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Full Length Research Article

Probabilistic Cellular Automata Modelling and Simulation of Land-Use Changes in Okomu National Park

***S. J. Okonkwo, A. E. Adeniji, O. A. Adekugbe, P. A. Ukoha and A. R. Adewoye**
Environmental Modelling and Biometrics Department, Forestry Research Institute of Nigeria, Forest Hill, Jericho Ibadan
[*Corresponding Author: E-mail: sj.okonkwo@gmail.com]

ABSTRACT

Land use, land cover (LULC) change technique is essential for measuring ecological quality, environmental sustainability, and uncontrolled development at various spatiotemporal scales. To construct effective land use management plans, the probable future scenario of LULC changes can be easily detected utilizing a simulation technique.This study monitors and models spatiotemporal land-use changes in Okomu National Park over two decades (2000 – 2020) to project forest cover changes for the near future. A probabilistic cellular automata (CA) model was created and used to simulate land-use changes with the aim of predicting future land-use scenarios. Landsat7 ETM+ satellite images for years 2000, 2005, 2010, 2015, and 2020 were classified into Forest and Non–Forest using a maximum likelihood supervised classification algorithm. A probabilistic cellular automata model using Moore's neighborhood with a Von Neumann extension was used to simulate land-use changes for years 2005, 2010, 2015, and 2020 with the year 2000 as the base year.The overall classification accuracy for the years under study was 98.18%, 97.52%, 96.33%, 91.67%, and 94.61%with overall kappa coefficients of 0.97, 0.96, 0.95, 0.86, and 0.91 respectively. State transition probabilities for 2000–2005, 2005–2010, 2010–2015, and 2015–2020 were calculated from the classified images. Simulation accuracywas 77.46%, 74.1%, 70.98%, and 78.27% for the year 2005, 2010, 2015, and 2020 respectively. Projections were made for years 2025 and 2030 and it shows a 27.41% decline from the base year by 2025 anda 29.90% decline by 2030.The amount of forest cover in the actual and simulated land-use changes shows a gradual drop from 185.15 km^2 in the base year 2000 to 136.07 and 135.30 km^2 in the year 2020, respectively.Spatial simulation models, which provide a scientific basis for supporting sustainable forest management based on different simulation scenarios alsocontribute significantly to the implementation framework for the United Nations' Reducing Emissions from Deforestation and Forest Degradation (REDD/REDD+) program, as well as reference scenarios for REDD/REDD+ incentive payments.

Keywords: Cellular automata, Markov chain, Simulation, Supervised classification

INTRODUCTION

Cellular Automata (CA) provides a useful way for modeling and simulating the natural dynamics of cellular structures.It is characterized by a neighborhood configuration with discrete space, a transition in discrete time, and finite state space for each cell (Ponselet, 2013). Natural, physical, and biological systems can be broken down into their cellular automata components (Ozah *et al*., 2010). Since its discovery by Von Neumann, 1951c, CAand hybrid models of CA as Stochastic Cellular Automata, Cellular Automata Logistic Regression, Cellular Automata Markov Chain, and Cellular Automata Logistic regression Models have found a wide range of applicability in simulating ruralland use dynamics across Lake Chad basin (Ozah *et al*., 2010), wildland fire spread dynamics (Almedia and Macau, 2011), traffic flow (Schreckenberg *et al*., 2014), urban growth modeling (Tripathy and Kumar, 2019; Falah *et al*., 2020).

Land-use changes are dynamic complex geographical processes caused by natural and anthropogenic influences which are difficult to precisely model (Yang *et al*., 2014). Land-use change modeling with cellular automata is necessary for the quantitative assessment of change dynamics and projection into future characteristics of the study area in question (Tripathy and Kumar, 2019). These models are designed to understand the main factors responsible for the change dynamics and the ability to predict future scenarios (Eastman & He, 2020).This study monitors and models spatiotemporal land-use changes in Okomu National Park over two decades (2000 – 2020) with the specific aim of designing a probabilistic cellular automata (CA) model for simulating land-use changes using Moore's neighborhood with a Von Neumann extension (Figure 1) and transition probabilities and projecting future forest cover.

