

Towards achieving Sustainability of coastal environments: Urban Growth analysis and prediction of Lagos, State Nigeria

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Abstract

The most extensive urban growths in the next 30 years are expected to occur in developing countries. Lagos, Nigeria - Africa's second most populous megacity- is a prime example. To achieve more sustainable and resilient cities, there is a need for modeling the urban growth patterns of major cities and analyzing their implications. In this study, the urban growth of Lagos state was modeled using the Multi-Layer Perceptron (MLP) neural network for the transition modeling and the Markov Chain analysis for the change prediction, achieving a model accuracy of 81.8%. An innovative visual validation of the model results using the ArcGIS was combined with kappa correlation statistics. The results show that by 2031, built-up areas will be the most spatially extensive LULC class in the study area with percentage coverage of 34.1% as opposed to 9% in 1986. The coverage of bare areas is also expected to increase by 53% between 2016 and 2031. Conversely, 24.9% and 68.3% loss of forestlands and wetlands respectively, are expected between 2016 and 2031. In view of the 11th goal of SDGs which focuses on achieving sustainable cities and communities, the objectives of African Union's Agenda 2063, and based on the urban growth trends observed, the study recommends a prioritization of vertical expansion as opposed to the current horizontal urban growth trends in the study area.

Keywords: *Urbanization growth prediction; Sustainable development; Land Change Modeler; IDRISI Selva; Land use land cover; Coastal cities; Lagos; Markov Chain; Multi-Layer Perceptron; Sustainability; Agenda 2063.*

1. Introduction

A century ago, only 20% of the global population resided in urban areas, but this is projected to reach 70% by the year 2050 (WHO 2010). Globally, the most extensive urban growths between 2014 and 2050 will occur in developing countries, and the leading country is Nigeria (United Nations 2014). It currently experiences the 3rd highest urban growth rate in the world and urban dwellers are

projected to reach 212 million by 2050 (United Nations 2014)- a double-fold increase from slightly over 100 million in 2019 (Worldometers 2019).

Coastal cities are of greater concern due to their significant roles as hubs of international commerce. Hence, coastal cities in many parts of the world experience a relatively higher population and urban growth rates than the national average trends (Wong *et al.* 2014). Three of the megacities (with population > 10 million) to emerge in Africa by 2030, - Lagos, Luanda, and Dar es salam -, are coastal (UNDESA 2018). The population increase experienced by these coastal cities, coupled with climate change-related events aggravate coastal challenges like seawater intrusion and groundwater contamination (Ezekiel *et al.* 2016, Idowu *et al.* 2017), coastal flash floods (Ajibade *et al.* 2013), urban sprawls (Li *et al.* 2016), land subsidence (Showstack 2014) amongst others. These challenges necessitate deliberate and proactive management plans for sustainable development. The Sustainable Development Goals (SDGs) 11 emphasizes the need for proactive actions towards ensuring “*Sustainable Cities and Communities by making cities safe, inclusive, resilient, and sustainable*” (UN 2017). One of the pivotal steps towards achieving this target is the generation of empirical knowledge on spatial changes in land use land cover and the observation of the transformation of these cities (McPhearson *et al.* 2016).

The number of land cover predictive models has increased rapidly in the last two decades because they have been found valuable for urban planning and environmental management (Kumar *et al.* 2015, Giri 2012). The predictive models aid a better understanding of the complex systems and invariably support land use planning and policy decisions (Megahed *et al.* 2015). Verburg *et al.*, (2004) highlights the six important concepts in land use *modeling*- Level of analysis; Level of integration; Spatial interaction and neighborhood driving forces; Cross-scale dynamics; Temporal dynamics; and driving forces. The characteristics of some of the models are also reported in Verburg, *et al.*, (2004) and Table 1 highlights recently used LULC change prediction models and their applications. This paper combined the modeling capabilities of the Land Change Modeler (LCM) in IDRISI with the spatial capabilities of the ArcGIS software to assess the urban growth trend in the study area.

