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SATELLITE-BASED PREDICTION OF FOREST LOSS IN OLUWA FOREST RESERVE, ONDO STATE, NIGERIA

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ABSTRACT

This study set to evaluate the recent forest cover of Oluwa forest and its future status. The 18-year interval (2002 and 2020) land cover maps used in this study were produced using Landsat images for these years. The image processing and analysis were carried out in Idrisi environment. CA-Markov analysis was run in Idrisi software to test a pair of land cover images and outputs a transition probability matrix and a transition areas matrix for the analysis and prediction of forest cover Results showed that there was a continuous increase in forest cover and decrease in non-forest area. Degraded forest increased from 3.7% in 2002 to 3.92%in 2020. Projection revealed that the forest reserve will experience increase in forest cover by about 0.1% in 2038. It also showed a projected gain of 0.39% and 0.98% forest loss (from degraded and non-forest areas in 2038. This development poses severe ecological disorder as such would alter surface energy balance. To avert this ecological threat, the activities of loggers and other anthropogenic activities within the study area should be checked.

Keywords: Forest cover, ecosystem, Landsat images, energy balance and Anthropogenic activities

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INTRODUCTION

Sustainable forest resource management can only be achieved when the facts of the forest ecosystem are available for effective policy and decision making (Alo *et al,* 2020). FAO, 2000, defined Forests as an area occupied by trees above the height of 5m in the absence of other predominant land use. The functions of forest ecosystems in sustaining the earth are many including environmental, socio-cultural and socio-economic functions. The forest provides home to terrestrial biodiversity and improves life's quality on earth (Popoola, 2017 and Canada Center for Remote Sensing, 2008). Nigeria is one of the world's tropical countries experiencing huge deforestation and forest degradation and losses its forest at 3.5% per annum (Ladipo, 2010). The existence of man with his activities on earth transformed the world environment immensely. Reports have it that there are few landscapes remaining on the earth's surface that have not been significantly changed by humans (Yang, 2001 and Suhaili *et al*., 2006).

Forests have been providing human needs throughout the globe for years and people have harvested fuelwood, fodder, hunted wild animals for meat and grazed their livestock in forests (Olarewaju *et al,* 2016). Millions of households in developing countries, Nigeria inclusive depend majorly on forests for their products and benefits (Tewari, 2012). The production of forest resource maps was carried out using forest inventories from field survey (Suhaili *et al*., 2006). Recently, the advent of geospatial techniques (Remote Sensing (RS) and Geographic Information

System (GIS)) have provided a cost-effective means for forest mapping (Suhaili *et a*l., 2006). The techniques provide repetitive data for forest monitoring, quantification of forest cover pattern, change detection and adequate data that can be used to predict forest cover effectively (Loveland and Dwyer, 2012 and Fichera *et al*., 2012).

Several researchers have examined changes in use/land cover using geospatial techniques to detect forest cover change (Agbor *et al*, 2012; Oludare *and* Clement, 2014, Makinde and Agbor, 2019 and Buba *et al*,2020). However, little has been done on the prediction of change locations in forest cover in tropical rain forest reserve. Therefore, this study focused on assessing forest cover changes and identifying the locations of such changes in Oluwa forest reserve. To achieve this, the study (1) classified acquired Landsat images into forest, degraded and non-forest areas, (2) examined forest changes and (3) predict change locations of forest cover. The results of this study would equip policy-makers and scientists with adequate quantitative information for sustainable management of the Forest Reserve.

MATERIAL AND METHODS

Study Area

The study area is one of the major forest reserves in Ondo State, southwest Nigeria. It located approximately between latitudes 6˚37' and 7˚20' North and longitudes 4˚27' and 5˚05' East (Orimoogunje, 2014). The reserve has been separated from the Omo and Shasha reserves, and covers about 1012 km^2. The forest reserve is characterized by undulating topography and a mean elevation of 90 m above sea level, mean relative humidity of 80%, and a daily temperature of 25˚C, characterized by a moist semi-evergreen rainforest (Udoakpan, 2013). Oluwa forest reserve has an annual rainfall which exceeds 2000 mm with two distinct seasons: the rainy season which starts mostly in February and ends in October and a dry season that starts in November and ends in January.

