Spatio-temporal urban growth dynamics of Lagos Metropolitan Region of Nigeria based on Hybrid methods for LULC modeling and prediction

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ABSTRACT
An accurate information on the amount and location of Land use and land cover (LULC) changes is necessary to develop and implement a sustainable-urban planning. This research investigates the potential of an integrated Multi-Layer Perceptron and Markov Chain Analysis (MLP-MCA) to map and accurately predict the future LULC change scenarios in Lagos Metropolitan Region of Nigeria. Multi-temporal LULC datasets derived from remotely sensed Landsat images from 1984, 2000 and 2015 were used for modeling, validation and prediction. Predicted LULC changes for 2030 and 2050 were performed based on the LULC map of 2015 using MLP-MCA method. The result reveals a significant expansion of built-up areas during the whole study period. Analysis of LULC distribution in Lagos metropolitan region shows that about 50% of urban land expansion happened beyond the administrative boundary of Lagos State during the period of 2000–2015. It is predicted that more than 75% of future urban growth will occur across the border of Lagos State, in the neighbouring Ogun State by 2050. These results imply that a strong and consistent collaboration between different states is crucial to establish an effective regional planning framework and ensure a proper planned growth of the metropolitan region.

Introduction
Today, urban growth is one of the most important issues in Africa. According to the prediction of the United Nations, the population of Africa will double within the next 40 years: from about 1 billion in 2010, Africa is expected to reach 2 billion inhabitants around 2045 (United Nations Population Division, 2010). In 1950, only two African cities accommodated more than 1 million residents. By 2010, this number has reached 48, and it is predicted to increase to 68 by 2025 (UN-Habitat, 2008). Present urban growth in Africa is driven by both high natural growth rates and the concurrent rural-urban migration (UN-Habitat, 2010)

Most of this rapid urbanization will take place on agricultural land, vegetation and other natural land cover. It is shown that the rate of urban physical expansion is much faster than urban population growth in many cities (Seto, Sánchezrodríguez, & Fraggias, 2010), which is often referred to as urban sprawl, presenting the increasing pressure on land resources. The increasing scarcity of limited land resources due to anthropogenic activities – particularly by urban growth – has not been given enough attention, which poses a great challenge to achieve the goals of sustainable development (Haber, 2007).

Across the continent, Lagos has been one of the largest and fastest-growing cities. Nowhere in West Africa is the urban growth in the last few decades as unprecedented as Lagos. As the economic focal point of Nigeria and the West Africa sub-region, the Lagos metropolitan region has been the hub of intense settlement, the prime destination of local and international migrants (Braimoh & Onishi, 2007). The remarkable population growth adds to the ever-increasing pressure on urban land supply with profound environmental implications. Inadequate housing and infrastructure, slum proliferation, haphazard land development, incessant flooding, widespread poverty and unemployment are among the major issues of unsustainable urban growth requiring the intervention of town planners and decision makers. Actually, for a long time, Lagos has been described as a laissez-faire megacity (Okwuashi, 2011); and the issues and challenges of urban sprawl in Lagos are generally perceived as intractable problems (Abiodun, 1974; Gandy, 2006).

In developing countries’ large cities such as Lagos, the lack of timely, accurate and credible data on the location, spatial extent, rate and driving factors of urban growth has always been a crucial obstacle for implementing suitable and effective planning policies and city management. Given the fact that dynamic spatial-temporal change process of urban development cannot be prevented, modeling, simulation
and prediction of cities’ future growth would be applicable as a powerful planning tool to understand the interactions between the natural and anthropogenic environment, and the problems arising from rapid urban growth. Therefore, clarification and prediction of the Land Use and Land Cover (LULC) change are crucial to present a holistic and principled view on more efficient management of natural resources, protection of agricultural land and adoption of long-term sustainable policies to minimize the impacts of human activities on environment (Norman, Feller, & Guertin, 2009).

