Journal of Agriculture and Environment Vol. 16 No. 1, 2020: 129-142
ISSN: 1595-465X (Print) 2695-236X (Online)

MODELLING FOREST COVER DYNAMICS IN SHASHA FOREST RESERVE, OSUN STATE, NIGERIA

A.A. Alo[1], A.A. Adetola[1] and C.F. Agbor[2]

[1]Department of Social and Environmental Forestry, University of Ibadan, Nigeria
[2]Forestry Research Institute of Nigeria, P.M.B 5054, Jericho, Ibadan

ABSTRACT

Understanding the dynamics of forest cover change is vital to forest manager for planning, formulation of policies and decision making. Nigeria's forest reserves have witnessed significant changes over the years due to various anthropogenic activities. Incessant activities of poachers, illegal fellers and other farming activities in Shasha Forest Reserve have adverse effects on the ecosystem with consequence for global warming. However, there is no up-to-date information on the dynamics of forest cover in Shasha Forest Reserve. Therefore, this study aimed at assessing forest cover changes using remote sensing in Shasha Forest Reserve. Landsat Thematic mapper (TM), Enhanced Thematic Mapper (ETM+) and Operational Land Imager (OLI) data for the periods of 1984, 2000 and 2017 were obtained. The Landsat images were pre-processed and classified using maximum likelihood classification algorithm. The Classification was based on Anderson scheme of land use/cover for change detection between 1984 and 2017. Kappa coefficient was used for accuracy assessment. The future pattern of forest cover changes for 2034 was forecast using the Multi-Layer Perception (MLP) Markov chain model in IDRISI. Three land cover classes were identified: Built up, Shrubs and Forest land. Built up and Shrubs increased at an annual rate of 0.09% and 0.18% respectively and forest decreased at an annual rate of 0.27% between 1984 and 2017. Large area of forest land has been converted to built-up and shrubs with no significant replacement from 2000 till date. The forest was projected to decrease between 2017 till 2034 at the rate of 0.15% per annum.

Keywords: Forest cover dynamics; classification; prediction; Landsat TM; ETM+ and OLI

INTRODUCTION

Reliable information on previous, current and future conditions of a forest ecosystem is a prerequisite for sustainable forest resource management. Such information is vital for policy and decision making. Forests is determined by the presence of trees above the height of 5 m and the absence of other predominant land use (FAO, 2000). Forests play an important role in balancing the earth's carbon (IV) oxide (CO_2) supply and exchange, and acts as a link between the atmosphere, biosphere and hydrosphere. Tropical rainforests in particular house an immense diversity of species, more capable of adaptation and therefore surviving and changing environmental conditions (Canada Center for Remote Sensing, 2008).

The existences of human beings on the earth and his modification of its landscape have had a profound effect on the natural environment. It was also reported that there are few landscapes remaining on the earth’s surface that have not been significantly changed by humans in some manner (Yang, 2001; Suhaili *et al*., 2006). The multifarious anthropogenic activities such as agriculture, mining, deforestation and construction have influence on shifting patterns of land use/cover, which are primary components of many current environmental concerns. This is due to the fact that land use change is gaining recognition as a key driver of environmental change. Changes in land use pattern are increasing rapidly, and can cause adverse impacts and implications at local, national regional and global scales (Yang, 2001). Urban growth together with ts associated population increase is a major factor affecting natural vegetation cover, and this has resulted in a significant effect on local weather and climate. Thus, it is essential that land use land cover dynamic be appropriately monitored and analysed.

Change detection is the concept of identifying contrasts or discrepancies in the state of an object or phenomenon by observing it at different times (Mejebi, 2008). In fact, understanding of land cover change especially in relation to the forest is a pressing need for sustainable development (European Environmental Agency, 2007). Forest resource maps were traditionally prepared from forest inventories involving fieldwork (Suhaili *et al*., 2006). However, Remote Sensing (RS) and Geographic Information System (GIS) techniques provide an alternative and economic tool for forest mapping (Suhaili *et al*., 2006). Satellite remote sensing is an important source of data source for monitoring, detection, quantification and mapping of forest cover pattern and changes, because of its repetitive data acquisition, digital format appropriate for computer processing, and accurate georeferencing approaches (Loveland and Dwyer, 2012). The techniques further provide accurate source of data, which can be used to update land cover information efficiently and cheaply, so as to monitor the changes in the land cover (Fichera *et al*., 2012). Studies have determined land use/land cover changes using RS and GIS techniques to determine trends of forest cover change (Oludare and Clement, 2014). However, little has been done on the degree of dynamics in forest cover transitions, which serves as a key driver to global changes. Therefore, the study focused on modeling the dynamics in forest cover in Shasha Forest Reserve, Osun State, Nigeria, using Landsat, providing quantitative and special land use/land cover information with a view to equipping the policy-makers and scientists with adequate information for decisions on that enhance sustainable forest management.

