A = \begin{pmatrix} x_{a_{11}} & x_{a_{12}} & x_{a_{13}} \\ x_{a_{22}} & x_{a_{22}} & x_{a_{23}} \\ x_{a_{31}} & x_{a_{32}} & x_{a_{33}} \end{pmatrix} B = \begin{pmatrix} x_{b_1} \\ x_{b_2} \\ x_{b_3} \end{pmatrix} C = \begin{pmatrix} x_{c_1} \\ x_{c_2} \\ x_{c_3} \end{pmatrix} \ldots \ldots 9$$

Where

$A =$ Array of probability values of land cover types conversion.

$B =$ Percentages of land cover types for the base year. $C =$ Projected matrix

The product of A and B matrices produced the forecast values matrix C for each land cover type. The output of projection by calculation was compared with the output of projection module in Idrisi software.

Forest Landscape Characterization using Metric Models

Some spatial metrics were selected to measure and monitor the landscape fragmentation, land use complexity, proximity and diversity (McGarigal, *et al*, 2008). These spatial metrics were computed using FRAGSTAT interfaced with ArcGIS to explain the landscape dynamics of the area. The selected metrics include in table 3. These indices have been used by ecologists to measure landscape composition (Turner, 1990a, Rajesh *et al*, 2009, and Bharath *et al*, 2012).

Table 2: Landscape Metrics

S/No.	Indicators	Formula	Range	Significance/ Description
1	Mean patch size (MPS)	$MPS = \frac{\sum_{i=1}^{n} a_i}{n_i} \frac{1}{10{,}000}$	MPS>0,without limit	MPS is widely used to describe landscape structure. MPS is a measure of subdivision of the class or landscape.
2	Class diversity index	$C_d = -\ln \sum_{a=1}^{n} P_a^2$	$C_d \geq 0$ C_d = 0 when the area contains only 1 fragment and it means no diversity.	This measures the relative patch diversity of class a. This diversity index has been used by ecologists to measure landscape composition.
3	Proximity Index (MPI):	$\boldsymbol{p_{rox}} = \sum_{s=1}^{n} \frac{\boldsymbol{w_{abs}}}{\boldsymbol{d^2}_{abs}}$	$Prox \geq 0$.	This is the sum of patch area (m^2) divided by the nearest edge-to-edge distance squared (m^2) between the patch and the focal patch of all patches of the corresponding patch type whose edges are within a specified distance (m) of the focal patch
4	Number of Patches	$N_p = n_a$	$NP \geq 0$, without limit. NP = 1 when the landscape contains only 1 patch.	Number of patches of a particular patch type is a simple measure of the extent of subdivision or fragmentation of the patch type.
5	Class Evenness Index	$C_e = -\ln \sum_{a=1}^{n} P_a^2 \div \ln n$	$0 \leq C_e \leq 1$	This measures the patch distribution and abundance of class a

W_{abs}= Area of patch abs; d^2=Distance between the patch squared; abs = Distance between patch abs and patch abs; s=Class; Np= Number of Patches; N_a= Number of a particular patch type; C_d= Class diversity; P_a^2= Patch diversity of class a; ln=Natural log

RESULTS

Forest Cover Dynamics between 1985 and 2017

The values in tables 3 and 4 illustrate the changes and rate of changes in forest cover between 1985 and 2017. From table 4, there was increase in bare land between 1985 and 2017. Grass land increased at decreasing rate between 1985 and 2017 and projection revealed that the forest will experience a decrease of about 4% between 2017 and 2033.