In the last 20 years, remote sensing (RS) and geographical information systems (GIS) have been acknowledged as powerful and effective tools for the management of land and other natural resources. These technologies have proved their efficacy for updating and managing spatial data in developing countries by providing the advantage for rapid data acquisition to collect LULC information regularly at a much lower cost than traditional ground survey methods (Dong, Forster, & Ticehurst, 1997). The application of RS and GIS in urban and environmental planning has led to the formation of spatial modeling methods as a decision support tool, such as Markov chain (MC) model (Arsanjani, Kainz, & Mousivand, 2011), logistic regression (LR) model (Hu & Lo, 2007), artificial neural network (ANN) model (Maithani, Arora, & Jain, 2010; Pijanowski, Brown, Shellito, & Manik, 2002), cellular automata (CA) model (Clarke, Hoppen, & Gaydos, 1997; Kamusoko, Aniya, Adi, & Manjoro, 2009; Yuan, 2010), a modified cellular automata-based SLEUTH model (Clarke et al., 1997; Hua, Tang, Cui, & Yin, 2014) and conversion of land use and its effects (CLUE) model (Veldkamp & Fresco, 1996; Verburg et al., 2002). These models have proved their capability in providing a quantitative tool to facilitate the decision-making process for urban and environmental planning, and suitability assessment of lands for development, which is essential to the efficient management of a large metropolis (Yang, 2002).

Alternatively, the limitations of individual model are also discussed in many studies (Araya & Cabral, 2010; Balzter, 2000; Triantakonstantis & Mountrakis, 2012). Therefore, the integrated modeling approaches are widely used for LULC change simulation and projection to overcome the limitations of individual models (Al-Sharif & Pradhan, 2015; Basse, Omranı, Charif, Gerber, & Bódis, 2014; Guan et al., 2011; Mishra, Rai, & Mohan, 2014).

There is no doubt that modeling the urban land use dynamics of an area such as Lagos requires the employment of robust techniques and tools that can model the growth, complexity and dynamics of the city (Barredo, Demichelis, Lavalle, Kasanko, & McCormick, 2004). Several studies have revealed that the integrated Multi-Layer Perceptron-Markov chain analysis (MLP-MCA) method is a robust tool to quantify and model the spatio-temporal LULC changes that combines remote sensing and GIS efficiently (Ahmed & Ahmed, 2012; Mishra et al., 2014; Oztürk, 2015). In the MLP-MCA hybrid model, the MLP neural network is trained by supervised backpropagation (BP) algorithm with efficient generalization capability for each LULC transition and simulation (Maithani, 2015), while the MCA model determines transition probability areas to predict likely LULC changes in the future (Dadhich & Hanaoka, 2011).

The objective of this study is to analyze and simulate LULC changes in Lagos Metropolitan Region from 1984 to 2015 and then predict scenarios of future LULC changes quantitatively and spatially for 2030 and 2050 based on MLP-MCA methods. The results show that many LULC classes will change significantly. This kind of analytical study also gives a better understanding of the functions of the land use systems and the support needed for planning and policy making for sustainable development.

Study area

Located in the south-west part of the Nigerian Federation, Lagos has a complicated administrative structure: Lagos refers to both a city and a state. Lagos State lies approximately between latitudes 6°37’N and 6°70’N and longitude 2°70’E and 4°35’E, with a territory of 3577 km² including 2798 km² land areas and 779 km² waterbodies. It is bordered on the west by the Republic of Benin, and on the north and east by Ogun State of Nigeria, with its southern boundary formed by the Atlantic coastline. It is characterized by a relatively flat terrain (mean elevation of approximately 24 m) and littoral depositional landform features: wetlands, islands, beaches, low-lying tidal flats and estuaries (Figure 1).

In the 2006 census, Lagos State was reported to have a population of 9 million inhabitants although the figure has been contested by Lagos State government, who argues that Lagos State accommodates more than 20 million people. Nonetheless, Lagos is one of the most populous and fastest-growing urban areas in the world (United Nations, 2014). Within Nigeria, Lagos, as a state capital, has a high concentration of administrative, commercial and industrial functions. As an urban conurbation, Lagos is currently expanding inland, forming an urban corridor linking Lagos with cities in the hinterland, notably Ibadan. There is no single administrative unit covering the entire metropolitan region. Within Lagos State, the metropolitan region covers approximately 16 out of the 20 Local Government Areas,
accommodating about 90% of the state’s total population (Rigon et al., 2015). Now the urban expansion has extended beyond the territory of Lagos State and engulfed separate towns and settlements of Ogun State.