MATERIALS AND METHODS

Study Area

Shasha Forest Reserve is situated in Ife South Local Government Area of Osun State in the southwestern part of Nigeria. It is located between Latitudes 6º 50' and 7˚5' N and Longitudes 4˚15' and 4˚58'E (Figure 1). It covers about 310 km^2 and lies on the boundaries of southern part of Osun State. It is one of the three forest reserves, collectively referred to as the Omo-Oluwa-Shasha forest complex (Oludare and Clement, 2014). The reserve is in the mixed moist semi-evergreen rainforest zone with high forest type. The natural vegetation, which was previously lowland tropical rainforest (moist evergreen type), has reduced to secondary forest, thickets and varying degree of fallow regrowth or annual and perennial crops, except in some parts of the forest reserves (Chenge and Osho, 2016) as a result of continuous human activities, mainly logging and farming for almost a century, which has changed the reserve remarkably (Jimoh *et al.*, 2002). The soils are predominantly Ferruginous tropical type (Ola-Adams, 1999). They are of the Ferric Luvisols type at the higher category of classification (Chijioke, 1980). The reserve is made up of several soil types but all belong to the tertiary sediments (Ola-Adams, 1999).

The rainy season commences from March/April and lasts till November with annual rainfall range from 890 mm to 2200 mm (Salami *et al.*, 2007). The average relative humidity is 70% while the mean monthly temperature is 28^{0}C. There are two main seasons in the year, a dry season with dry Northeast trade wind-harmattan predominantly from November to March, and a rainy season characterized by the South-west trade wind bringing rains from April to October (Olokeogun *et al.*, 2014).

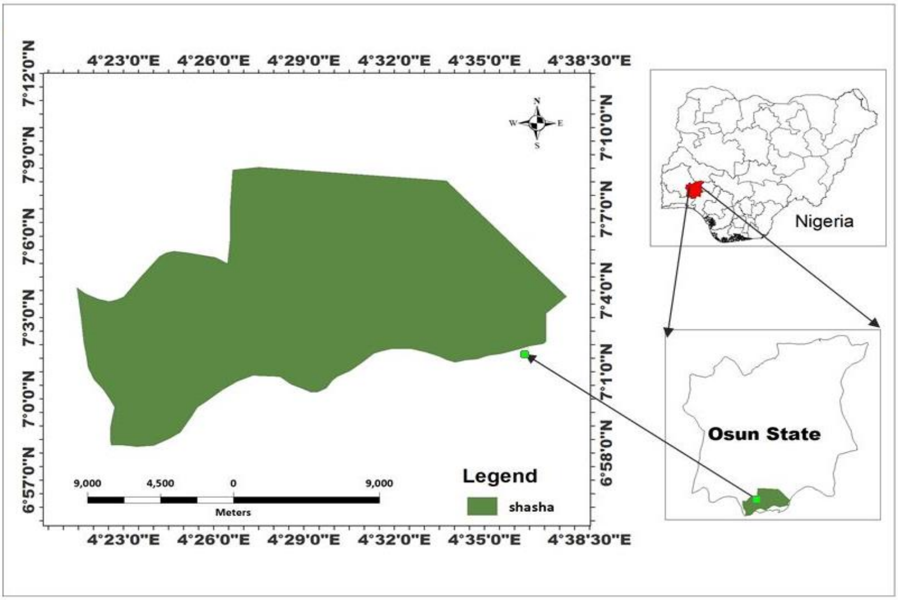

Figure 1: Shasha Forest Reserve, Osun State

Data Collection and Analysis

The study area is located in the Landsat path 190 and row 55 with the pixel sizes of 30 m×30 m (Chander, 2003). The Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+) and Operational Land Imager (OLI) for 1984, 2000 and 2017 images respectively, were used for the forest cover maps of the area. The images were downloaded from the archive of the official website of US Geological Survey (USGS). All the images were obtained in dry season. The Landsat datasets obtained were pre-georeferenced by the provider to UTM zone 31 North projection using WGS-84 datum. The images were prepared for visual interpretation of forest cover through spectral enhancement. The images were subset to show only the area of interest using Shasha Forest Reserve's shapefile. The ground survey was used to collect data of forest cover and to verify the results of visual interpretation of satellite imagery.

Assessment of Forest Cover Dynamics

The digital numbers of the images were converted to reflectance values (equation 1) and mosaicked to produce false colour composites, which were classified into built up, shrubs and forest areas (Giannini *et al.*, 2015 and Gyanesh *et al.*, 2009).

$$L\lambda = \left(\frac{(L_{MAX}\boldsymbol{\lambda} - L_{MIN}\boldsymbol{\lambda})}{Q_{CAL}\lambda}\right) Q_{CAL}\lambda + L_{MIN}\boldsymbol{\lambda} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where;
$L\lambda$ =Spectral radiance at the sensor's aperture [W/(m^2 sr µm)]
$Q_{CAL}\lambda$ = Quantized calibrated pixel value [DN]
$L_{MIN}\ \lambda$ = Spectral at-sensor radiance that is scaled to Q_{CAL}MIN [W/(m^2 sr µm)]
$L_{MAX}\boldsymbol{\lambda}$ = Spectral at-sensor radiance that is scaled to QcalMAX [W/(m 2 sr µm)]
Q_{CAL}MIN = Minimum quantized calibrated pixel value corresponding to $L_{MIN}\lambda$ [DN]
Q_{CAL}MAX = Maximum quantized calibrated pixel value corresponding to $L_{MAX}\boldsymbol{\lambda}$) [DN]
Converting radiance to Top of Atmosphere (TOA) reflectance

$$\rho\lambda = (\pi L\lambda d^2)/(E_{sun\lambda} [\![\mathrm{Cos}\theta_{sz}]\!] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