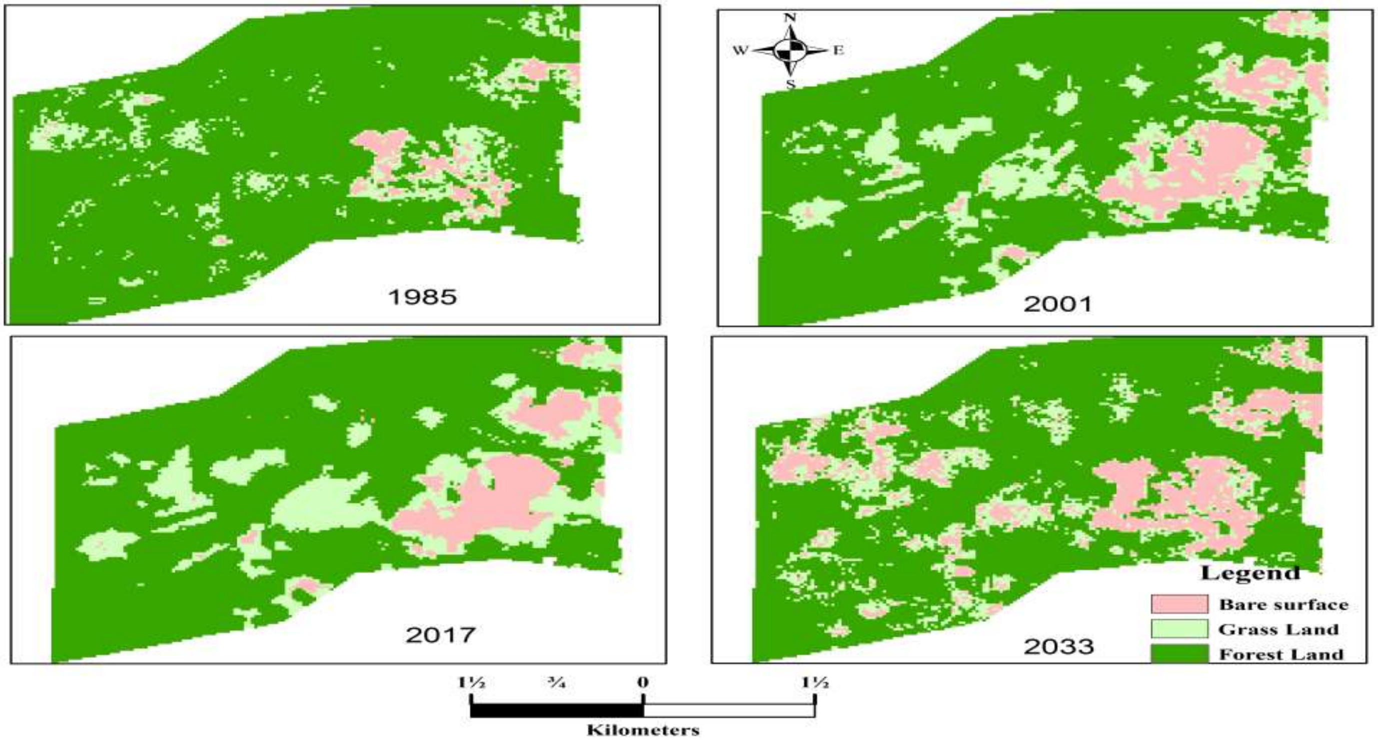

Figure 3: Land Use Land Cover Distribution

Table 3: Land Use Land Cover Distribution between (1985 and 2033)

Land Use/Land Cover Categories	1985		2001		2017		2033	
	Area (Ha.)	Area (%)	Area (Ha.)	Area (%)	Area (Ha.)	Area (%)	Area ($\Delta Ha.$)	Area (Δ%)
Bare surface	52.56	3.36	134.29	8.59	144.99	9.3	250.57	16.02
Grass Land	161.01	10.30	271.44	17.36	290.61	18.6	228.61	14.62
Forest Land	1350.18	86.34	1158.03	74.05	1128.2	72.1	1084.62	69.36
TOTAL	1563.8	100	1563.8	100	1563.8	100	1563.8	100

Table 4: Land cover change rate.

LULC	1985-2001		2001-2017		2017-2033	
	Area($\Delta Ha.$)	Area (Δ%)	Area ($\Delta Ha.$)	Area (Δ%)	Area ($\Delta Ha.$)	Area (Δ%)
Bare surface	81.73	5.23	10.7	0.71	105.59	6.72
Grass Land	110.43	7.06	19.17	1.24	-62	-3.98
Forest Land	-192.15	-12.29	-29.83	-1.95	-43.58	-2.74

One crucial aspect of change detection in forest landscape is to determine the rate of change. This study examined the transition of one land cover type to another. This information revealed both the desirable and undesirable changes and classes that are “relatively” stable overtime. The results in table 5 show that about 71% of the total forest reserve transitioned from forest to other land cover types. Only about 11% of other land cover transitioned to forest land. This trend must be discouraged to sustain and ensure that the forest does not disappear. The forest was more stable between 1985 and 2001 as less transitioning occurred. The experience between 2001 and 2017 is a threat to any ecosystem and should be avoided by checkmating the activities of loggers and other intruders.