Thus, the Lagos metropolitan region as mentioned in this study refers to not only the islands of the former municipality of Lagos, the mainland suburbs such as Mushin, Ikeja and Agege within Lagos State, but also the adjacent towns and settlements in Ogun State that have been fully integrated into the urban fabric. Specifically, the study covers an area of 80 km × 60 km including Lagos metropolis and its surrounding areas in Lagos State, part of the neighbouring Ogun State including Ado-Odo/Ota, Ifo, Obafemi Owode, Sagamu Local Government Area, etc.

Data and methodology

The methodology of this study is based on the evaluation of LULC changes, LULC analysis, LULC change potential modeling and LULC change prediction of Lagos Metropolitan Region using remote-sensing data analysis, GIS and MLP-MCA methods as shown in Figure 2, which will be discussed in details in the following sections.

Image pre-processing and LULC classification

In this study, digital remote-sensing data of the Landsat series satellites were used to map various LULC classes in Lagos Metropolitan Region, Nigeria. Landsat is among the most widely used satellite remote-sensing data, and its long-term
continuous availability, cost-effectiveness, and timeliness made it invaluable resource for monitoring LULC change. General technical information on Landsat data has been presented in vast literature (Chander, Markham, & Helder, 2009; Markham & Helder, 2012; Modica et al., 2016; Roy et al., 2014). Satellite images of Landsat-5 Thematic Mapper (Landsat TM) (1984), Landsat Enhanced Thematic Mapper Plus (Landsat ETM+) (2000) and Landsat Operational Land Imager (Landsat OLI) (2015) images were collected from the official website of US Geological survey (USGS). The details of remote-sensing data used in this study are listed in Table 1. Other data used in the study include digital elevation model (DEM) and road networks. The ASTER DEM of 30-m spatial resolution data was downloaded from USGS website and used for generation of slope and elevation. The shape files of the roads are extracted from the Google Earth image.

All images were spatially referenced in the Universal Transverse Mercator (UTM) projection system within zone 31 north with World Geodetic System (WGS) 1984 (EPSG: 32,631), and the spatial resolution is 30 m. A series of image pre-processing steps, including atmospheric correction, cloud and

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### Table 1. Details of satellite data used in the study.

| Satellite sensor | Path/row | Data acquired | LULC map naming | Spatial resolution (m) |
|------------------|----------|---------------|-----------------|-----------------------|
| Landsat TM       | 191/55, 191/56 | 18/12/1984 | LULC 1984    | 30                    |
| Landsat ETM+     | 191/55, 191/56 | 06/02/2000 | LULC 2000    | 30                    |
| Landsat OLI_TIRS | 191/55, 08/12/2015 | 2015 | LULC 2015 | 30                    |
cloud shadow detection, and composite/fusion/metrics techniques were performed for Landsat images before applying change detection algorithms (Chander et al., 2009; Zhu, 2017). Bands 4, 3 and 2 for Landsat TM and ETM+ images, and bands 5, 4 and 3 for Landsat OLI_TIRS image were adopted to generate false colour composite images, respectively.

The classification of Landsat imagery was carried out with ERDAS Imagine V. 9.2 software based on supervised maximum likelihood classification where each pixel was classified in one of the following classes: built-up land, non-built-up land and water-bodies. Build-up areas include all paved areas such as residential, commercial, industrial buildings, roads and transportation, mixed urban, rural settlements and bare soil. Non-built-up lands include cultivated lands (such as crop fields, fallow lands, vegetable lands), vegetation (such as deciduous forest, mixed forest lands, palms, conifer, scrub and others) and floodplain (include permanent and seasonal wetlands, low-lying areas, marshy land, rills and gully swamps). Waterbodies include river, permanent open water, lagoons, lakes, ponds and reservoirs.

A confusion matrix was developed to evaluate the overall classification accuracy. The accuracy assessment is consist of producer accuracy, user accuracy, overall accuracy and kappa value (Congalton & Green, 1999). Kappa value above 0.8 indicates strong-to-perfect agreement or accuracy between two maps (Zheng, Shen, Wang, & Hong, 2015). In this study, the accuracy of the classified LULC maps was assessed using 200 randomly selected validation points outside of the training sites.