Where:
$\rho\lambda =$ Planetary TOA reflectance (unitless)
π= mathematical constant approximately equal to 3.14159 (unitless)
$L\lambda =$ spectral radiance at the sensors aperture [w/(m^2 sr µm)]
$d^2 =$ the earth-Sun distance (Astronomical unit)
$E_{SUN\lambda} =$ mean atmospheric solar irradiance [w/(m^2 sr µm)].
θ_{SZ}= the solar zenith angle (degree). The cosine of this angle is equal to the sine of the sun elevation θ_{SE}. That is, $\theta_{SZ} = 90 - \theta_{SE}$.

These are rescaling factors given in metadata. Image classification was thereafter carried out using Maximum Likelihood Classifier (MLC) with Idrisi Selva software. The MLC was supplied with sufficient spectral training sample points to avoid poor image classification (Lillesand *et al*, 2008 and John *et al*., 2006). A modified version of the Anderson scheme of land use/cover classification was adopted and the categories include: forest area (areas dominated by trees), shrubs/grass land (areas dominated by shrubs or herbaceous vegetation), and built up area (areas with a mixture of constructed materials and vegetation mostly in form of lawn grasses). Classification accuracy of 1984, 2000 and 2017 images were assessed to determine the quality and reliability of information obtained from the data. If the derived information is useful in analysing detected changes, it is important to carry out accuracy assessment for each classification (Butt, *et al*, 2015). A total of 100 sample points were randomly selected in the field for ground validation and combined with the images to assess the accuracy of image classification. These points were saved in ArcGIS environment for easy upload. The class values were collocated with the sample points, developed error matrix, estimate accuracy totals and Kappa statistics (equation 3) for accuracy assessment of the classified images.

$$\mathbf{K} = \frac{(\textbf{Total x sum of correct pixels}) - \textbf{Sum of the all the } (\textbf{row total x column })}{(\textbf{Total squared} - \textbf{sum of the all the } (\textbf{row total x column total})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(3)}$$

The dynamics of land use land cover in the forest reserve between 1984 and 2000, and between 2000 and 2017 were compared using weight model in equation 4 (Liu *et al.*, 2010).

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

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 use dynamic degree in the period of T.

The values of S_I and ΔS_{I-J} were obtained from cross classification of LULC images between 1984 and 2000, and between 2000 and 2017. The future pattern of the forest cover changes in the study area was achieved by developing a transition probability matrix of the forest cover for 2017. The prediction was done for 2034 using CA_Markov based Model in IDRISI. The flowchart for the methodology is shown in figure 2.

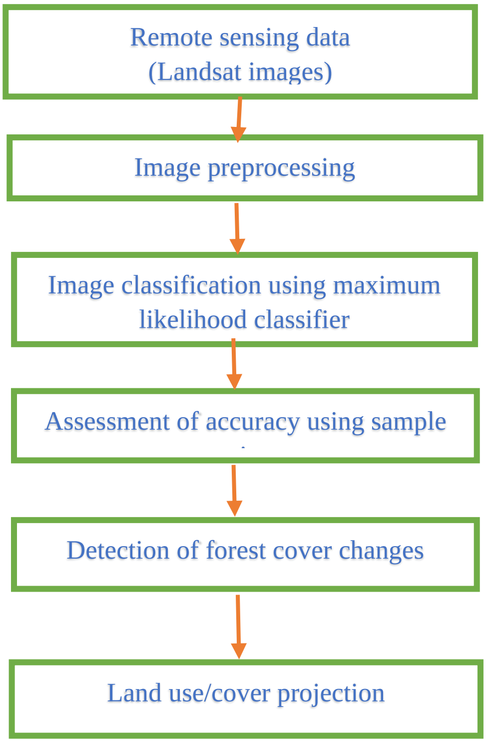

Figure 2: Method used for the forest cover dynamics

RESULTS AND DISCUSSION

Forest, shrubs and built-up areas are the land use land cover identified in Shasha Forest Reserve (Figures 3 to 5 and Table 1). Generally, there is an appreciable increase in Shrubs (6.06%) and Built up area (2.76%), while there is a decrease in Forest (-8.82%) for these thirty-three years (Table 1). Considering the trend of each land use land cover from the base year, there is an increase in the area covered by shrubs between 1984 (5,120 ha) to 2000 (7,618 ha). Between 2000 and 2017, Built up area increased from 1,557 ha to 2,345 ha with a gain of about 788 ha, at an average rate of 2.46%. This could be attributed to increase in human population and associated road project experienced in the study area within this period. This finding is in agreement with that of Orimoogunje *et al*. (2009) who reported that the rate at which human population is increasing is alarming and a threat to natural ecosystem. However, area of land covered by shrubs decreased from 7,618 ha to 7,056 ha of about -562 ha of land loss, at an average rate of -1.78%. This can be traced to the reclaiming of reserve and forceful ejection of farmers from the reserve, which contributes to significant reduction in area of land covered by shrubs (Popoola, 2017). The increase in shrubs (2,498 ha) and built up area (95 ha) between 1984 and 2000 can be traced to encroachment of farmers and illegal settlers, lack of proper management and presence of developmental projects around the study area as discovered during field visit. Within this same period, there is a decrease in the Forest from 25,388 ha to 22,794 ha, a decline of about -2,594 ha, at an average rate of -8.11%. The findings prove that there is a major decline in the Forest, which is typical of most forest reserves in the country especially where there is severity of anthropogenic activities (Ilelakinwa and Alo, 2018) caused by increase in human population (Popoola, 2017).

