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Monitoring and prediction of land cover change in the Anambra River Basin using neural network classification and Ca-Markov model

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ABSTRACT

This study investigates the spatio-temporal variations in land cover within the Anambra River Basin of south-eastern Nigeria at three epochs: 1987, 2000, and 2018. The land cover scenario for 2030 was also predicted. Land cover was extracted using neural network classification, while the prediction was implemented with the Cellular Automata (CA) Markov chain modeling tool in Idrisi TerrSet 18.31 software. Results show that between 1987 and 2018, there was a loss of 1431.73km^2 in the wetlands. In the same period, there was a gain of 214.59km^2, 1,176km^2, 34.72km^2 and 4.19km^2 in the areal extent of built-up areas, vegetation, bare lands, and water bodies respectively. This outcome could be attributed to the rise in the human population within the basin, increasing demand for agricultural land, infrastructural development, and housing. The land cover projection between 2018 and 2030 shows a loss of 0.79km^2, 12.62km^2, and 4.96km^2 in the water bodies, wetlands, and bare lands respectively. In comparison, there was a gain of 23.6km^2 in vegetation. It is recommended that sustainable conservation practices and good land cover management policies be established to safeguard the river basin.

1. Introduction

Land cover change detection is essential for a better understanding of landscape dynamics (Rawat and Kumar, 2015). The neural network classification technique is widely used in land cover change modelling. It uses standard backpropagation for supervised learning, has an easy adaptation to different types of data and input structures, and has good generalization capabilities over statistical and analytic approaches (Huang et al., 2002; Thakur, 2017; Nair, 2016; Boateng et al., 2020).

Simulation of land cover change can provide insights into the pattern and trajectory of future development. Land cover change simulation models can provide probabilistic prediction of where the change may occur (Halmy et al., 2015). The Cellular Automata and Markov Chain (CA-Markov) model is useful in land use policy design, and it may also be used as an early warning system (Parsa et al., 2016). Authors that have applied the CA-Markov model include Subedi et al. (2013), Rendana et al. (2015), Nguyen et al. (2017), Singh et al. (2017) and Koko et al. (2020).

The aim of this research is to monitor land cover changes in the Anambra River Basin between 1987 and 2018, and to predict the future scenario for 2030. The land cover was extracted using the neural network classifier, and the prediction for 2030 was done using the CA-Markov chain technique.

2. Methods

2.1. Study area

The Anambra River Basin is one of the energy-rich inland sedimentary basins in Nigeria and is situated west of the Benue Trough between longitudes 6° 47' 15.47" E to 6° 52' 43.95" E, and latitudes 6° 17' 30.49" N to 6° 21' 33.12" N. The basin covers a total area of approximately 11,179km^2. The basin has a maximum elevation of 600m and a minimum elevation of 3m. It is characterized by two seasons, the dry season (October/November – March) and the rainy season (April –

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September/October), which approximately corresponds to the dry and flood phases of the hydrological regimes of the region. The area has accumulative annual rainfall between 1900 - 2707mm. The study area map is shown in Figure 1.

2.2 Datasets

Landsat 4-5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) imageries covering the study area were downloaded from the United States Geological Survey (USGS) data archive.

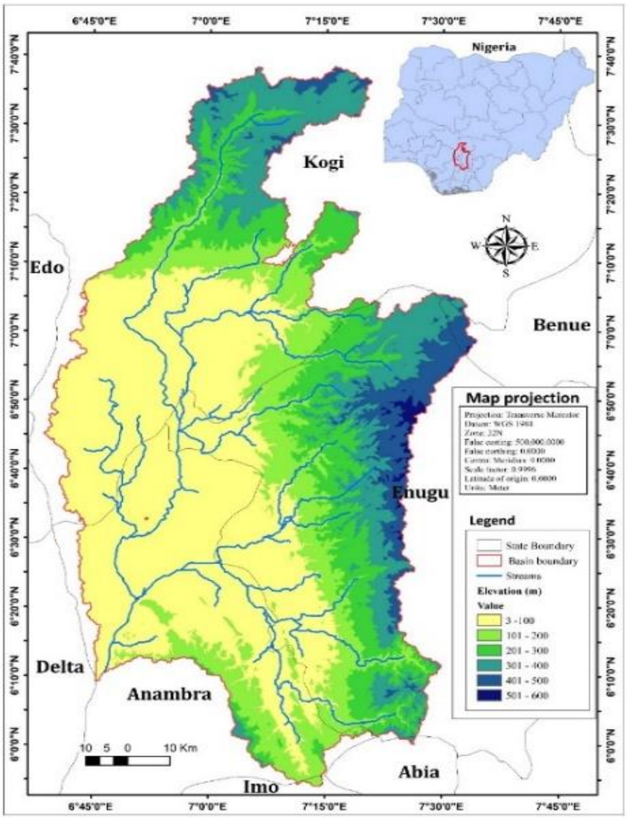

Figure 1. Map of Anambra River basin

2.3 Image Processing and Analysis

The neural network classifier in ENVI 5.3 was adopted for the land cover extraction. Post-classification refinement was performed within ArcGIS software. In the CA-Markov model, the prediction of future land cover changes can be calculated based on the conditional probability formula (Yousheng et al., 2011; Ma et al., 2012):