**LULC change analysis**

The LULC change analysis, simulation and future LULC change prediction were carried out using the Land Change Modeler (LCM) in IDRISI. The chronological series of Land use change maps was analyzed to detect changes. The LCM provides quantitative assessment of land use class changes in terms of net changes, swap, gains, losses and total changes (Eastman, 2015), which were extracted from images of consecutive dates, and the results are shown in maps and statistics. The change analysis is performed on the LULC changes between time 1 and time 2. In this study, the cross-tabulation analysis was utilized to quantify LULC changes during 1984–2000 (period 1), 2000–2015 (period 2), and 1984–2015 (period 3), respectively. This analysis can identify the areas changed from one LULC class to another during a particular time period spatially and quantitatively. In addition, the statistics of the changes occurred in the area during different periods, such as the gains and losses by LULC classes, contributions to net change in built-up area, and analysis of spatial trend of change for built-up area for period 1, period 2 and period 3 were also generated in a graphical form.

**LULC change potential modeling**

The main goal of this step is to create transition potential maps with acceptable degree of accuracy to develop the actual transition models. The transition potential maps allow us to group transitions into a set of sub models and explore the potential power of explanatory variables. Variables can be added to the model either as static or dynamic components. Static variables express aspects of basic suitability for the transition under consideration, and are unchanging over time. Dynamic variables are time-dependent drivers such as proximity to existing development or infrastructure and recalculated over time during the course of prediction.

The transition potential maps are in essence, maps for each transition in LCM. A collection of transition potential maps is organized within an empirically evaluated transition sub-model that has the same underlying driver variables. A transition sub-model can consist of a single land cover transition or a group of transitions that are considered to have the same underlying driver variables. These driver variables are used to model the historical change process. The transition potential maps are obtained by multi-layer perceptron (MLP) in LCM. The MLP option can run multiple transitions and undertakes the classification of remote-sensing imagery through an artificial neural network of multi-layer perceptron technique, and it uses an algorithm to set the number of hidden layers (Eastman, 2015).

**Selection of LULC transitions**

There are minor to major transitions that exist between LULC maps of two time periods. In this study, only major transitions that occurred among LULC classes were selected because they play an important role in the dynamics of the study area. The major transitions were incorporated in the transition sub-model to enhance the performance of MLP neural network. Here, two major transitions were selected, namely non-built-up to built-up and water-bodies to built-up.

**Selection of variables**

The selection of driving forces for LULC changes varies for different studies (Geneletti, 2013; Mitsuda & Ito, 2011). Constraints are the criteria that restrict the expansion of built-up land use. Physical constraints can be existing built-up area, water bodies (streams), road network, etc. The constraints are explained in Boolean maps: the areas that are excluded from future land use changes being assigned a value of 0 (not suitable) while those considered for...
land use changes being assigned a value of 1 (suitable) (Eastman, 2015). For this study, water and existing built-up areas were considered as constraints.

Factors are not ‘hard rule’ like constraints, they are criteria that enhance or reduce the suitability of a particular alternative for the activity under concern. It gives a degree of suitability for an area to change (in many cases on distance basis). Physical factors, socioeconomic factors, neighbourhood factors, land-use policy and planning have been widely identified as significant determinants on urban growth rates and patterns. Physical factors, such as topography, climate, etc., are important factors of urban LULC change. Topography affects city size and its spatial distribution by limiting water supply and suitable land provision (Müller, Steinmeier, & Küchler, 2010). In general, slope and elevation are acknowledged as the most important topographic factors that affect urban growth (Braimoh & Onishi, 2007; Reilly, O’Mara, & Seto, 2009; Ye, Zhang, Liu, & Wu, 2013).

For socioeconomic factors, proximity factors such as distance to road (Luo & Wei, 2009; Müller et al., 2010; Poelmans & Rompaey, 2009), distance to socioeconomic center (Vermeiren, Rompaey, Loopmans, Serwajja, & Mukwaya, 2012) and distance to water (Cheng & Masser, 2003; Luo & Wei, 2009) are crucial influential factors that determine urban growth. Roads and socioeconomic centers always play a significant role in urbanization as they provide residents higher accessibility to daily needs and resources. Besides, population and GDP are also considered as macro-factors that influence urban expansion (Lu, Wu, Shen, & Wang, 2013; Wu & Zhang, 2012). Neighbourhood effects usually illustrate that a non-built-up cell is more likely to be converted into built-up land if it is surrounded by built-up land. As for land-use policy and planning, it varies due to different institutional context of different study areas, in the case of Lagos metropolitan region, urban growth can be influenced by master plans, zoning, and other planning regulations and guidelines.