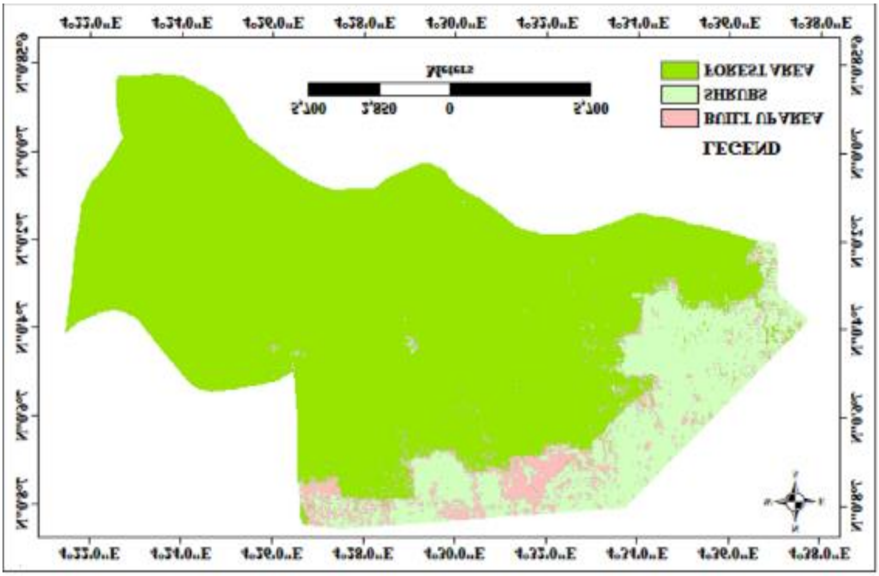

Figure 3: Land Cover Classification in 1984

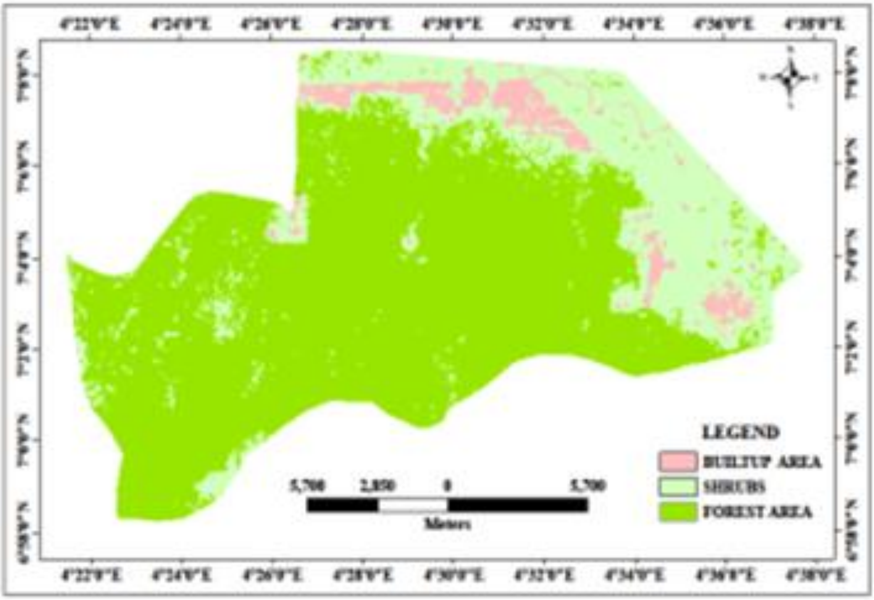

Figure 4: Land Cover Classification in 2000

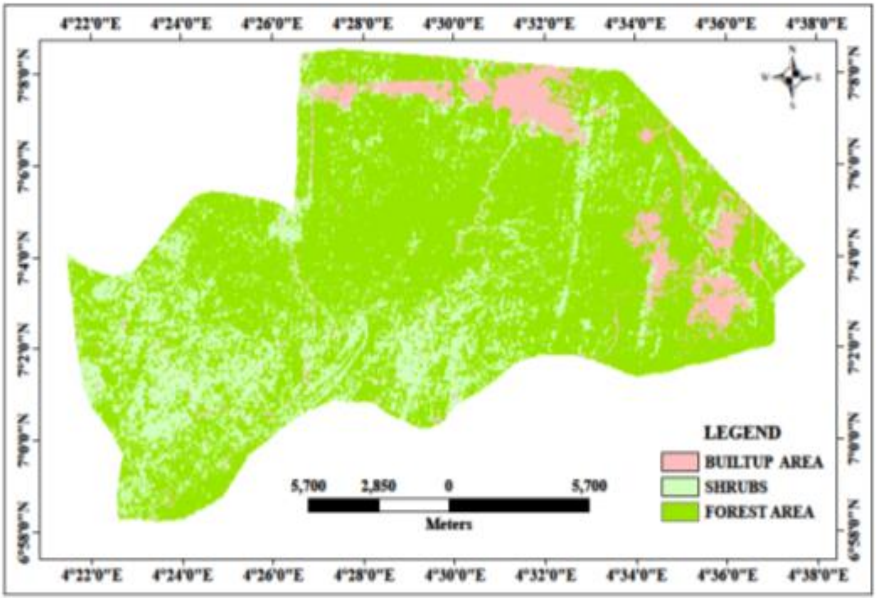

Figure 5: Land Cover Classification in 2017

Table 1: Land cover classes and percentage change in 1984, 2000 and 2017

LULC categories	1984 Area (ha)	2000 Area (ha)	2017 Area (ha)	% Change	
Built up	1462	1557	2345	2.76	Increase
Shrub	5120	7618	7056	6.06	Increase
Forest	25388	22794	22569	-8.82	Decrease

Source: Landsat TM 1984, ETM+ 2000 and OLI 2017; (LULC *means land use land cover. –ve sign mean decrease*)

Image Classification Accuracy Assessment

The Kappa Coefficient is summarized in Table 2. The overall statistics shows that the image classification is reliable for the forest cover analysis. Thus, for the 1984 land cover classification, an overall accuracy is 80%, that of 2002 land cover classification is 86.55% and 2017 land cover classification records overall accuracy of 78.5%. These values according to Altman, (1991) indicate good image classification.

Table 2: 1984, 2000, and 2017 error matrix

Class Name	1984		2000		2017	
	$Pa\%$	$Ua\%$	$Pa\%$	$Ua\%$	$Pa\%$	$Ua\%$
Built up area	80	74	60	83	70.16	71.3
Shrubs	71	75	78.82	88.13	76	75
Forest	76	82	77	80	77.80	80
Kappa Statistics (k)	0.70		0.75		0.88	
Overall accuracy	80%		86.55%		78.5%	

Pa means Producers accuracy and Ua means User accuracy

Land Cover Distribution between 1984 and 2017

The spatial extent of the 1984 Land Cover Change (LCC) map (Figure 2) shows that the forest covers the highest percentage of the land area 25,388 ha (79.41%). This is basically found at the Central, Eastern and Western parts of the forest reserve with the highest concentration around the Western part of the Shasha Forest Reserve. This is followed by Shrub, which covers about 5,120 ha, accounting for about 16.02% of the total land area. However, the built-up area covers about 1,462 ha, accounting for 4.57% of the total land area. This is located along the eastern part of the reserve and with small patches at the central part of the forest reserve. Going by the spatial distribution of land use land cover in 2000, forest also occupies the largest area 22,794 ha (71.30%) as compared to other land cover type (Figure 3). It is largely concentrated at the central and western parts of the reserve and with small patches of shrubs all over the entire reserve. The shrub covers an area of 7,618 ha, accounting for about 23.83%, which is towards the Eastern and with a few patches at the Western and Central parts of the forest reserve. Built up area occupies the least area (1,557 ha), accounting for 4.87% of the total land area. This is located along the Northeastern part and small patches at the Northwestern part of the reserve. Similarly, in the 2017, forest still occupies the largest area 22,569 ha (70.59%) which widely spread the entire reserve. Shrub covers an area of 7,056 ha (22.07%) which is more to the Western part and Central part with a few patches around the Eastern part of the forest reserve. Built up area occupies an area of

2,345 ha (7.34%), which is found more to the Eastern part and small patches around the remaining part of the reserve. The maps have revealed that the forest has progressively reduced from the base year to the last year considered, which is typical of the forest ecosystems in the tropics where there are significant anthropogenic activities (FAO, 2000; Orimoogunje, 2009; Meyfroidt *et al.*, 2010; Alo and Aturamu, 2014; Ilelakinwa and Alo, 2018; Duguma, 2019).

Land Cover Dynamic

Figures 5 and 6 show the maps of the forest cover/land cover classified images of 1984 and 2000 and 2000 and 2017 that were cross classified to detect conversion of land cover types into other types over the years. The extracted data are presented in Table 3. It is clear that over the years, the highest degree of conversion occurred between Built-up area and shrubs between 1984 and 2000 (3.39%) and shrubs and forest area between 2000 and 2017 (4.18%). There is also evidence of high degree of change of built up area to shrubs between 2000 and 2017 (3.77%). A total of 2.31% of forest cover were converted to other land use/cover types. This is similar to what Meyfroidt *et al.*, (2010) that about 61% of the tropical forest of the globe has transited to some other land uses between 2000 and 2005. In the same vein, Africa recorded the highest rate of deforestation of all regions in the world. This is also corroborated by Drummond, *et al.* (2010) and Owolabi (2019).