Study Area

OkomuNational Park is located in Ovia South-West Local Government Area ofEdo State.The National Park lies between latitude 6˚15'N to 6˚ 25' N andlongitude 5˚ 09'E to 5˚ 23'E (Figure 1). The topography of Okomu National Park is sloping and ranges between 30m and 60m above sea level (Orhiere, 1992). Rainfall is between 1,524mm and 2,540mm and the mean monthly temperature is 30.2ºC while relative humidity in the afternoons is 65% all through the year (Orhiere, 1992). The vegetation of the park is a Guinea-Congo lowland rainforest which includes areas of swamp-forest, high forest, secondary forest, and open scrub (Okomu National Park, 2010).

MATERIALS AND METHODS

Land-use change dynamics maps were created using Landsat 7 ETM secondarydatasets acquired from USGS (2021), for the years 2000, 2005, 2010, 2015, and 2020 (see Figure 2) using maximum likelihood classifier in two major classes Forest and Non–Forest. Landsat 7 Enhanced Thematic Mapper (ETM) satellite images for years 2000, 2005, 2010, 2015, and 2020 with bands 4, 3, 2 were downloaded and each was classified into forest and nonfForest using maximum likelihood supervised classification algorithm. To achieve uniformity in data collection, Landsat 7 ETM+ was used for all years, and images were collected during the dry season (between November and March)

Before modeling, we ensured that all classified images had the same path and row, had the same dimension; that is all images have the same number of pixels on the rows and the same number of pixels on the column and were of the same resolution.