In this study, since the census data about GDP, population density, neighbourhood factors and the effects of land-use policy are based on administrative units which are not considered as the calculation units in the analysis; therefore, these factors are not included in the sub-model. Topographic and proximity factors were selected to examine their effects on urban growth. After testing the potential explanatory power of possible variables using Cramer’s V analysis (a high Cramer’s V value indicate that the potential explanatory of the variable is good), a total of six static and dynamic variables are considered. Static variables for this study included elevation, slope, distance from town center, distance from waterbodies, while distance from major roads, distance from existing built-up areas were considered as dynamic variables. Static variables don’t change over time while dynamic variables change and are calculated over time throughout the course of a prediction. The variables used in this study are shown in Figure 3.

**Transition potential modeling**

In the sub-model with major LULC transitions defined earlier, a specific LULC transitions that occurred in a desired epoch were explained by different variables. Then, transition potential maps were produced on the basis of LULC transitions as well as dynamic and static variables using the MLP neural network integrated in LCM to visualize the suitability of LULC classes for future scenarios.

The MLP is one of the most suitable algorithms for classification and prediction of LULC changes and able to solve non-linear separable problems (Ahmed & Ahmed, 2012). Based on the supervised Backpropagation (BP) algorithm, the MLP is a feed

![Figure 3](image-url). Different variables used in the study: (a) elevation, (b) slope, (c) town center cost-distance, (d) distance from water, (e) distance from major roads and (f) distance from built-up areas.
forward artificial neural network model that maps sets of input data into a set of appropriate output. It consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. The calculation is based on information from training sites. Compared with other algorithms, the MLP uses minimal parameters and it offers an automatic mode that requires no user intervention.

Hence, the MLP was employed to analyze LULC changes between each of the two maps of 1984, 2000 and 2015 based on the major LULC transitions occurred in the study area. The random sample of cells that followed each of the selected transitions in the modeling was created by neural network. A network of neurons with weights was also formed to compute its errors of training and adjust the weight and improve accuracy (i.e. the RMS error decreases as the weight is adjusted). Accuracy rate around 80% is acceptable (Eastman, 2012). In this study, the results of the MLP after 10,000 iteration of training and testing, produced an accuracy of 87.50% for LULC changes between 1984 and 2000, and 78.73% for LULC changes between 2000 and 2015. The transition potential maps were generated based on this function. Then the generated transition potential maps were used to predict LULC changes for future years.

**LULC change prediction and validation**

This study used a hybrid model of integrated MLP and MCA to predict the future LULC change in specific time. The MCA was employed to predict the quantity of changes using two LULC maps (1984 and 2000). Combined with MLP, the module can provide the weights of the transitions that will be integrated in the probability matrices of Markov chain for future LULC change prediction. The LULC changes of 2015 are predicted based on the transition probability function from sub-model transitions and the calculation of Markov chain using the year 2000 as the reference date. The intermediate output of Markov chain is a matrix with the expected quantity of changes for each considered transitions till the projected dates. Thus, the prediction of LULC map of 2015 was based on the transition probability matrix of LULC changes between 1984 and 2000.

In the previous step, we produced two types of results: a hard prediction (scenario) and a soft prediction (vulnerability) for the year 2015. The hard prediction is a scenario chosen from many equally plausible scenarios; therefore, whenever there are more eligible locations for change than the actual amount of change, it is going to be very difficult to attain an accurate hard prediction (Eastman, 2015). In many cases, it is important for us to have a sense of the vulnerability of land use in the study area apart from a single scenario out of many possible ones in the future. Here is where the soft prediction comes into play. The soft prediction is a comprehensive vulnerability map based on the set of transition, the values of the soft prediction outputs are usually between 0 and 1 (Megahed, Cabral, Silva, & Caetano, 2015).