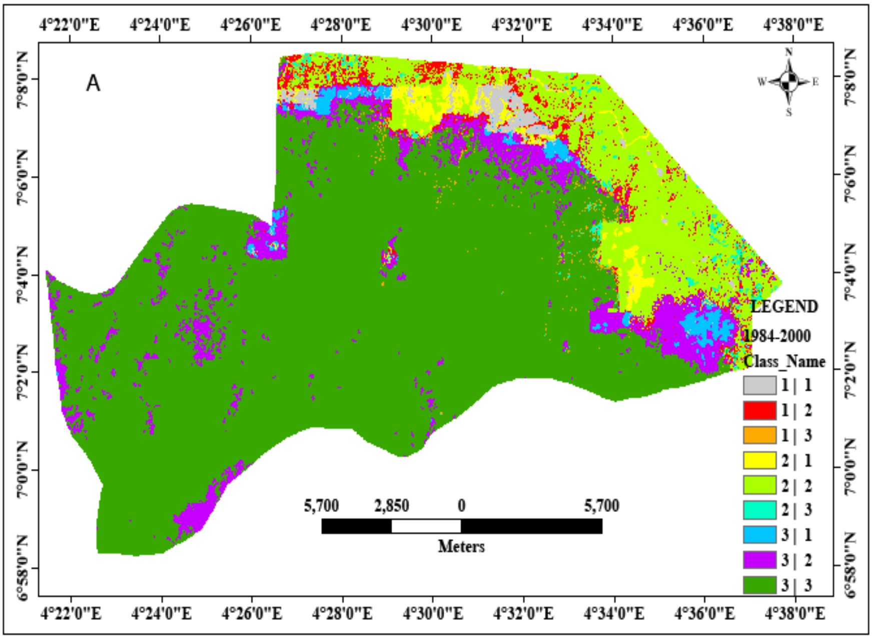

Figure 5: The LULC Conversion between 1984 and 2000

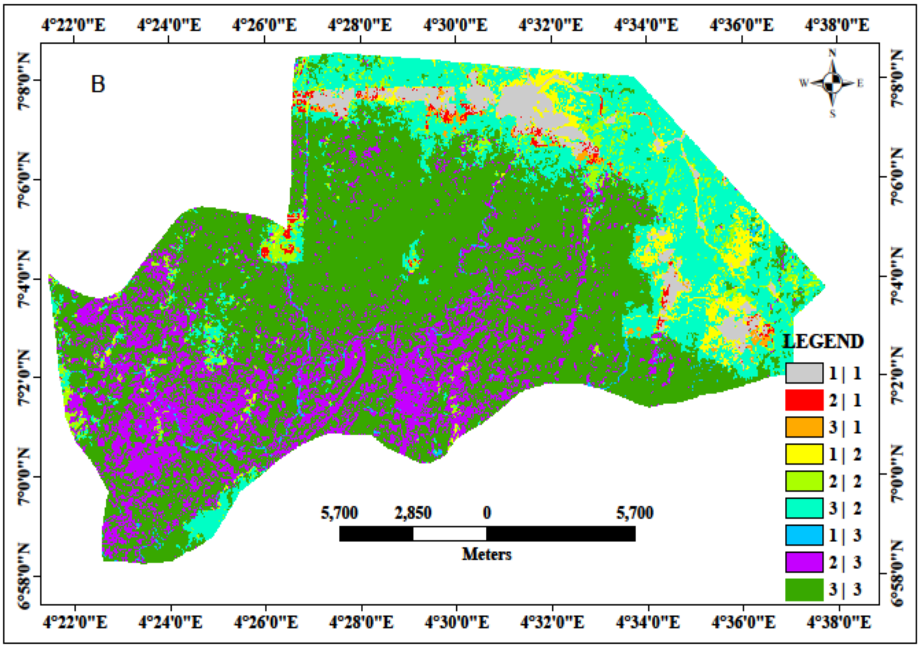

Figure 6: The LULC Conversion between 2000 and 2017

Table 3: The land cover change density between 1984 and 2017

LULC category	Transition	1984-2000 S_I (ha)	ΔS_{I-J} (ha)	S (%)	2000-2017 S_I (ha)	ΔS_{I-J} (ha)	S (%)
Shrubs to built area	2/1	5120	549.18	0.67	7618	223.11	0.17
Forest to built area	3/1	25388	507.33	0.05	22794	193.23	0.05
Built area to shrubs	½	1462	792.81	3.39	1557	998.1	3.77
Forest to shrubs	3/2	22794	2720.97	0.75	22794	5645.16	1.46
Built area to forest	1/3	1462	166.59	0.71	1557	205.74	0.78
Shrubs to forest	2/3	5120	243.18	0.30	7618	5407.74	4.18

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

Predicted Pattern of Forest Cover Changes in the Area

Figure 7 and Table 4, show projected distribution pattern of forest cover of Shasha Forest Reserve. The forest areas have been projected to decrease between 2017 till 2034 at the rate 0.15%. The projection shows an increase in non-forest area suggesting increase in lumbering, forest clearing for agriculture and other anthropogenic activities. This suggests changes in the classes between 2017 and 2034, but comparing the area in hectares, the Table 4 shows no appreciable change for Built up area, but there is a significant change for Shrub and Forest area.