The Land Change Modeler (LCM) is a component of an ensemble software platform - IDRISI (Eastman 2012). IDRISI Selva (version 17), possesses faster processes and additional tools in comparison to previous versions of the software (Clark Labs 2012). This paper 1) explores the effectiveness of a loose coupling of LCM with the ArcGIS for predicting the urban growth change of coastal cities and links the results with sustainable development goals, and 2) identifies some current challenges inherent in the use of the LCM prediction model and areas requiring improvements. Integrating the LCM and ArcGIS platforms has two advantages; 1) the LCM can also be utilized as an extension to ArcGIS and 2) ArcGIS has the capability to summarize LULC areas based on the number of pixels, generate tables and export to excel which is not currently achievable with the LCM in IDRISI.

Table 1: Predictive models currently in use and their applications

Model	Study Area	Land change application	References
MC – CA ¹	Su-Xi-Chang region, China, Harbin prefecture, China	LULC prediction for Ecosystem Services	(Yirsaw <i>et al.</i> 2017) (Gong <i>et al.</i> 2015)
LCM ²	Asmara, Eritrea, Cairo Egypt	Urban growth prediction	(Tewolde & Cabral 2011) (Megahed <i>et al.</i> 2015)
LTM-MC	SEWI ³ , & MRW ⁴ , Michigan, USA	Modeling multiple Land cover types	(Tayyebi & Pijanowski 2014)
SLEUTH ⁵	Rajasthan (India)	Urban growth prediction	(Jat <i>et al.</i> 2017)
CLUE ⁶ & CLUE-S	Farmlands in Europe, Romania	Modeling future dynamics of Land use and cover types	(Verburg & Overmars 2009) (Grigorescu <i>et al.</i> 2019)

¹ MC-CA: Markov Chain-Cellular Automata; ² LTM-MC: Land Transformation Model-Multiple Classifications; ³ SEWI: South-Eastern Wisconsin; ⁴ MRW: Muskegon River Watershed; ⁵ SLEUTH: “Slope, Land use, Exclusion, Urban extent, Transportation and Hill shade”; ⁶ CLUE: Conversion of Land Use and its Effects *modeling* framework

2. Study area

Lagos is a coastal megacity located slightly above the equator in southwest Nigeria (Fig. 1) and is one of three megacities in Africa alongside Cairo and Kinshasa (UNDESA 2018). It is currently the second most populous city on the continent (after Cairo) with a population growth rate of 6 – 8% per annum which is more than twice the national average of 2.6% per annum (UNDESA 2018, The World Bank 2019). It is a low lying coastal plain, characterized by a flat topography with notable geographical features such as; the mainland, lagoon, creeks, wetlands, seaports, several small Islands, and reclaimed lands such as the Banana Island and Eco Atlantic City. Although it is the most populous state in Nigeria, its 3,577km² land area is only about 0.4% of the country’s landmass (MPPUD 2016). Urbanization expressed as the outward expansion of built-up areas and the conversion of primary agricultural and forestlands into industrial and residential uses (Opoko *et al.*, 2014), and land reclamation activities are visibly evident in Lagos Nigeria (Idowu & Home 2015).

Lagos state’s status and relevance as the commercial, business, and financial hub of Nigeria and sub-Sahara Africa (MPPUD 2016) makes it a pivotal point of reference for the African Union's 2063 Agenda to become more prosperous through sustainable development and all-inclusive growth (African Union Commission 2015). The success of the agenda is contingent upon the effective management of the urban growth of its cities and megacities.



Figure 1: Location map of Lagos, Nigeria.

3. Methodology

3.1. Data

Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) images were obtained for the years 1986 and 2001 while multi-sensor SENTINEL 2A data was acquired for the year 2016. The years were chosen based on the availability of cloud-free images at 15 years intervals. The images were obtained from the United States Geological Survey's portal (USGS 2020) and the Copernicus Open access hub (ESA 2020). The ancillary data such as the Digital Elevation Model (DEM) and the road layers were downloaded from the United States Geological Survey and *Geofabrik* platforms respectively (USGS 2017, Geofabrik 2017). All datasets were in the World Geodetic System (WGS) 1984, UTM Zone 31N coordinate system.