To evaluate the performance of the hard prediction, the model validation is launched by comparing the predicted map with the observed map. Therefore, the predicted LULC map of 2015 was compared with the observed LULC map of 2015 using kappa index statistics (Kamusoko et al., 2009; Wang, Zheng, & Zang, 2012). The kappa index includes kappa for no information (K_{no}), kappa for grid cell level location (K_{location}) and kappa for stratum-level location (K_{locationStrata}) in addition to kappa standard (K_{standard}) which is equivalent to kappa (Cohen, 1960; Geri, Amici, & Rocchini, 2011; Pontius, 2000). For the validation of the soft prediction, we carried out Receiver Operation Characteristic (ROC) statistics analysis to determine how well a continuous surface predicts the locations given the distribution of a Boolean variable. Finally, the predictions for 2030 and 2050 were carried out using MLP-MCA and possible changes in LULC were processed.

**Results and discussion**

**LULC maps and accuracy assessment**

The LULC maps for 1984, 2000 and 2015 were created using classification of Landsat TM/ETM+/OLI images of respective years using the maximum-likelihood classifier. The overall accuracy values and the kappa values for the classified images of 1984, 2000 and 2015 were calculated. The kappa values for all LULC maps are greater than 0.90, which represents strong to perfect agreement (Zheng et al., 2015). Therefore, the classified LULC images were sufficiently accurate to conduct change analysis.

The spatial and quantitative distribution of LULC classes for the three years are presented in Table 2, Figures 4, 5. It is clearly shown that there are significant changes in LULC and growth of built-up area from 1984 to 2015. It is observed that in 1984, built-up covered an area of 367.99 km² (7.66% of total area), and it increased to 625.29 km² (13.01%).

| Year | LULC class       | Area (km²) | Area (%) | Area (km²) | Area (%) | Area (km²) | Area (%) |
|------|------------------|------------|----------|------------|----------|------------|----------|
| 1984 | Built-up land    | 367.99     | 7.66     | 625.29     | 13.01    | 1,393.98   | 29.01    |
|      | Waterbodies      | 729.76     | 15.19    | 779.20     | 16.22    | 802.86     | 16.71    |
|      | Non-built-up land| 3,707.04   | 77.15    | 3,400.32   | 70.77    | 2,607.95   | 54.28    |
|      | Total            | 4,804.80   | 100.00   | 4,804.80   | 100.00   | 4,804.80   | 100.00   |

Table 2. Area statistics of LULC in 1984, 2000 and 2015.
in 2000 and 1393.98 km$^2$ (29.01%) in 2015, respectively. The built-up area grew by 5.35% during period 1, and 16.00% during period 2. The non-built-up covered an area of 3707.04 km$^2$ (77.15% of total area), and it decreased to 3400.32 km$^2$ (70.77%) in 2000, and 2607.95 km$^2$ (54.28%) in 2015. During period 3, built-up area increased from 7.66% of the total area in 1984 to 29.01% in 2015 indicated in Table 2. There is a great change of 21.35% in built-up area between 1984 and 2015. The built-up area increased dramatically, which resulted in the decrease of non-built-up area during the study period. The rapid population growth linked with high demand for land and urban supplies could be responsible for the LULC changes. It is also shown that waterbodies in the study area did not experience great changes during the periods, it increased from 729.76 km$^2$ (15.19% of total area) in 1984 to 779.20 km$^2$ (16.22% of total area) in 2000, later increased to 802.86 km$^2$ (16.71% of total area) in 2015.

### LULC change analysis using LCM

The LULC change analysis during the study period was also carried out using LULC maps of years 1984, 2000 and 2015 with the change analysis tool in LCM. The gains and losses of LULC changes experienced by different classes were evaluated and most of the classes are showing both gains and losses.

During period 1, non-built-up lost 360.34 km$^2$ (−9.72%) and gained 53.61 km$^2$ (1.58%), with a net loss of 306.73 km$^2$ (−9.02%). Waterbodies lost 33.76 km$^2$ (−4.63%) and gained 83.20 km$^2$ (10.68%), with a net gain of 49.44 km$^2$ (6.34%). Built-up area lost 50.46 km$^2$ (−13.71%) and gained 307.75 km$^2$ (49.22%), with a net gain of 257.29 km$^2$ (41.15%). The major features that contributed to the net change of built-up area during period 1 are as follows: 236.74 km$^2$ (6.39%) of non-built-up lands were transferred to built-up area, while 20.55 km$^2$ (2.82%) of waterbodies were transferred to built-up area.