$$S(t + 1) = P_{ij} \times S(t) \ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

$$P_{ij} = \begin{pmatrix} P_{11} & P_{12} & P_{1n} \\ P_{21} & P_{22} & P_{2n} \\ P_{n1} & P_{n2} & P_{nn} \end{pmatrix} \ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

$$\left(0 \leq P_{ij} < and \sum_{j=1}^{N} P_{ij} = 1, (i, j = 1, 2, \ldots\ldots.n) \right)$$

Where S(t) is the state of the system at time t, S (t +1) is the state of the system at time (t +1), and Pij is the matrix of transition probability in a state. To predict the land cover of 2030, we first predicted the land cover of 2018 so that the performance of the prediction could be compared with the actual data obtained from the image classification. A transition probability matrix for 1987–2000, suitability maps, and a 5 × 5 contiguity filter were used for this purpose. Using the kappa coefficient statistic, a comparison was carried out between the actual and simulated maps of 2018. Based on the successful simulation, the 2018 map was then set as a base map and the transition probability matrix for 2000–2018 was used to simulate land cover for 2030.

To perform the land cover change detection, a post-classification detection method was employed. The area was calculated using the "calculate geometry" function in ArcGIS to populate the field with area values. The statistics shows sum of the area obtained. The area values for all the classes were transferred to a Microsoft Excel worksheet for further analysis.

3. Results

The imageries of the study area obtained for each year were classified and the features were grouped into 5 categories (Waterbody - WB, Built-up area - BA, Wetland - WL, Vegetation – VG, and Bare land - BL) as shown in Figure 2. Table 1 shows that between 1987 and 2018, bare lands, vegetation, built-up areas and water bodies increased by 34.72km^2, 1,776km^2, 214.59km^2 and 4.19km^2 respectively. However, there was a 1431.73km^2 loss in wetlands.

Table 2 shows that between 1987 and 2018, vegetation had the highest probability of 92.37% to remain as vegetation in 2018. Whereas water bodies, built-up areas, wetlands, and bare lands had 73.01%, 50.98%, 42.83%, and 17.20% probabilities respectively to remain unchanged.

Table 1. Changes in land cover area (km^2) for 1987-2000, 2000-2018 and 1987-2018

	1987-2000	2000-2018	1987-2018
WB	4.88	-0.68	4.19
BA	33.14	181.45	214.59
WL	-1377.57	-54.16	-1431.73
VG	1270.49	-94.49	1176
BL	66.73	-32.01	34.72

Table 2. Transition probability matrix for land cover from 1987–2018

Changing from:	Probability of changing by 2018 to:				
1987	WB	BA	WL	VG	BL
WB	0.730	0.002	0.102	0.128	0.038
BA	0.000	0.510	0.000	0.468	0.022
WL	0.002	0.003	0.428	0.567	0.000
VG	0.009	0.025	0.037	0.924	0.014
BL	0.022	0.063	0.000	0.743	0.172

WB - Water body; BA- Built-up area; WL – wetland; VG – vegetation; BL – Bare land

To validate the land cover prediction given by the CA-Markov model, the simulated land cover was compared with the actual land cover (Table 3).