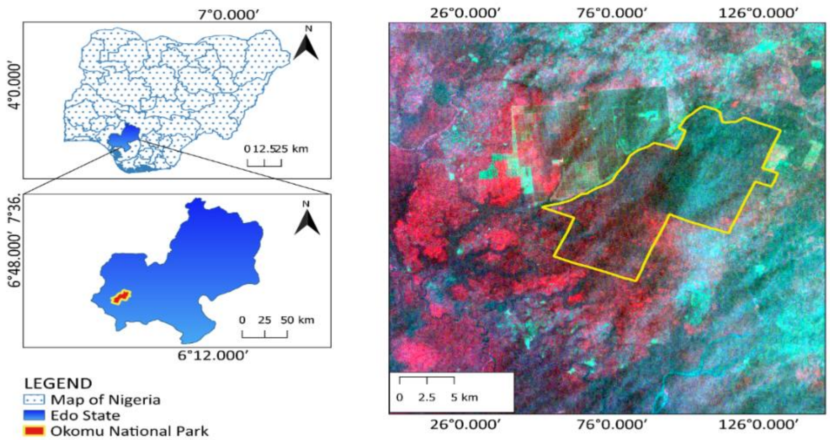

Figure 1: Map of Okomu National Park in Edo State

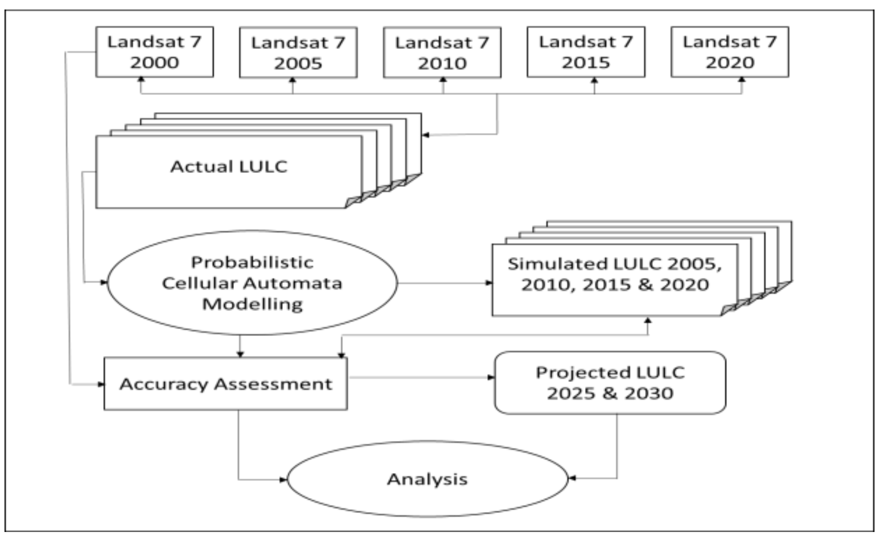

Figure 2: Methodology of the study

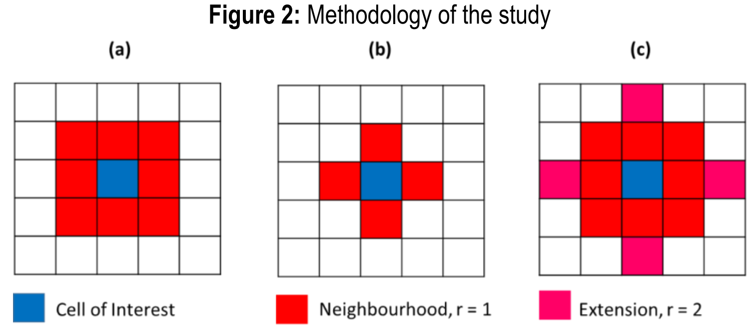

Figure 3: Cellular Automata images showing the cell of interest (Blue), Neighbourhood (Red) and Extensions (Pink).(a) Moore Neighbourhood (b) Von Neumann Neighbourhood(c) Moore Neighbourhood with von Neumann extension

Cellular–Automata Algorithm

Let ${c^t}_{i,j}$ be the cell of interest representing the test pixel at moment $t$in the center of a cellular automata kernel with size3×3 or size$5 \times 5$for an extended neighborhood. Also, let ${c^t}_{i,j}$ be in a state $s$at moment t denoted by s^t and belonging to a binary state space $S = \{1, 2\}$. The kernel $C_{i,j}$ at moment t represented by $C^t_{i,j}$ is defined by any of the following matrices:

$$C^t_{i,j} = \begin{bmatrix} {c^t}_{i-1,j-1} & {c^t}_{i-1,j} & {c^t}_{i-1,j+1} \\ {c^t}_{i,j-1} & c_{i,j} & {c^t}_{i,j+1} \\ {c^t}_{i+1,j-1} & {c^t}_{i+1,j} & {c^t}_{i+1,j+1} \end{bmatrix} \qquad (1)$$

$$C^t_{i,j} = \begin{bmatrix} & {c^t}_{i-1,j} & \\ {c^t}_{i,j-1} & {c^t}_{i,j} & {c^t}_{i,j+1} \\ & {c^t}_{i+1,j} & \end{bmatrix} \qquad (2)$$

$$C^t_{i,j} = \begin{bmatrix} & & {c^t}_{i-2,j} & & \\ & {c^t}_{i-1,j-1} & {c^t}_{i-1,j} & {c^t}_{i-1,j+1} & \\ {c^t}_{i,j-2} & {c^t}_{i,j-1} & {c^t}_{i,j} & {c^t}_{i,j+1} & {c^t}_{i,j+2} \\ & {c^t}_{i+1,j-1} & {c^t}_{i+1,j} & {c^t}_{i-1,j+1} & \\ & & {c^t}_{i+2,j} & & \end{bmatrix} \qquad (3)$$

Where ${c^t}_{i,j}$ is in state 1 or 2.