3.2. Methods

An object-based image analysis and post-classification comparison were performed on the multi-temporal datasets for the three years - 1986, 2001, and 2016- to obtain the LULC maps of each year (Idowu *et al.* 2020). The maps contain six LULC classes- bare areas, built-up areas, forestlands, shrublands, waterbodies, and wetlands, according to the CORINE classification nomenclature as described in an earlier study (Idowu *et al.* 2020). The TIFF formats of the 1986 and 2001 LULC maps were subsequently imported into IDRISI where they were first converted into RST before uploading on the Land Change Modeler. The comparative LULC changes were analyzed and subsequently, the transition potentials and sub-models were generated, forming the basis for creating the predicted 2016 LULC by the model. The model's accuracy was assessed by validating the

predicted 2016 with the actual 2016 LULC map. Once validated, the model was used to predict urban growth by the year 2031. Fig. 2 gives an overview of the steps taken in the modelling process.

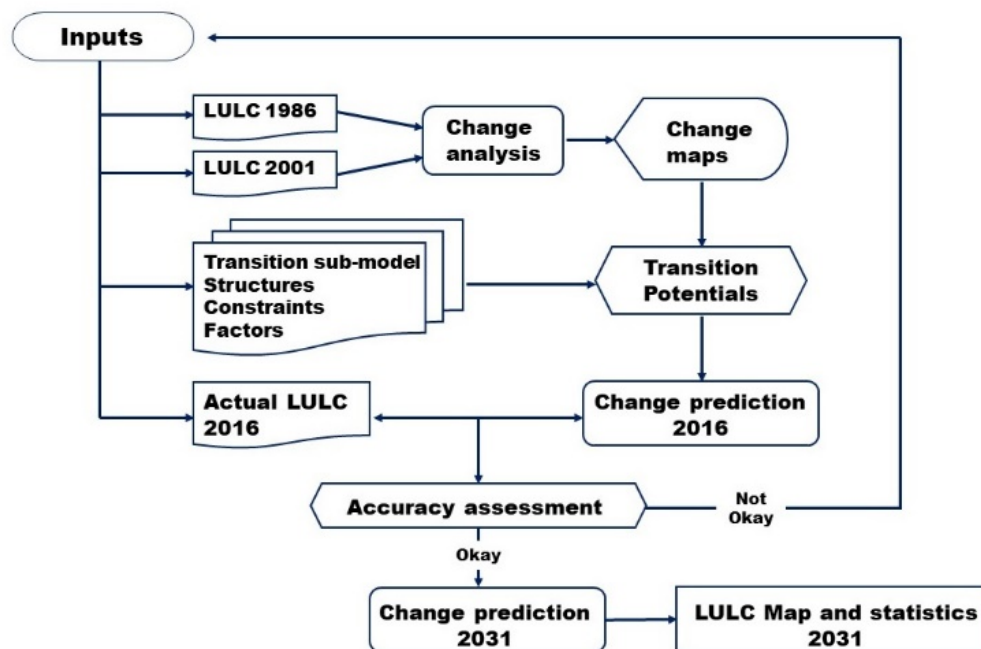


Figure 2: Methodology flowchart for the urban growth prediction

3.3. LCM model implementation

The model's four major procedures which include; Change analysis; transition potential modeling and driving forces determination; change prediction; and model validation are well detailed by Eastman, (2012).