Table 5: Location of Change in Land Use Land Cover

S/No.	1985-2001 Area(ΔHa)	2001-2017 Area (Δ Ha)	Legend
1	52.56	93.15	Bare Land- Bare land
2	-	25.56	Bare Land-Grass Land
3	-	15.57	Bare Land-Forestland
4	161.01	70.47	Grass Land-Bare Land
5	-	83.61	Grass Land-Grass Land
6	-	117.36	Grass Land-Forest Land
7	-	49.95	Forest Land-Bare Land
8	227.61	118.44	Forest Land-Grass Land
9	1122.57	989.64	Forest land-Forest Land

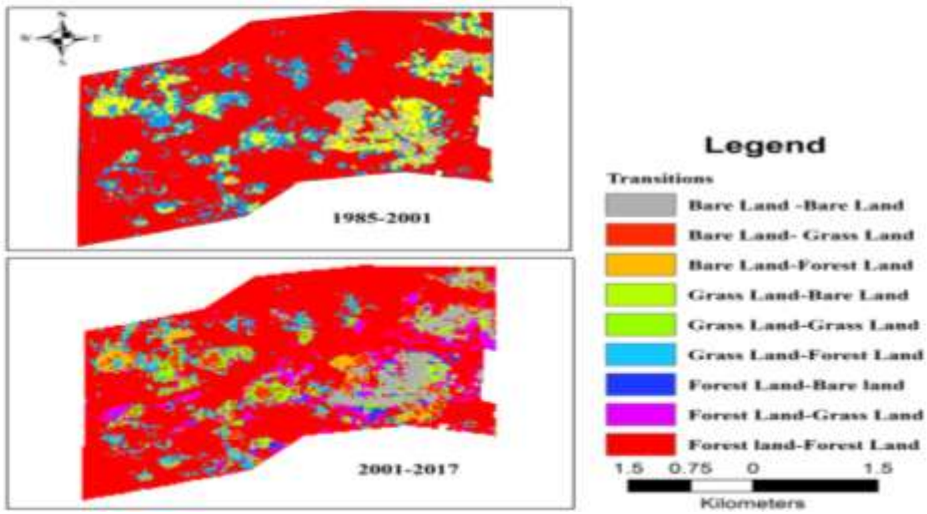

Figure 4: LULC conversion between 1985 and 2001and between 2001 and 2017

Land Cover Change dynamic was calculated using Land Use Dynamic Degree model (equation 4). This model describes land cover trend quantitatively in terms of weight, which plays a unique role in comparing the differences of land cover changes (Lingling *et al*, 2011). It also explains the level of human disturbance to forest landscape. The higher the disturbance level, the more intensively landscape changes.

Table 4: The land cover change density between 1985 and 2017

LULC	1985-2001 S_I (Ha.)	ΔS_{I-J}	S (%)	2001-2017 S_I (Ha.)	ΔS_{I-J}	S (%)
Forest Land-Bare Land	-	-	-	1122.57	49.95	0.3
Forest Land-Grass Land	1350.18	227.61	1.1	1122.57	118.44	0.7
Forest land-Forest Land	1350.18	1122.57	5.2	1122.57	989.64	5.5

S_I = area of land type, ΔS_{I-J} = total area of land cover type I converted into other types. T = study period; and S = land cover dynamic degree in the period of T.

Map Projection and Forest Cover Change Equilibrium *STATE*

One of the objectives of this research was to find out if the forest reserve has reached its equilibrium state where land cover will remain unchanged or change at a very steady rate. The results in table 5 show that the forest reserve will continue to experience decrease in forest cover. This is because as at 2017, the forest cover (72.1%) was still higher than the forest cover at equilibrium (43%). This was determined by applying equation 8 using Markov probability matrix values as coefficients.

Table 5: The land cover change at equilibrium

LULC	2017 Area ($\Delta Ha.$)	2017 Area (Δ%)	2033 Area ($\Delta Ha.$)	2033 Area (Δ%)	f_e (equilibrium) Area ($\Delta Ha.$)	f_e (equilibrium) Area (Δ%)
Bare surface	144.99	6.34	250.57	16.02		
Grass Land	290.61	30.67	228.61	14.62	891.4	57
Forest Land	1128.2	62.99	1084.62	69.36	672.4	43
Total	**1563.8**	**100**	**1563.8**	**100**	**1563.**	**100**

Image Classification Accuracy Assessment

The sample points used for the accuracy assessment were 100 as determined using the binomial model. The error matrix is presented in terms of estimated area proportions instead of absolute sample counts (table 6). The estimated area proportions normalize the absolute sample counts by the map area and were used to calculate the users and producer's accuracy (FAO, 2016). The accuracy statistics (table 7) provides producer's accuracy (Pa), user's accuracy (Ua), overall accuracy and error-adjusted area (Pontus *et al*, 2014). The accuracy values show acceptable image classification operations. To determine error-adjusted area the standard error for each class at 85% confidence interval was calculated from error area-estimated matrix (table 7). This reveals pixels misclassification in hectares.

Standard Error of Area Estimates

These are functions of area proportions and sample counts determined from the error matrix.