Equation (1) is the 3×3 Moore Neighbourhood (Weisstein, 2001a), Equation(2)is the 3×3von NeumannNeighbourhood (Weisstein, 2001b), and Equation (3) is the5×5 Moore Neighbourhood with aVon Neumann extension also known as a von Neumann Neighborhood with Manhattan distance $r = 2$ (Figure 3).Let $C^t_{i,j}$ be the chosen kernel for a CA model, and let $S_t$be a set ofstates of the number of cells in $C^t_{i,j}$at moment t. The set of states of the finite number of cells at moment $t + 1$ signified byS_{t+1} is a function of the previous set of states and the chosen neighborhood of each cell (Kumar *et al*., 2009; Liping *et al*., 2018).

$$S_{t+1} = f(S_t, C^t_{i,j}) \qquad (4)$$

Such that:

$${c^{t+1}}_{i,j} = f(\, C^t_{i,j}) \qquad (5)$$

Where f is called the transformation ruleof the local space, and Equation (4) is the Cellular AutomataAlgorithm. However, the transition rule for this study includes a combination of conditional statements that incorporates the nature of the kernel $C^t_{i,j}$ at moment $t$and transition probabilities.

Transition Probabilities

It is important to match all the pixel pieces to ensure that $c_{i,j}$ is the same pixel for all classified images. The transition probabilities were computed using the actual LULC images of the years 2000–2005, 2005–2010, 2010–2015, and 2015–2020 (Table 1) which results in a transition matrix for each pair of raster images as shown in equation (6) below:

$$P_{ij} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \qquad (6)$$

Let i be the state of a pixel at moment t, and j be the state of the pixel at moment $t + 1$. The transition probability from state i to state j is given as:

$$p_{ij} = \frac{Number\ of\ Pixels\ that\ transitioned\ from\ State\ i\ to\ State\ j}{Total\ Number\ of\ Pixels\ that\ were\ in\ State\ i} \qquad (7)$$

Where $i, j = 1, 2,\ p_{ij} \geq 0$, and $\sum_{j=1}^{2} p_{ij} = 1$ for all i (Figure 4).

Table 1: Transition probabilities of land use changes in Okomu National Park

PERIOD	LAND USE	FOREST	NON–FOREST
2000 – 2005	Forest	0.8344	0.1656
	Non–Forest	0.6342	0.3658
2005 – 2010	Forest	0.7867	0.2133
	Non–Forest	0.3098	0.6902
2010 – 2015	Forest	0.8173	0.1827
	Non–Forest	0.4561	0.5439
2015 – 2020	Forest	0.8085	0.1915
	Non–Forest	0.2150	0.7850

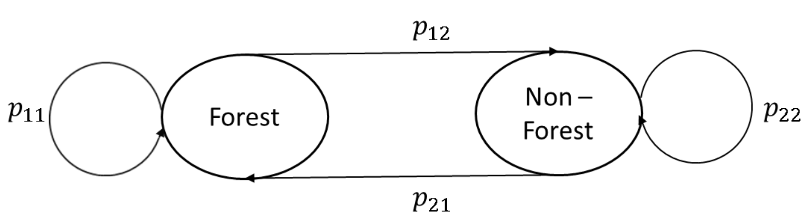

Figure 4: State transition with probabilities from forest to forest (P_{11}), forest to non-forest (P_{12}), non-forest to forest (P_{21}) and non-forest to non-forest (P_{22}).

Simulation

The simulation was initiated using the actual LULC for the year 2000 to simulate for 2005, then using the actual LULC for the year 2005 to simulate for the year 2010, followed by using the actual LULC for the year 2010 to simulate for the year 2015, then simulating for the year 2020 with the actual LULC for 2015. The model used the transition probabilities of the actual LULCs to simulate for the target years while using different CA kernels as filters for forests and non–forests. The script also monitored forest loss and forest gain for both actual and simulated LULCs.