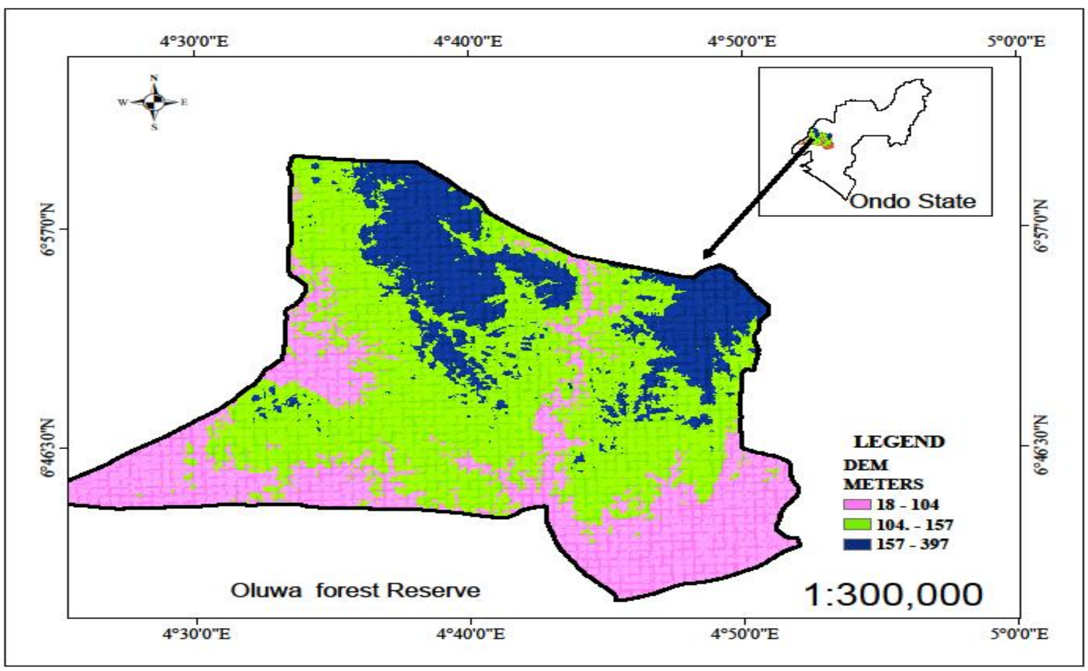


Figure 1: Oluwa Forest Reserve

Data Collection

To assess and predict forest loss in Oluwa forest reserve, Landsat images of 2002 and 2020 were downloaded from the official website of US Geological Survey (USGS) and processed in order to achieve the research objectives. The study area is located in the Landsat path 190 and row 55. The pixel sizes of the images were 30×30m for 2020 and 28.5x28.5m for 2002.

Production of Forest Cover Change Map
Different tools have been developed over the years for the assessment of land cover changes including prediction of forest cover changes such as Markov Chain (Balzter, 2013), Logistic Regression (McConnell *et al*, 2004), and Artificial Neural Network (ANN) (Civco, 1993 and Agbor *et al*, 2020). Land cover patterns for the years 2002 and 2020 were mapped using the preprocessed Landsat images. To classify the images, a modified version of the Anderson (1976) scheme of land use/cover classification was adopted and the categories include (Table 3.4).

Table 1: A modified version of the Anderson scheme of land use/cover classification.

2. Forest	Plantation and mixed forest.
3. Degraded forest	transitional area and Cropland,
4. Non-forest	Residential, transportation, streams, and bare surfaces

This study employed Maximum Likelihood classification process to group image features into three general classes: forest, degraded forest and non-forest areas. This study used Markov process to describing and predict land cover changes in the forest reserve and its future status (Kampanart *et al*, 2005, and HAA-R R and Alnajjar, 2013). The CA-Markov analysis was run in Idrisi software to test a pair of land cover images and outputs a transition probability matrix and a transition areas matrix. Below is an array of probability values of land cover types conversion adopted from Lingling *et al*, (2011)

Table 2. Array of probability values of land cover types conversion.

Land cover	**x**	**y**	**y**
x	x	xy	xz
y	yx	y	yz
y	zx	zy	z

Note: $x = forest, = degraded\ forest$ and $= non - forest$

The transition probability matrix explains the probability that each land cover category changed to every other category. The transition areas matrix is the number of pixels that are expected to change from each land cover type to every other land cover type over the specified number of time units. Based on this a three-state markov probability matrix was developed (table3).

Prediction of Forest Cover Change Map
To project, the study used cellular automata markov change prediction module in Idrisi software (Agbor *et al*, 2012 and Bangladesh, 2013). This was also manually calculated using matrix model (equation 1). This method utilized the transition probability matrix generated from image cross classification.