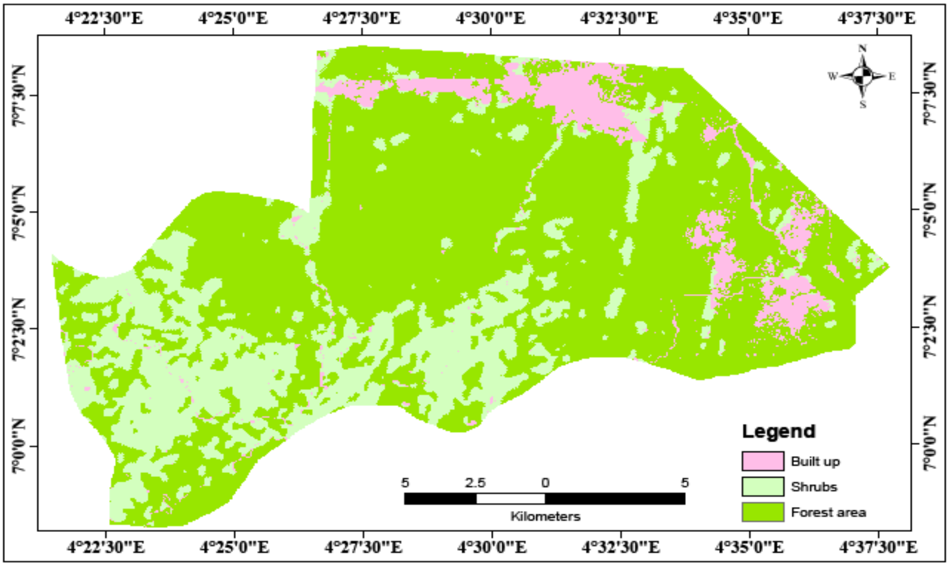

Figure 7: Land Cover Map of Shasha forest reserve in 2034

Table 4: Projected land cover classes and rate of change between 2017 and 2034

Forest cover categories	2017 Area (ha)	2034 Area (ha)	Change Area (ha)	% Change	Average rate of change ha/yr	%	
Built up area	2345	2416	71	0.22	0.01	0.00	Increase
Shrubs	7056	7813	757	2.38	44.53	0.14	Increase
Forest	22569	21741	-828	-2.59	-48.71	-0.15	Decrease

(+ve sign means increase, while –ve sign mean decrease)

CONCLUSION

The forest cover change in Shasha Forest Reserve is an outcome of anthropogenic effects. The forest has experienced a declining trend in the last 33 years and a considerable large area of forest land has been converted to built-up and shrubs. There is also very low degree of change of non-forest to forest land, which implies that there has been little or no replacement of lost forest area from 2000 till date. The forest areas have been projected to decrease between 2017 till 2034 at the rate of 0.15% per annum provided the effects of all human activities remain the same. On the other hand, this study had demonstrated the capabilities of geographic information system tools and remote sensing techniques to capture data and produce useful information on characteristics of forest cover which can be an effective approach for analyzing forest cover change through the use of time series of remotely sensed dataset

REFERENCES

Alo, A.A. and Aturamu, O.A., (2014). Spatial distribution of colleges of education and effects on the forest ecosystem: A case study of College of Education Ikere, Nigeria. *International Journal of Research in Agricultural Sciences*, 1(6): 379-384.

Altman, D.G. (1991). Practical statistics for medical research, London, England: Chapman and Hall South African. *Journal of Geometrics*, 6(3):126-136

Canada Centre for Remote Sensing Tutorials. (2008). Fundamentals of Remote Sensing Introduction Date Modified: 2008-01-29. www.ccrs.nrcan.gc.ca/resource/tutor/fundam

Chakravarty, S., Ghosh, S. K., Suresh C. P., Dey, A. N. and Shukla, G (2012). Deforestation: Causes, Effects and Control Strategies. *Global Perspectives on Sustainable Forest Management. Pp28.*

Chander, G. (2003). Landsat 5 thematic mapper radiometric calibration procedures and post calibration dynamic range. *IEEE Transaction on Geoscience and Remote Sensing*, 4(3):2674-2677.

Chenge, I.B. and Osho, J.S.A. (2016). Matrix growth model for a Natural forest in Shasha Forest Reserve, Nigeria. *Journal of Natural Science Research*, 6(14): pp 99-106.

Chijioke, E.O. (1980) The impact on soils of fast growing forest species in lowland humid tropics. FAO Forestry Paper No 21, Rome, pp. 111.

Drummond, M.A. and Loveland, T. R., (2010). Land-use Pressure and a Transition to Forest-cover Loss in the Eastern United States. *Bio Science*, 60(4): 286-298.

Duguma, L.A., Atela, J., Minang, P. A., Ayana, A. N., Gizachew, B., Nzyoka, J. M. and B. Florence (2019). Deforestation and Forest Degradation as an Environmental Behavior: Unpacking Realities Shaping Community Actions. 8(26). Pp17.

EEA (2007). Land use scenarios for Europe. Qualitative and Quantitative Analysis on a European scale. EEA Technical Report, 9/2007, European Environmental Agency (EEA), Luxembourg. Pp14.

FAO (2000). On definitions of forest and forest change. Forest Resources Assessment Programme, Working Paper 33, Rome, Italy, p 15.

FAO (2007). Manual on Deforestation, Degradation, and Fragmentation using Remote Sensing and GIS. Pp49.

Fichera, C.R., Modica, G. and Pollino, M. (2012). Land Cover Classification and Change-Detection Analysis Using Multi-Temporal Remote Sensed Imagery and Landscape Metrics. *European Journal of Remote Sensing*, 45: 1-18.