3.3.1. Change analysis

The changes being investigated include gains and losses in each LULC class, the net changes in each class, and the contributors to the changes. At this stage, the analyzed changes in the LULC between the 1986 and 2001 maps helped identify transitions from one land cover type to another. The process was crucial in identifying the dominant transitions contributing to urbanization which formed the basis for the resulting transition sub-models created. It was observed in previous studies that one of the major drivers of land-use change in Lagos, Nigeria is accessibility (Braumoh & Onishi 2007). Hence, ancillary data - DEM and road layers - were entered to account for the impact of topography and road development on possible urban growth. These data act as structures and factors for guiding the creation of the transition sub-models.

3.3.2. Transition potential modeling and driving forces determination

The transition potential modeling helps to determine the location of the change, and it results in the generation of transition potential maps (Eastman 2012). The driver variables are either static or dynamic and natural or anthropogenic driven. In this study, the dominant driving force was urbanization induced by an increase in population and evidenced by the transition of other land cover categories into built-up and bare areas. One of the challenges encountered in LULC change prediction is the need to account for the dynamic nature of land cover change where the different land cover types transition into each other simultaneously. The multi-layer perceptron (MLP) neural network module in the LCM addresses the challenge in that it can model multiple transitions into a single sub-model. Therefore, the MLP was used to model the transitions and develop the transition sub-models in this study. In ensuring optimum accuracy of the transition sub-models, the *variable transformation utility* (VTU), based on evidence likelihood transformations was run to address issues of non-linearity in the transition sub-model. The Cramer's V obtained from the VTU is a correlation coefficient ranging from 0.0 to 1.0 indicating *no* and *perfect* correlation, respectively (Eastman 2012). Cramer's V does not necessarily imply a high performance, but it acts as a guide in determining if a driving force is worth considering or not (Khoi & Murayama 2010, Eastman 2012).

3.3.3. Change prediction

The predicted change in each transition was modeled using the Markov chain analysis. Markov Chain is a random procedure that measures the expected transitions to the predicted date based on the projections of the transition potentials (Mishra *et al.* 2014). The two basic models of change- the *hard* and *soft* prediction models were obtained. The *hard* prediction yields LULC maps with discrete values and similar legends to the input maps while the *soft* produces a vulnerability map with continuous pixel values of probability of change from 0 to 1.

3.3.4. Model validation/accuracy assessment

The two broad types of validation are visual and statistical validations. The VALIDATE module in the LCM, a visual validation process was used to analyze the degree of agreement between the reference (actual) and the predicted 2016 maps by generating a map of correctness and error. Statistical validation is based on Kappa correlation statistics. These statistics include K_{no} , $K_{location}$, and $K_{standard}$, where K_{no} reflects the overall accuracy of the simulation run; $K_{location}$ measures the level of agreement of location and $K_{standard}$ is the ratio of the proportion assigned correctly to the proportion which is correct by chance (Tewolde & Cabral 2011, Megahed *et al.* 2015). Some predictive studies employed the statistical approach only (Feng *et al.* 2016, Hamdy *et al.* 2016), while some utilized the visual validation method only (Mahmoud *et al.* 2016). Few studies adopted both approaches but were not elaborate with the detailed steps taken (Megahed *et al.* 2015). This study combined both and went further by using the ArcGIS to analyze the map of correctness and error to determine the Hits, Null

success (persistence), Misses, and False alarms. Hits and persistence represent the correctness of the predicted map while the misses and false alarms represent the discrepancy between the predicted map and the actual map (Megahed *et al.* 2015). Once the visual and statistical validations were found satisfactory, the model was used to predict the LULC map of 2031.

4. Results

The results of the hard prediction which yields discrete values like the LULC input maps show that from 2016 to 2031, the LULC is likely to undergo drastic changes towards massive urbanization and deforestation (Table 2). Increases in bare areas which may be due to land reclamation activities and built-up areas are direct indicators of urbanization. On the other hand, the losses in forestland and gradual increase in shrublands – *areas dominated by low lying plants with few scattered trees such as agricultural lands and developing areas*- are pointers to deforestation.

Over 30% (>28,000ha) and 50% (>17,000ha) increases in built-up and bare areas, respectively are expected between 2016 and 2031 (Table 2). There may be wetland losses of almost 70% (>600ha), while further deforestation (over 35,000ha loss) may occur in the same period.