During period 2, non-built-up lost 866.42 km$^2$ (−25.48%) and gained 74.06 km$^2$ (2.84%), with a net loss of 792.36 km$^2$ (−30.38%). Waterbodies lost 91.78 km$^2$ (−11.78%) and gained 115.45 km$^2$ (14.38%), with a net gain of 23.66 km$^2$ (2.95%). Built-up area lost 18.53 km$^2$ (−2.96%) and gained 787.23 km$^2$ (56.47%), with a net gain of 768.70 km$^2$ (55.14%). The contributions to the net change of built-up area

![Figure 4. Changes of LULC from 1984 to 2015 in graphical form.](image1)

![Figure 5. Classified LULC maps of Lagos Metropolitan Region for years (a) 1984 (b) 2000 and (c) 2015.](image2)
during period 2 are as follows: 744.98 km$^2$ (21.91%) of non-built-up lands were transferred to built-up area, while 23.72 km$^2$ (3.04%) of waterbodies were transferred to built-up area.

During period 3, non-built-up lost 1144.73 km$^2$ (−30.88%) and gained 45.64 km$^2$ (1.75%), with a net loss of 1099.09 km$^2$ (−42.14%). Waterbodies lost 55.32 km$^2$ (−7.58%) and gained 128.42 km$^2$ (16.00%), with a net gain of 73.10 km$^2$ (9.10%). The contributions to the net change of built-up area during period 3 are as follows: 993.92 km$^2$ (26.81%) of non-built-up lands were transferred to built-up area, while 32.07 km$^2$ (4.39%) of waterbodies were transferred to built-up area.

The results clearly showed that during all periods, the considerable changes and transitions were observed among different LULC classes. Gains and losses in LULC (in km$^2$) and contributions to net change of built-up area (in km$^2$) during period 1, period 2 and period 3 are displayed in Table 3 and Figure 6(a–c). Gains and losses in various LULC during 1984–2015 and the combined LULC change map during 1984–2015 are shown in Figure 7(a–d).

Analysis of LULC distribution in Lagos metropolitan region shows that during period 1, a number of 205.69 km$^2$ (79.94%) out of 257.29 km$^2$ built-up land growth was located within Lagos State, and 51.61 km$^2$ (20.06%) occurred beyond Lagos State boundary, in the neighbouring Ogun State. During period 2, 386.12 km$^2$ (50.23%) out of 768.69 km$^2$ built-up land growth was located within Lagos State, and 382.57 km$^2$ (49.77%) was located in Ogun State. During period 3, 591.80 km$^2$ (57.68%) out of 1025.99 km$^2$ built-up land growth happened in Lagos State, with 434.19 km$^2$ (42.32%) built-up land growth in Ogun State (Table 4).

Notably, about 20% of the built-up land expansion in Lagos metropolitan region happened beyond the administrative boundary of Lagos from 1984 to 2000; and from 2000 to 2015, nearly half of the urban growth exceeded the boundary of Lagos State, expanding into Ogun State. Analysis on the distribution of waterbodies and non-built-up land in Lagos State and Ogun State during periods 1, 2 and 3 also

### Table 3. Gains, losses and net changes in LULC during periods 1, 2, and 3 (in km$^2$).

| Year       | 1984–2000 (period 1) | 2000–2015 (period 2) | 1984–2015 (period 3) |
|------------|----------------------|----------------------|----------------------|
| LULC class | Losses               | Gains                | Net changes          | Losses               | Gains                | Net changes          | Losses               | Gains                | Net changes         |
| Built-up land | −50.46               | 307.75               | 257.29               | −18.53               | 787.23               | 768.70               | −27.54               | 1,053.53             | 1,025.99             |
| Waterbodies | −33.76               | 83.20                | 49.44                | −91.78               | 115.45               | 23.66                | −55.32               | 128.42               | 73.10                |
| Non-built-up land | −360.34             | 53.61                | −306.73              | −866.42             | 74.06                | −792.36              | −1,144.73             | 45.64                | −1,099.09             |