Simulation Evaluation

At each step of the simulation, accuracy was measured by comparing the corresponding pixels of the actual and simulated LULCs and creating a confusion matrix of true and false positives and negatives.The overall accuracy of each simulation was calculated using the following equation:

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Number\ of\ Classified\ Pixels} \quad (8)$$

RESULTS AND DISCUSSIONS

Okomu National Park, a low land rain forest and a protected area is rich in biological diversity. Increase in population and the need for economic expansion has necessitated the destructive incursion into the national Park. Figure 5 shows the loss of forest cover in nonforest activities between the year 2000 and 2020. Results of the forest cover analysis using Landsat images at an interval of five years clearly show remarkable changes in the forest cover with high accuracies.The classification accuracy achieved for each year was high (Table 2): 98.18%, 97.52%, 96.33%, 91.66%, and 94.61% for Landsat ETM images of 2000, 2005, 2010, 2015, and 2020, respectively.

The simulation in this study is similar to Kamusoko *et al*. (2011), where accuracy ofspatial simulation modelling of future forest cover changesof Lao PDR was 80%.Similar classification accuracies using the Probalistic Cellular automata modeling technique were achieved by Liu *et al.* (2014); Lau and Kam, (2005); Islam *et al* (2018).There was a 21.56% decrease in the amount of forest cover from 185.15 Km^2 to 136.07 km^2 during the period 2000–2020. Periodic observation shows that forest cover was 164.04 km^2 (81.22% of total area) in 2005, which decreased to 159.57 Km^2 (79.01% of total area) in 2010 with a 2.21% decrease primarily in the southwestern and northeastern parts of the study area (Figure 6; Table 4).

The forest cover declined further by 3.42% in 2020 with intensified deforestation from the south, and a decline in deforestation from the north. The spatiotemporal LULC mapping reveals that most of the remaining forest cover of the study area is situated primarily in the northern region. The overall and periodic changes in the non–forest cover are the additive inverse of the overall and periodic changes in the forest cover respectively (Table 3). These classified images are designated Actual LULC in Figure 6. Each image was used as the base year to simulate the LULC for the next period i.e., classified image for the year 2000 was used to simulate for the year 2005, classified image for the year 2005 was used to simulate for the year 2010, the classified image for the year 2010 was used to simulate for the year 2015, and that of 2015 for the year 2020 which were in turn termed Simulated LULC.

The result of the spatial simulation of the land-use dynamics in the study area is presented in Figure 7 and Table 3. Simulation accuracy was high for each year shows that the overall accuracy for the simulated land-use changes was 77.46% for the year 2005, 74.1% for the year 2010, 70.98% for the year 2015, and 78.27% for the year 2020.This result in agreement with similar simulation results using cellular automata by Lau and Kam (2005), and Liu *et al*. (2014) by 86 and 85%, respectively.

The land-use changes were parallel for both actual and simulated LULC over the years 2000– 2020. Spatial accuracy was 77.46% for the year 2005, 74.10% for the year 2010, 70.78% for the year 2015, and 78.27% for the year 2020. The study focused on creating a Probabilistic CA model and testing the accuracy of the said model for use in projecting forest cover into the near future (Figure 8; Table 5). Projected forest cover for the year 2025 is 124 km^2, a 27.41% decline from the actual forest cover of the year 2000, and a 5.85% decline from the actual forest cover of the year 2020 while projected forest cover for the year 2030 is 119.223 km^2 a 29.90% decline from the actual forest cover of the year 2000, and an 8.34% decline from the actual forest cover of the year 2020.

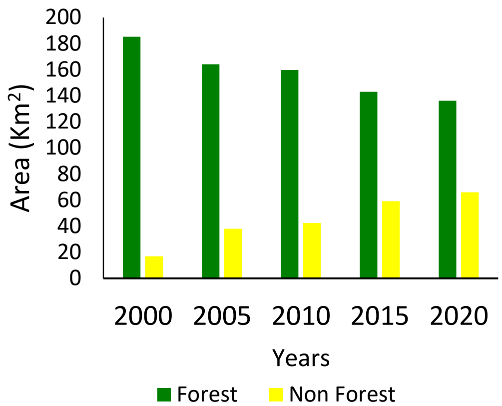

Figure 5: Land use change of Okomu National Park for years 2000 – 2020 showing amount of forest and non-Forest