Table 2: Comparison of the LULC Maps in 1986, 2001, 2016 and the predicted 2031 map

LULC CLASS	1986		2001	2016	2031		Changes (2016 to 2031)	
	(Ha)	(%)	(Ha)	(Ha)	(Ha)	(%)	(Ha)	(%)
Bare Area	627.2	0.2	1,423.9	3,313.4	5068.1	1.4	1754.8	53
Built Up Area	32,200	9.0	59,878.6	93,113.2	121,918.5	34.1	28,805.3	30.9
Forestland	227,390.6	63.6	189,426.6	143,848.8	108,086.9	30.2	-35,761.9	-24.9
Shrubland	13,653.8	3.8	24,375.8	36,914.7	43,274.3	12.1	6359.7	17.2
Waterbody	81,621.9	22.8	80,773.5	79,647.8	79,098.2	22.1	-549.6	-0.7
Wetland	2,235.5	0.6	1,849.7	890.1	282	0.1	-608.1	-68.3
TOTAL	357,728	100	357,728	357,728	357,728	100		

NB: Ha = Hectares; % = percentages

The waterbodies in the study area mainly comprise the lagoon and the creeks found in different parts of Lagos state. The progressive losses (although <1%) over the years can be attributed to the land reclamation activities and widespread floating informal settlements sprawled on these water bodies. The LULC in 2016 and the predicted LULC map by the year 2031 are represented in Fig. 3.