Jimoh, S.O., Amusa, T.O. and Azeez, I.O. (2012). Prevalence, Utilization and Conservation Strategies for Non-Timber Forest Products in South-western Zone of Nigeria. *Resources and Environment*, 2(1): 46-54

Giannini *et al*. (2015). Land surface Temperature from Landsat 5 TM images comparison of different methods using airborne thermal data. *Journal of Engineering Science and Technology, Review*, 8(3): 83-90.

Gyanesh, C., Brian, L.M. and Dennis, L.H., (2009). Remote Sensing of Environment. 113 (5): 889-1112.

Ilelakinwa, G.A. and Alo A.A. (2018). Land Use Land Cover Dynamics of Faculty of Agriculture and Forestry Practical Demonstration Site, Ileogbo. *In*: Isah, A.D., Shamaki, S.B. Adekunle, V. A. J and Bello, A.G. (Eds.). *Proceedings of 6th Biennial National Conference of Forests and Forest Products Society*. 23- 27 April, 2018. Usmanu Danfodiyo University, Sokoto, Nigeria. 242-250pp

Isichei, A.O. (1995). Stock of Nitrogen in Vegetation and Soil in West African Moist Savanas and Potential Effects of Climate change and Land Use on these stocks. *Journal of Biogeography*, 22 (2/3) Terrestrial Ecosystem Interactions with Global change, 1 (March- May, 1995), pp.393-399.

Jimoh, S.O., Amusa, T.O. and Azeez, I.O. (2002). Prevalence, utilization and conservation strategies for non-timber forest products in South-western Zone of Nigeria. *Resources and Environment*, 2(1): 46-54

Liu, X. (2010). Simulating land use dynamics under planning policies by integrating artificial immune systems with cellular automata, *Int. J. Geogr. Inf. Sci.* pp.783-802.

Loveland, T.A. and Dwyer, J.L. (2012). Landsat: Building a strong future. *Remote Sensing of Environment*, 112: 22-29.

Mejebi, D.J.J. (2008). An assessment of the various types of land degradation within the River Kubanni Basin of Zaria, Nigeria. *In*: Bisong, F.E. (Ed.). *Geography and the Millennium Development Goals: Translating Vision into Reality*, Ultimate Index Books Publishers, Calabar, 64-70.

Meyfroidt, P., Rudel, T.K. and Lambina, E.F. (2010). Forest transitions, trade, and the global displacement of land use. Proceedings of the National Academy of Sciences of the United States of America. 107(49): 20917-20922.

NEST (1991). Nigerian Environmental Study/Action Team. The challenges of Sustainable Development in Nigeria, *T. Nest Ibadan*, 1, 6-12.

Ola-Adams (1999). Impacts of land use changes on soil quality of a biosphere reserve in Southwestern Nigeria. Country report on Biosphere Reserve for Biodiversity Conservation and Sustainable Development in Anglophone Africa (BRAAF) Project, pp 11-13.

Olokeoguna, O.S., Iyiolab, O.F. and Iyiolac, K. (2014). Application of remote sensing and GIS in land use/land cover mapping and change detection in Shasha Forest Reserve, Nigeria. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume 40-8, 2014 ISPRS Technical Commission VIII Symposium, 09 – 12 December 2014, Hyderabad, India, Workshop 1.2, 6208.

Oludare, H.A. and Clement, O.A. (2014). Spatial patterns of land cover change using remotely sensed imagery and GIS. A case study of Omo-Shaha-Oluwa Forest Reserve, Southwestern Nigeria (1986-2002). *Journal of Geographic Information System*, 6: 375-385.

Orimoogunje, O.O.I, Ekanade, O. and Adesina, F.A. (2009) Land use changes and forest reserve management in a changing environment: South-western Nigeria experience, *Journal of Geography and Regional Planning*, 2: 283-290.

Owolabi, S. (2019). Forest Loss in Nigeria, the Impact on Climate and People from the perspectives of illegal Forest activities and Government Negligence. Degree thesis for Bachelor of Natural Resources Degree programme in Sustainable Coastal Management. 30pp.

Popoola, L. (2017). Implementation of the government’s White Paper on Shasha Forest Reserve in Ile-Ife. www.channelstv.com, June 5, 2017.

Salami, A.T., Balogun, B.O. and Oloyede-Kosoko, S.O.A. (2007). Geospatial data application in the assessment of population impact on a tropical lowland rainforest of Southwest Nigeria. Geo Observateur 16:31-37.

Suhaili, A.B., Helmi, Z.M., Shafri, N.A. and Ainuddin, A.G. (2006). Improving Species Spectral Discrimination Using Derivatives Spectra for Mapping of Tropical Forest from Airborne Hyperspectral Imagery. 34: 126-130

Taha, H. (1997). Urban climates and heat islands: albedo, evapotranspiration and anthropogenic heat. *Energy and Buildings*, 25:99-103.

Yang, X (2001) Change Detection Based on Remote Sensing Information Model and its Application on Coastal Line of Yellow River Delat. Earth Observation Research Center, NASDA 1-9-9 Roppongi, Minato-ku, Tokyo, 106-0032, China.