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

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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 accuracies were 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 and a 9.20% decline by 2030. The amount of forest cover in the actual and simulated land-use changes shows a gradual drop from 165.15 km² in the base year 2000 to 136.07 and 135.30 km² in the year 2020, respectively. Spatial simulation models, which provide a scientific basis for supporting sustainable forest management based on different simulation scenarios also contribute 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

Okomu National Park is located in Ovia South-West Local Government Area of Edo State. The National Park lies between latitude 6°15’N to 6°25’N and longitude 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 30.2°C 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 secondary datasets 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 non-forest 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 size $3 \times 3$ or size $5 \times 5$ for an extended neighborhood. Also, let $c^t_{i,j}$ be in a state 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:

$$C^t_{i,j} = \begin{bmatrix}
    c^t_{i-1,j-1} & c^t_{i-1,j} & c^t_{i-1,j+1} \\
    c^t_{i,j-1} & c^t_{i,j} & c^t_{i,j+1} \\
    c^t_{i+1,j-1} & c^t_{i+1,j} & c^t_{i+1,j+1}
\end{bmatrix}$$

(1)

$$C^t_{i,j} = \begin{bmatrix}
    c^t_{i,j-1} & c^t_{i,j} & c^t_{i,j+1} \\
    c^t_{i-1,j-1} & c^t_{i-1,j} & c^t_{i-1,j+1} \\
    c^t_{i+1,j-1} & c^t_{i+1,j} & c^t_{i+1,j+1}
\end{bmatrix}$$

(2)

$$C^t_{i,j} = \begin{bmatrix}
    c^t_{i-1,j-1} & c^t_{i-1,j} & c^t_{i-1,j+1} \\
    c^t_{i,j-1} & c^t_{i,j} & c^t_{i,j+1} \\
    c^t_{i+1,j-1} & c^t_{i+1,j} & c^t_{i+1,j+1}
\end{bmatrix}$$

(3)

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

Equation (1) is the $3 \times 3$ Moore Neighbourhood (Weisstein, 2001a), Equation (2) is the $3 \times 3$ von Neumann Neighbourhood (Weisstein, 2001b), and Equation (3) is the $5 \times 5$ Moore Neighbourhood with a Von 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 of states 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 by $S_{t+1}$ is a function of the previous set of states and the chosen neighborhood of each cell (Kumar et al., 2009; Liping et al., 2018).

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

(4)

Such that:

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

(5)

Where $f$ is called the transformation rule of the local space, and Equation (4) is the Cellular Automata Algorithm. 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 $c^t_{i,j}$ 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:

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

(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:

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

(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 Okumu National Park

<table>
<thead>
<tr>
<th>PERIOD</th>
<th>LAND USE</th>
<th>FOREST</th>
<th>NON–FOREST</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000 – 2005</td>
<td>Forest</td>
<td>0.8344</td>
<td>0.1656</td>
</tr>
<tr>
<td></td>
<td>Non-Forest</td>
<td>0.6342</td>
<td>0.3658</td>
</tr>
<tr>
<td>2005 – 2010</td>
<td>Forest</td>
<td>0.7867</td>
<td>0.2133</td>
</tr>
<tr>
<td></td>
<td>Non-Forest</td>
<td>0.3098</td>
<td>0.6902</td>
</tr>
<tr>
<td>2010 – 2015</td>
<td>Forest</td>
<td>0.8173</td>
<td>0.1827</td>
</tr>
<tr>
<td></td>
<td>Non-Forest</td>
<td>0.4561</td>
<td>0.5439</td>
</tr>
<tr>
<td>2015 – 2020</td>
<td>Forest</td>
<td>0.8085</td>
<td>0.1915</td>
</tr>
<tr>
<td></td>
<td>Non-Forest</td>
<td>0.2150</td>
<td>0.7850</td>
</tr>
</tbody>
</table>

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:

\[
\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total Number of Classified Pixels}} \tag{8}
\]

RESULTS AND DISCUSSIONS
Okomu National Park, a lowland 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 of spatial simulation modelling of future forest cover changes of Lao PDR was 80%. Similar classification accuracies using the Probabilistic 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 km² to 136.07 km² during the period 2000–2020. Periodic observation shows that forest cover was 164.04 km² (81.22% of total area) in 2005, which decreased to 159.57 km² (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 is 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 km², 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 km² 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 7: Simulated Past and Futuristic Outlook of Land Use Change of Okomu National Park.
Table 2: Land use and cover accuracy assessment