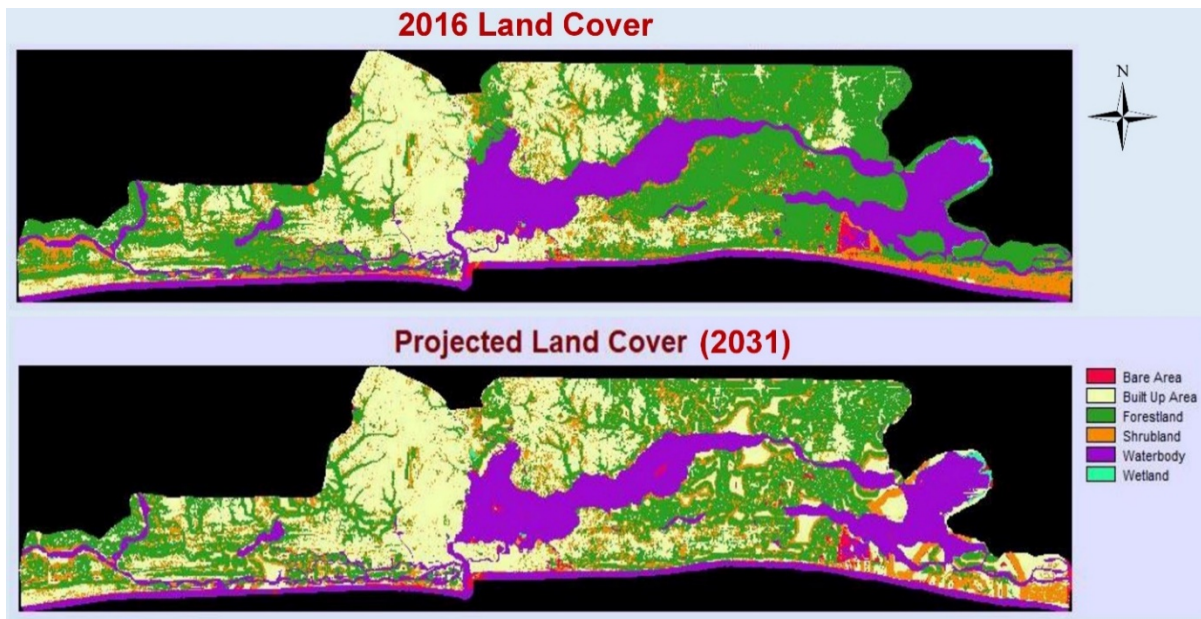


Figure 3. The LULC Maps for 2016 and the predicted 2031

The prediction results indicate that by 2031, built-up areas will likely have surpassed forestlands and waterbodies as the most extensive LULC coverage in the study area at 121,918.5ha (about 34%). To put that in perspective, built-up area coverage was only 9% (32,200ha) of the total land cover in 1986. In contrast, massive deforestation (>35,000ha loss) may occur in the same period with a decrease from 143,848.8ha (40%) to 108,086.9 (30%). When Fig. 3 is compared with actual administrative maps, the projected urban growth trend are evident in areas such as the Badagry axis; areas along the Lagos – Badagry express road including Agbara; Ikorodu / Ibese axis and areas along the Ikorodu – Epe road; areas along Lekki – Epe express road; and the Lekki lagoon’s environs.

Therefore, as with the changes observed between 1986 and 2016, the model predicts that between 2016 and 2031 there will be net gains in shrublands, built-up and bare areas, massive losses of forestlands and wetlands, and slight losses in waterbody areas (Fig. 4). The most significant gains and losses between 1986 and 2016 were built-up areas and forestlands, respectively (Fig. 4a) and this trend is likely to continue (Fig. 4b) but the rapid losses in forestlands to other LULC classes will contribute to the emergence of built-up areas as the most spatially extensive land cover type by 2031 (Table 2). Built-up and bare area coverage may give a combined coverage of 126,986.6ha which is about 35.5% of the entire LULC of the study area. Fig. 5 shows the contributions to the transitions into each LULC class with Fig. 5a showing that the losses of forestlands will largely be to built-up areas, followed by shrublands and bare areas. These gains in built-up areas, shrublands, and bare areas at the expense of the forestland are clear indicators of rapid urbanization and it is also reflected in Fig. 5c where the main contributor to built-up areas are forestlands, shrublands, and bare areas. Also, the possible losses in waterbodies are due to an increase in built-up and bare areas (Fig. 5d).

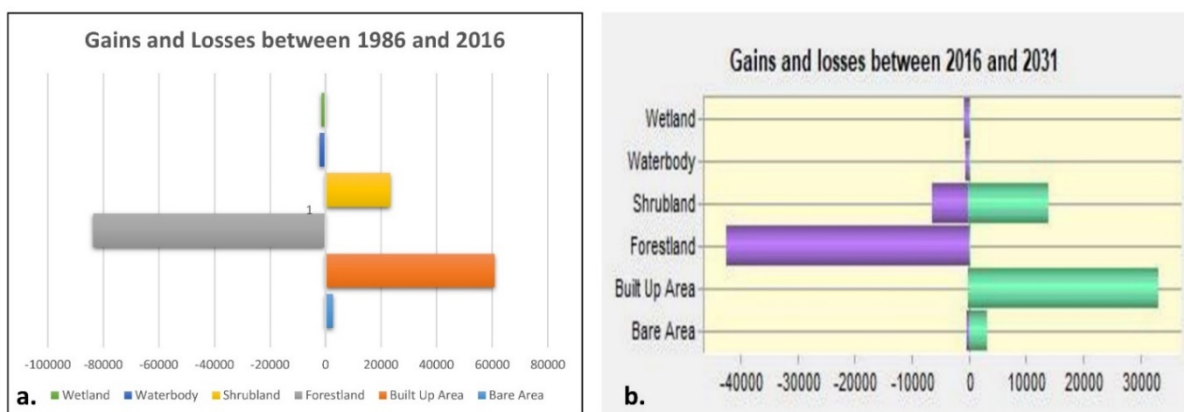


Figure 4: Gains and losses in the LULC Classes between a) 1986 and 2016; b) 2016 and 2031