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}, B = \begin{pmatrix} b_1 \\ b_2 \\ b_3 \end{pmatrix} \text{and } C = \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} \ldots\ldots 1$$

Where A is array of probability values of land cover types conversion.B is the Percentages of land cover types for the base year, while c represents the projected matrix The product of A and Bmatrices produced the forecast values matrix for each land cover type (Bayes *et al*, 2011).
Software used include (1) Idrisi Selva 17.0–this was used for processing the images and subsequent analysis, (3) ArcGIS 10.3 –for digitizing study (Bayes, 2011; Kritsana *et al*, 2013 and Makinde and Agbor, 2019),

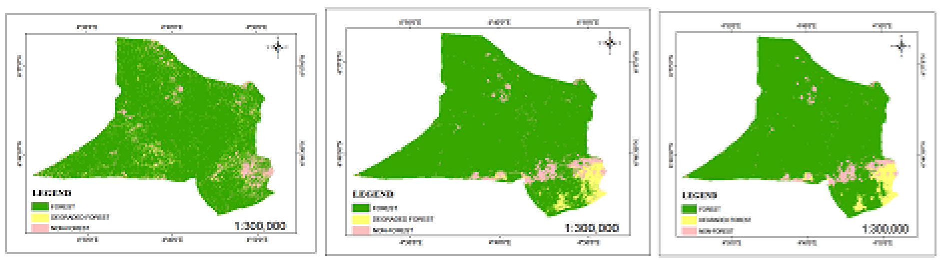
Accuracy Assessment
Classification errors were identified in a map by designing and implementing an accuracy assessment. Comparing the map and reference classification at each sample unit allows the construction of an error matrix. The map is

represented by rows and the reference data by columns. The matrix reveals errors of commission and omission (Pontus, 2013). The sample points used for the accuracy assessment were 100. The accuracy statistics (table 6) provides producer's accuracy (Pa), user's accuracy (Ua), Kappa statistics (k) and overall accuracy (Pontus *et al*, 2004). The accuracy values were calculated using Accuracy Assessment tool in idrisi. This reveals pixels misclassification in percentages/.

RESULTS

Forest Cover Change between 2002 and 2020

The values in tables 3 and 4 illustrate the changes and loss of forest cover between 2002 and 2020. From table 3, there was a continuous increase in forest cover and decrease in non-forest area. Degraded forest increased from 3.7% in 2002 to 3.92%in 2020. Projection revealed that the forest will experience decrease in degradation by about 0.1% in 2038.



a b c

Figure 2: Land cover distribution in (a) 2002 (b) 2020 and (c)2038

Table 3 Land cover distribution in 2002 and 2020

Land Cover Types	2002		2020		2038	
	Area km^2	%	Area km^2	%	Area km^2	%
Forest	916.295	90.545	921.587	91.073	927.670	91.674
Degraded Forest	36.941	3.650	39.640	3.917	39.146	3.868
Non-Forest	58.747	5.805	50.692	5.009	45.104	4.457
Total	**1011.983**	**100**	**1011.919**	**100**	**1011.919**	**100**

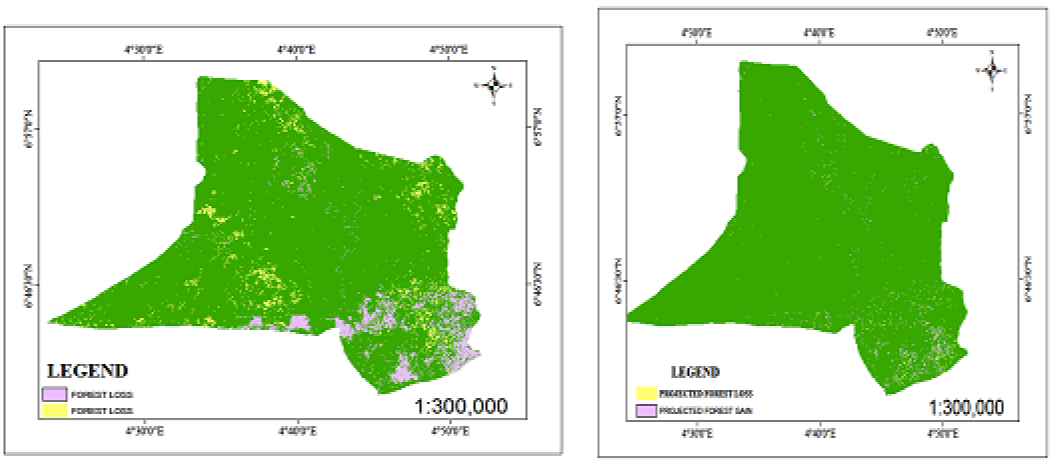
One imperative reason for carrying out change detection of land/forest cover is to determine the probability of one cover type changing to the other. The transition probability matrix in table 5 provides information that reveals loss and gains of land cover types overtime. For instance, the probability that forest cover changed to other classes is about 4% of the total forest reserve, while the probability that degraded forest and non-forest cover changed to forest is about 90% and 57% respectively. The high probability (90%) is a reflection of the 5.5% forest gain in table 4. The forest appeared stable, however, the 57% probability of non-forest changing to forest cover is weak and a threat to the forest cover. The transition matrix also shows that the 3.5% forest cover loss is more of non-forest than degraded area (Table 5). The Kappa Statistics (k) are 60% and 58% for 2002 and 2020 respectively while the overall accuracies of mage classification are approximately 89% for both years (Table 3).