Table 6: 1985, 2001, and 2017 accuracy statistics

Class Name	1985 $Pa, Ua.$	2001 $Pa, Ua.$	2017 $Pa, Ua.$
Bare land	95, 86	95, 92	95,92
Grass land	100, 89.5	81. 91	83,95.5
Forest	98.5,100	98.7,98	99,98.5
Overall accuracy	98%	97.5	97.9

Ua= User's accuracy and Pa=Producer's accuracy

Table 7: Standard error of area estimates

Landscape	S_e 1985	S_e 2001	S_e 2017	$A_i \pm 1.44 \times S_e$ 1985	$A_i \pm 1.44 \times S_e$ 2001	$A_i \pm 1.44 \times S_e$ 2017
Bare land	4.37	12.9	20.6	6.3	10.9	12.6
Grass land	5.87	22.2	11	8.5	18.8	7.5
Forest	4.37	26	7.6	6.3	18.8	24

Forest Landscape Characterization,

Adverse effects of landscape fragmentation and heterogeneity development are always serious issues to Ecologists and policy makers. One major problem that is associated with this phenomenon is the reduction of the total amount of land covered by forest trees. From tables 8, it is obvious that the number of patches (NumP) decreased while the mean patch size (MPS) increased. This is an indicator that the forest reserve experienced clearing of some forest patches and it shows the forest land is becoming a smaller single unit. The calculated forest land Mean Proximity Index (MPI) which increased over the years also indicates that the forest cover was shrinking.

Table 8: Metric statistics of landscape types

Metric models	1985				2001				2017			
Classes	All	Bare land	Grass land	Forest land	All	Bare land	Grass land	Forest land	All	Bare land	Grass land	Forest land
NumP	153	35	69	49	171	43	94	34	-	38	66	16
MPS	8.53	2.36	5.8	16.78	7.63	1.54	2.97	28.97	-	2.22	1.32	70.8
MPI	1184.9	125.2	756.98	2544.34	1104.42	32.01	134.38	5142.6	-	41.21	41.21	6235.29
SDI	0.83	0	0	0	0.71	0	0	0	0.48	0	0	0
SEI	0.75	0	0	0	0.64	0	0	0	0.44	0	0	0

DISCUSSION

Tables 3 and 4 show clearly that the area experienced general increase in bare land and grass land at the expense of forest land, which decreased over the years. This development may not be unconnected to logging and other anthropogenic activities within the forest reserve. Forest area decreased over the years and this development could be connected to clearing activities that must have led to increase in other land cover types. Though there was a general decrease in forest land, the period between 2001 and 2017 witnessed a drop in the rate of forest loss. Figure 4 shows the land cover transition map of the area at the 16 years interval. From Table 4, it is clear that over the years the degree of forest land area conversion to non-forest area is higher than the degree of forest remaining unchanged, which is an indication that the forest area were cleared for activities such as farming that could expose the forest land.

The observed development necessitated land cover projection which produced the values in table 5. The projected results compared with the equilibrium point value, show that the forest cover will still reduce by about 26% after year 2033 before reaching equilibrium. The rate of change between 2017 and 2033 was about 2%, and about 26% between 2033 the year it will attain equilibrium. This shows that the forest reserve still had 26% of the forest trees to exploit as at 2017, and will be exposed to long time deforestation if the activities of loggers are not checked. The 43% equilibrium state could be as a result of low deforestation rate due rough topography and Government policy that prohibits unauthorized felling of trees.

The classification accuracy in table 6 shows very good image classifications, but table 7 shows the actual implications of such good classifications in landscape change analysis. For example, the best performance observed in forest cover is still associated with error up to 26.8Km^2.

Diversity of classes which decreased over the years with the highest diversity in 1985 indicates that the segments of the classes decreased from 1985 to 2017. One could therefore conclude that reduced segments were given up to other land cover types at the expense of forest land which reduced over the years.

CONCLUSION AND RECOMMENDATIONS

For the period of 32 years, Ikere forest reserve experienced change that resulted to loss of forest cover, thus altering the forest ecosystem. The dynamic density model revealed that forest cover loss to other landscape types increased over the years, and the increase will continue until it gets to equilibrium. Metrics models adopted to assess the forest landscape revealed loss of forest cover to other land cover types probably due to logging and grazing activities. Landsat images used in this study were quite handy and the accuracy assessment shows that forest landscape monitoring requires images of higher resolution to increase accuracy level.

This study has shown that although remote sensing data are ideal for analyzing forest landscape changes, it is always better to ascertain quantitatively the level of uncertainty of the end results. The unavailability of high resolution images was a major setback in this study, which future study should endeavour to use in order to minimize error. The findings of this study should be adopted by relevant authorities as they would be very useful for operational sustainable forest management. In particular, knowledge of spatial and temporal changes of forest landscape could be useful in the afforestation and re-afforestation process.

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