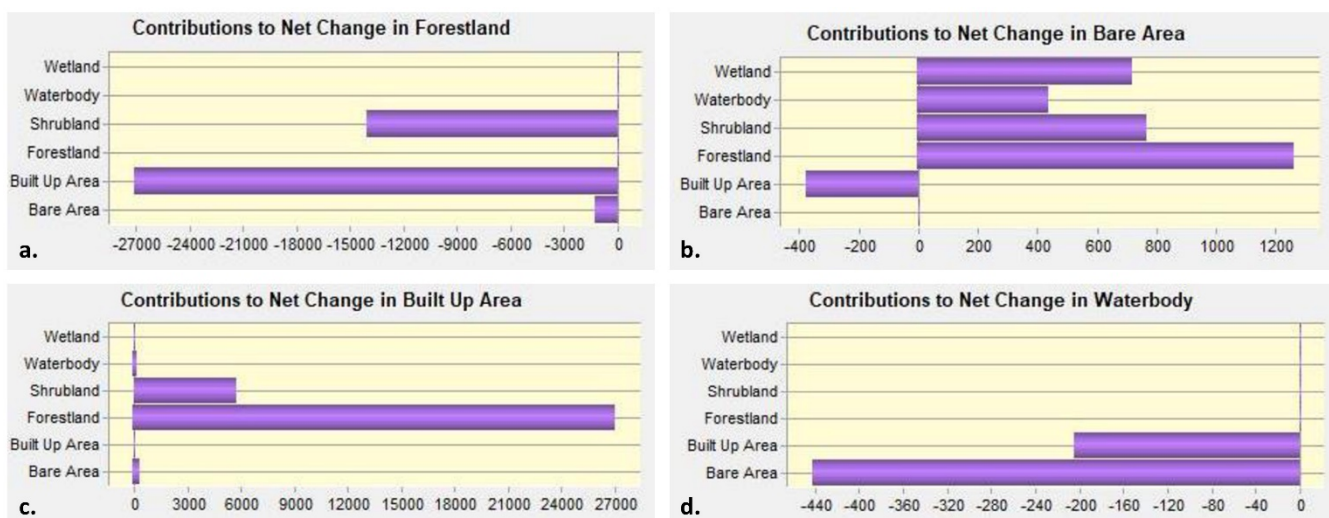


Figure 5: Contributors to the net changes in (a) Forestlands (b) Bare areas; (c) Built-up areas; (d) Waterbodies in Lagos from 2016 to 2031 (in Hectares).

4.1. Transition potential sub-model and model validation

An overall Cramer’s V of 0.53 and 0.55 were obtained for 1986 - 2001 and 2001 - 2016, respectively. Cramer's V of over 0.4 is considered highly suitable (Eastman 2012). Values ranging between 0.50 and 0.97 were observed for wetlands, forestlands, shrublands, and waterbodies. It suggests that these LULC classes experienced sizeable transitions into built-up areas during the period under study. The model’s accuracy was 81.84% (>80%) with training and testing errors of 0.1537 and 0.1539, respectively. The ArcGIS-based results of the map of correctness and error showed predicted map correctness of 71.4% (hits and persistence), while the misses and false alarms were 13.0% and 15.6% respectively. The statistical validation yielded high accuracy values of 80%, 84%, and 77% for the K_{no} , $K_{location}$, and $K_{standard}$ kappa values, respectively.

5. Discussion

Urban growth *modeling* in Lagos state is only just evolving. The earliest study on urban growth modeling in the study area was focused on the viability of cellular automata (CA) for simulating urban growth (Barredo *et al.* 2004). The more recent urban growth modeling and prediction study by Eyoh *et al.*, (2012) only focused on Lagos metropolis and not the entire study area by loosely coupling a logistic regression model in MATLAB with the ArcGIS. This paper goes further by *modeling* the urban growth of the entire Lagos state using the Multi-Layer Perceptron (MLP) neural network for the transition *modeling* and the Markov Chain analysis for the change prediction on the LCM. The 81.84% model accuracy and kappa correlation statistics of 80%, 84%, and 77% for the K_{no} , $K_{location}$, and $K_{standard}$ values, obtained between the predicted and reference maps in this study are relatively higher than that of earlier studies. For instance, a Kappa Statistics value of 0.6998 (69.98%) was obtained between the reference and predicted map Eyoh *et al.*, (2012) while *k*-statistic values ranging from 0.63 to 0.88 and an average value of 0.77 were obtained for the land cover classes in Barredo *et al.*, (2004).