Table 4: 2002 and 2020 Error Matrix

Class Name	2002	2020
	$Pa, Ua.$	$Pa, Ua.$
Forest	64, 78	58.33, 78
Degraded forest	51, 65	51.8, 63
Non-forest	96, 92	96.4. 93
Kappa Statistics (k)	0.60	0.58
Overall accuracy	88.75%	88.75%

Map Projection and Forest Cover Change

One of the objectives of this research was to find out if the forest reserve will experience either increase or decrease in forest cover in future. The results in table 3 show that in 2038, the forest reserve will experience increase in forest cover by about 0.5%. Degraded forest area will reduce by 0,05% while non-forest area will decrease by 0.55% of the total area. The projected gain is 0.39% and 0.98% as forest loss (loss from degraded and non-forest areas) in the next 18years as shown in table 4.



a b

Figure 3: Forest cover loss and gain (a) between 2002 and 2020 (b) in 2038

Table 5 Forest loss and forest gain in 2002 and 2038

Transitions	2020 forest loss/gain		Projected loss/gain	
loss/gain	Area	%	Area	%
forest gain	55.798	5.514	3.911	0.386
forest loss	35.726	3.531	9.993	0.988

Table 6 2002 and 2020 Transition matrix:

Land cover	Forest	Degraded forest	Non-forest	Total probability
Forest	0.9566	0.0214	0.0219	1
Degraded forest	0.8939	0.0271	0.0790	1
Non-forest	0.5710	0.1112	0.3178	1

DISCUSSIONS

Forest cover loss has contributed to the global warming and ecological disorder. Human activities such as logging and farming have changed the planet's landscape. Such development among other factors, is responsible for surface temperature changes and loss of ecosystem balance in the tropics. The experienced depleting of the forest cover is usually to meet the human needs of shelter and food (Makinde and Agbor, 2019). The results of this study show that the forest reserve will experience future increase in forest cover by about 0.5%. Degraded forest area will reduce by 0,05% while non-forest area will decrease by 0.55% of the total area. The projected gain however, is 0.39% and 0.98% as projected forest loss (loss from degraded and non-forest areas) in the next 18years. Again, the transition table reveals that the forest cover loss is more of non-forest than degraded area. According to Pickett *et al*. (2001), this development is an ecological threat as such would change ecological energy balance with a rise in environmental temperature. They reported that the removal of shrubs and trees reduces the natural cooling effects of shading and evapotranspiration, and forcing the development of meteorological events such as increased rainfall, which poses threat to the environment and the human population. Nowak *et al*. (2002) related similar findings that forest lost to human activities intensifies air pollution, alter rainfall pattern in our environment, change the composition of biodiversity and also contributes to global warming. United State Environmental Protection Agency (2015), buttressed the above assertions and suggested tree planting as one sustainable solution to such environmental problems. To save the reserve from forest cover loss, the activities of loggers and other human activities within the reserve should be checked.

CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates the ability of Remote Sensing in capturing, processing and analyzing spatial data for forest cover studies. Attempt was made to determine as accurate as possible three land cover classes as they change over time. The three land cover types were distinctly produced for each study year but with more emphasis on forest and non-forest land. since they are the ones that depict the impart of human activities within the forest reserve. In achieving this, markovian model was introduced into the research work. An attempt was also made at generating the probabilities of one land cover type changing to another. The results show a projected gain of 0.39% and 0.98% as forest loss from degraded and non-forest areas in 2038. This development poses severe ecological threat as such would alter surface energy balance with an increase in surface temperature. To avert this ecological disorder, the activities of loggers and other anthropogenic activities within the study area should be checked.

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