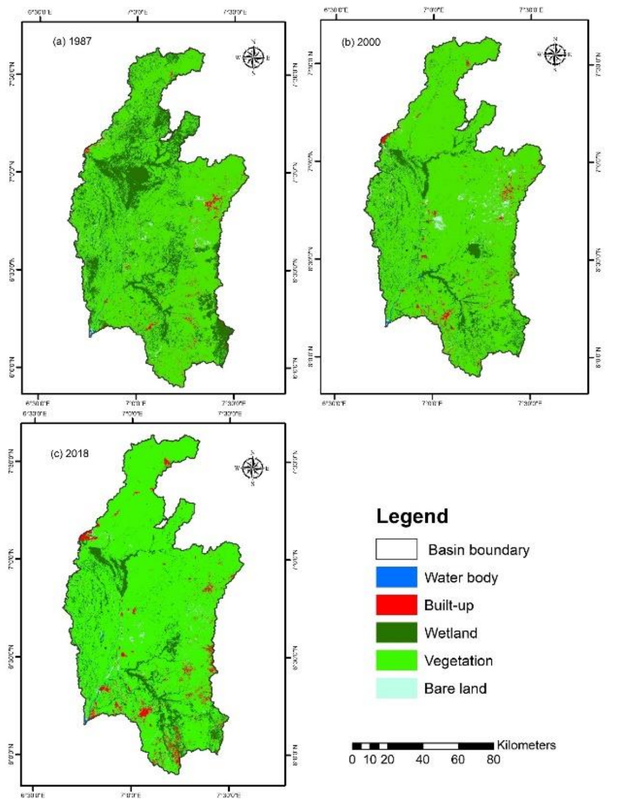

Figure 2. Land cover maps – (a) 1987 (b) 2000 (c) 2018

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Table 3. Comparison of actual and simulated land cover area (km^2) for 2018

Class	Actual 2018	Simulated 2018
WB	45.38	45.82
BA	382.87	199.98
WL	1047.99	1095.17
VG	9549.34	9655.30
BL	153.02	181.88
Total	11178.58	11178.14

WB - Water body; BA- Built-up area; WL – wetland; VG – vegetation; BL – Bare land

Table 3 indicates that water body, wetland vegetation and bare land have agreeable areas. There is a wide gap in built-up areas with 382.87km^2 actual and 199.98km^2 simulated area. A possible explanation for this is that the model was unable to capture random developing areas.

The results in Table 4 show that between 2018 and the projected 2030, there was a decrease in water body, wetland and bare land by 0.79km^2, 12.62km^2, 4.96km^2 respectively. Results also shows an increase in vegetation by 23.60km^2. The decrease in built up areas could be explained by other factors that drive land cover change which are not within the scope of this study.

Table 4. Comparison of 2018 and projected 2030 land cover area (km^2)

Class	2018	Projected 2030	2018 – 2030 change
WB	45.38	44.59	-0.79
BA	382.87	377.93	-4.94
WL	1047.99	1035.37	-12.62
VG	9549.34	9572.94	+23.60
BL	153.02	148.06	-4.96
Total	11178.58	11178.90	+0.32

4. Discussion

The natural environment such as wetland resources have been threatened due to the drastic reduction of 1431.73km^2. The increase in human population attracted infrastructural development and expansion of housing estates in the area, which consequently can have negative influences. The states within the Anambra River basin are known for their intensive agricultural practices such as fishing, field crop farming in small and large scale and animal pastorage etc. This is evident in the increase in vegetation as Government and private sectors are investing heavily in agriculture.

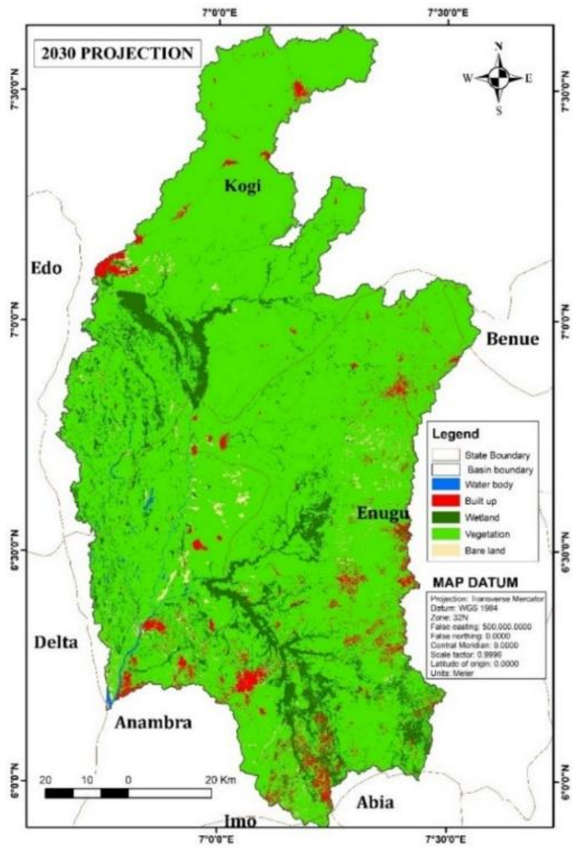

Figure 3. Map showing projected land cover for 2030

5. Conclusion

This research has established the usefulness of spatial and temporal analysis approach in monitoring and predicting land cover change. CA-Markov has proven to be useful in the prediction of land cover change. A further study could employ biophysical, socio-economic and policy-related factors in the prediction.

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