However, the findings of both studies show an upward trend in urban growth. For instance, Barredo *et al.*, (2004) predicted a 116% increase in informal settlements between the years 2000 and 2020, and similarly, Eyoh *et al.*, (2012) predicted an urban expansion of 129.49% between 1984 and 2030. Similarly, this paper shows that built-up areas represented 32,200ha in 1986, stood at 93,113.2ha in 2016, and is projected to reach 121,918.5ha by 2031 implying an increase of well over 200% in built-up areas (bare areas excluded). The study also shows that the transformation into urban areas will be more pronounced in the rapidly developing areas outside the metropolis. This confirms a cross-boundary study by Wang and Maduako, (2018) where it was concluded that over 75% of the urban growth expected between 2015 and 2030 will occur in neighboring Ogun State. However, other parts of the country showed relatively lower urban growth rates such as Akure – 53.41% increase between 2014 and 2034 (Owoeye & Popoola 2017); Ibadan Northwest – a combined 19% increase in bare, built-up and shrublands and a combined 25% loss in thick forest, waterbodies, and wetlands between 2000 and 2021 (Adebola *et al.* 2015); and Greater Port Harcourt – an 80% increase in urban areas between 2003 and 2060 (Dan-Jumbo *et al.* 2018).

Finally, while carrying out the modeling exercise, the major challenge observed in the IDRSSI-based LCM is its limited compatibility, as it only accepts TIFF raster files, therefore, the interaction between the stand-alone software and other software platforms is not yet seamless and needs improvement. Overall, the high model accuracy obtained in this study demonstrates the effectiveness of the loose coupling of LCM and ArcGIS while the findings shows the strong need for sustainable land use management to forestall further deforestation, losses of wetlands, and the effective management of the health and livelihoods of the burgeoning population.

6. Conclusion and recommendations

This study focused on the urban growth prediction in the study area by the year 2031. Between 1986 and 2016, there were net increases in bare areas, built-up areas, and shrublands, and a general decline in forestlands, waterbodies, and wetlands. The urban growth modeling shows that these trends are likely to continue into 2031 except drastic and proactive measures are taken. According to the analyses, bare and built-up areas will increase by 1754.8ha (53%) and 28,805.3ha (31%), respectively between 2016 and 2031. On the other hand, a wetland loss of 608.1ha (68.3% loss) should be expected. These do not only have socioeconomic implications but also ecological. Also, by achieving high model accuracy (>80%) and kappa statistics (>75%), the study demonstrates the effectiveness of loosely coupling the LCM (using the Multi-Layer Perceptron (MLP) neural network for the transition *modeling* and the Markov Chain analysis for the change prediction) with the ArcGIS for LULC Map statistics estimation. However, the quality and reliability of the outputs of current models can still be improved by introducing more input data. Nevertheless, since this study provides insights on the trends in urbanization, it will contribute to the achievement of goal 11 of SDGs which focuses on achieving sustainable cities and communities. At the continental level, the achievement of African Union's Agenda 2063- *a 50year development plan geared towards creating a dependent and prosperous Africa* (African Union Commission 2015)- will be hinged on timely and accurate predictive information data. Hence, this study's findings can be incorporated while making infrastructural plans for the next decade as it provides pointers to where possible expansions will be concentrated. Finally, to curtail the potentially massive deforestation (>35,000ha), which is largely at the expense of the gains in built-up areas, it is recommended that vertical expansion in the form of high-rise green buildings be prioritized as against the horizontal urban growth and urban sprawl trend currently being experienced.

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