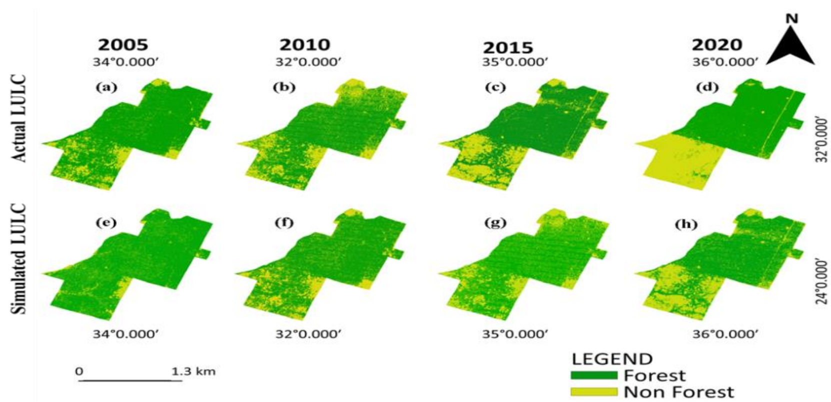

Figure 6: Classified and simulated maps of Okomu National Park (2005, 2010, 2015, 2020). Actual LULC – maps (a – d). Simulated LULC maps (e – h).

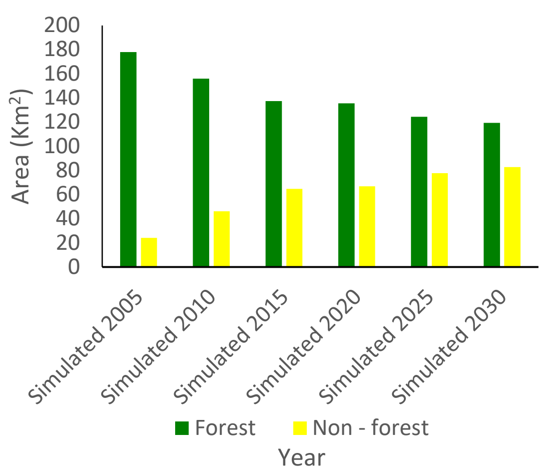

Figure 7: Simulated Past and Futuristic Outlook of Land Use Change of Okomu National Park

Table 2: Land use land cover accuracy assesssment

	ACCURACY (%)	FOREST	NON-FOREST	OVERALL ACCURACY (%)	KAPPA HAT
	Producers Accuracy	99.30	60.69		
2000	Users Accuracy	96.53	88.68	98.18	0.96
	Kappa hat	0.94	0.88		
	Producers Accuracy	97.96	80.30		
2005	Users Accuracy	95.56	90.09	97.52	0.96
	Kappa hat	0.93	0.89		
	Producers Accuracy	92.78	79.26		
2010	Users Accuracy	83.80	74.93	96.33	0.95
	Kappa hat	0.92	0.72		
	Producers Accuracy	82.74	79.30		
2015	Users Accuracy	93.77	74.96	91.66	0.86
	Kappa hat	0.90	0.70		
	Producers Accuracy	93.88	78.78		
2020	Users Accuracy	88.51	88.10	94.61	0.91
	Kappa hat	0.84	0.86		

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Table 3: Cellular Automata Simulation Accuracy for Okomu National Park

	LAND–USE CLASS	REAL	PREDICTED	CONFUSION MATRIX		OVERALL ACCURACY (%)
Simulated	Forest	182268	197742	164710	33032	77.46
2005	Non–Forest	42146	26672	17558	9114	
Simulated	Forest	156446	173135	135730	37405	74.10
2010	Non–Forest	67968	51279	20716	30563	
Simulated	Forest	158867	152540	123138	29402	70.98
2015	Non–Forest	65547	71874	35729	36145	
Simulated	Forest	142534	150405	122092	28313	78.27
2020	Non–Forest	81880	74009	20442	53567	