<table>
<thead>
<tr>
<th>Year</th>
<th>Producers Accuracy (%)</th>
<th>Users Accuracy (%)</th>
<th>Overall Accuracy (%)</th>
<th>Kappa Hat</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>99.30</td>
<td>60.69</td>
<td>98.18</td>
<td>0.96</td>
</tr>
<tr>
<td>2005</td>
<td>95.56</td>
<td>90.09</td>
<td>97.52</td>
<td>0.96</td>
</tr>
<tr>
<td>2010</td>
<td>83.80</td>
<td>74.93</td>
<td>96.33</td>
<td>0.95</td>
</tr>
<tr>
<td>2015</td>
<td>93.77</td>
<td>74.96</td>
<td>91.66</td>
<td>0.86</td>
</tr>
<tr>
<td>2020</td>
<td>88.51</td>
<td>88.10</td>
<td>94.61</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Table 3: Cellular Automata Simulation Accuracy for Okomu National Park

<table>
<thead>
<tr>
<th>LAND-USE CLASS</th>
<th>REAL</th>
<th>PREDICTED</th>
<th>CONFUSION MATRIX</th>
<th>OVERALL ACCURACY (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulated</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2005</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2015</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4: Land use and cover Changes in Okomu National Park

<table>
<thead>
<tr>
<th>TYPE</th>
<th>FOREST (km²)</th>
<th>%</th>
<th>△%</th>
<th>NON - FOREST (km²)</th>
<th>%</th>
<th>△%</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>Actual</td>
<td>185.15</td>
<td>88.93</td>
<td>–</td>
<td>16.82</td>
<td>11.07</td>
</tr>
<tr>
<td>2005</td>
<td>Actual</td>
<td>164.04</td>
<td>81.22</td>
<td>–7.71</td>
<td>37.93</td>
<td>18.78</td>
</tr>
<tr>
<td></td>
<td>Simulated</td>
<td>177.97</td>
<td>88.11</td>
<td>–0.82</td>
<td>24.00</td>
<td>11.89</td>
</tr>
<tr>
<td>2010</td>
<td>Actual</td>
<td>159.57</td>
<td>79.01</td>
<td>–2.21</td>
<td>42.40</td>
<td>20.99</td>
</tr>
<tr>
<td></td>
<td>Simulated</td>
<td>155.74</td>
<td>77.15</td>
<td>–10.96</td>
<td>46.15</td>
<td>22.85</td>
</tr>
<tr>
<td>2015</td>
<td>Actual</td>
<td>142.98</td>
<td>70.79</td>
<td>–8.22</td>
<td>58.99</td>
<td>29.21</td>
</tr>
<tr>
<td></td>
<td>Simulated</td>
<td>137.10</td>
<td>67.97</td>
<td>–9.18</td>
<td>64.68</td>
<td>32.03</td>
</tr>
<tr>
<td>2020</td>
<td>Actual</td>
<td>136.07</td>
<td>67.37</td>
<td>–3.42</td>
<td>65.90</td>
<td>32.63</td>
</tr>
<tr>
<td></td>
<td>Simulated</td>
<td>135.30</td>
<td>67.02</td>
<td>–0.95</td>
<td>66.67</td>
<td>32.98</td>
</tr>
</tbody>
</table>

*Percentage (%) changes
Figure 8: Projected land use changes showing forest and non-forest in Okomu National Park for the year 2025 (a) and 2030 (b)

<table>
<thead>
<tr>
<th>TYPE</th>
<th>FOREST AREA (km²)</th>
<th>%</th>
<th>*Δ%</th>
<th>NON–FOREST AREA (km²)</th>
<th>%</th>
<th>*Δ%</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000 Actual</td>
<td>185.15</td>
<td>88.93</td>
<td>–</td>
<td>16.82</td>
<td>11.07</td>
<td>–</td>
</tr>
<tr>
<td>2020 Actual</td>
<td>136.07</td>
<td>67.37</td>
<td>–21.56</td>
<td>65.90</td>
<td>32.63</td>
<td>21.56</td>
</tr>
<tr>
<td>2025 Simulated</td>
<td>124.26</td>
<td>61.52</td>
<td>–27.41</td>
<td>77.71</td>
<td>38.48</td>
<td>27.41</td>
</tr>
<tr>
<td>2030 Simulated</td>
<td>119.22</td>
<td>59.03</td>
<td>–29.90</td>
<td>82.75</td>
<td>40.97</td>
<td>29.90</td>
</tr>
</tbody>
</table>

*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.

REFERENCES