Table 4: Land use and cover Changesin Okomu National Park

	TYPE	FOREST (km^2)	%	*Δ%	NON – FOREST (km^2)	%	*Δ%
2000	Actual	185.15	88.93	–	16.82	11.07	–
2005	Actual	164.04	81.22	–7.71	37.93	18.78	7.71
	Simulated	177.97	88.11	–0.82	24.00	11.89	0.82
2010	Actual	159.57	79.01	–2.21	42.40	20.99	2.21
	Simulated	155.74	77.15	–10.96	46.15	22.85	10.96
2015	Actual	142.98	70.79	–8.22	58.99	29.21	8.22
	Simulated	137.10	67.97	–9.18	64. 68	32.03	9.18
2020	Actual	136.07	67.37	–3.42	65.90	32.63	3.42
	Simulated	135.30	67.02	–0.95	66.67	32.98	0.95

*Percentage (%) changes

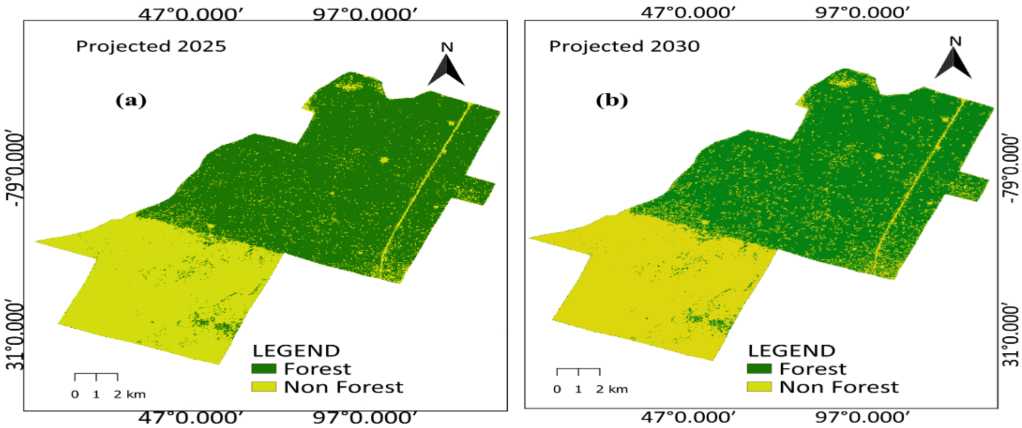

Figure 8: Projected land use changes showing forest and non-forest in Okomu National Parkfor the year 2025 (a) and 2030 (b)

Table 5: Projected land use statisticsin Okomu National Park for the years 2025 and 2030

	TYPE	**FOREST**			**NON – FOREST**		
		AREA (km²)	**%**	***Δ%**	**AREA (km²)**	**%**	***Δ%**
2000	**Actual**	185.15	88.93	–	16.82	11.07	–
2020	**Actual**	136.07	67.37	–21.56	65.90	32.63	21.56
2025	**Simulated**	124.26	61.52	–27.41	77.71	38.48	27.41
				–5.85			5.85
2030	**Simulated**	119.22	59.03	–29.90	82.75	40.97	29.90
				–8.34			8.34

*Percentage (%)changes

CONCLUSION

Understanding future changes in forest cover under various simulation scenarios has important implications for long-term forest management. Anthropogenic-induced land use changes impact negatively on the ecosystem's integrity and productivity and the effect of this change could be severe when the conversion disrupts crucial habitats of major plants and animals (Islam *et al*., 2018).The actual and simulated land-use changes show a steady decline in the amount of forest cover from 185.15 km² in the base year 2000 to 136.07 km² and 135.30 km² for the actual and simulated LULC, respectively in the year 2020. This study has important implications for sustainable forest management in the lowland rain forest areas of Nigeria.It also makes a significant contribution to the United Nations programme on Reducing Emissions from Deforestation and forest Degradation(REDD/REDD+) implementation framework, and as reference scenarios that can be used to build a baseline for REDD/REDD+ incentive payments.

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