**Figure 6.** Gains and losses in LULC (in km$^2$) and contributions to net change in built-up land (in km$^2$) during (a) 1984–2000, (b) 2000–2015 and (c) 1984–2015.
shows the same trend that the spatial growth of Lagos mega-city has fully expanded beyond the administrative territory of Lagos State, encroaching northward onto Ogun State, where the rapid expansion of built-up land has engulfed the indigenous towns and villages around the border of the two states, and continue to extend rapidly along the regional transportation corridor from Lagos to its northern hinterland towards Ibadan, Abeokuta, etc.

Driving factors of LULC change

Elevation is proved to be the most influential factors controlling non-built-up to built-up LULC change. The probable reason may be that Lagos is lying on a low land which is prone to flooding, therefore places with higher elevation are more suitable for settlement. Distance from water is also found to be an important spatial determinant for urban growth. Town center cost distance is another influential factor for LULC change, indicating that the closer non-built-up land is to the town center, the higher the probability that it will be changed to a built-up area. As urban infrastructure, job opportunities, and other socioeconomic resources are concentrated in the downtown city, areas close to the urban center are more accessible to these resources than those areas that are far away from the town center. Slope does not show much influence on urban growth in the study area. This could be attributed to the flat terrain of Lagos where the constraints of slope are not as significant as that in the mountainous areas.

Markov chain analysis

MCA which is an analysis that calculates the transition probability matrix of predicted LULC as shown in Table 5 indicates that the probability of change of non-built-up land to built-up land from 1984 to 2000 is 7.20%, while the probability of change of water-bodies to built-up land is 3.31%. For the period of 2000 to 2015, the probability of change of non-built-up land to built-up land increased to 22.27%, and the
The probability of change of waterbodies to built-up land increased to 3.85%. It can be seen that during the last three decades, the probability of change to built-up land increased remarkably from 7.20% to 22.27%. In contrast, the probability of change of built-up land to non-built-up land decreased from 11.68% to 1.96%. The huge changes of probabilities between the two periods reveals the intense decrease of non-built-up land in Lagos Metropolitan Region. Markov conditional probability images for 2030 and 2050 are shown in Figure 8 (c–d). Through the quantitative and visual analysis of classified maps of 2030, it is noticeable that there is a rapid urban growth in Lagos Metropolitan Region, which forms great challenges for the decrease of non-built-up land such as agricultural land, vegetation, etc.

**LULC prediction and validation results**

The MLP was utilized to generate transition potential maps for various transitions with an accuracy of above 80%. Then, the MLP-MCA method was applied to predict LULC patterns in 2015 using the LULC maps of the years 1984 and 2000. Next, the predicted LULC map of 2015 was compared with observed LULC map of 2015 for the validation of the model’s performance.

As we mentioned earlier, the model produced two types of prediction, both hard and soft prediction maps. A kappa index statistics was applied to compare the hard predicted LULC map of 2015 with the observed LULC map of 2015. The statistics shows that K\text{no} value is 0.7180, K\text{location} value is 0.8352, K\text{locationStrata} value is 0.8352, and K\text{standard} value is 0.6663 (overall kappa), respectively. It showed that the kappa index values are acceptable, and the performance of MLP-MCA method to identify grid cell level location of future change is quite satisfactory (here, K\text{location} value is 0.8352, where K\text{location} value of 1 is perfect). For the validation of the soft prediction, the ROC statistic was used to compare the soft predicted LULC map of 2015 with the observed LULC map of 2015. The result of ROC shows a value of 0.837 which means the consistency of the prediction and the real land cover map in 2015 is quite strong.

The validation process has shown a successful prediction of both hard and soft predicted LULC map for 2015. After that, we can continue to predict the LULC change map for the future. By using the LULC map of 2015 as base map, transition potential maps in Figure 8 (c–d) and the transition probability matrix of time period 2000–2015 in Table 5, the future LULC change maps were predicted for 2030 and 2050 as shown in Figure 8 (a–b). The corresponding area statistics of various LULC classes are represented in Table 6.

The MLP-MCA based prediction for 2030 shows that built-up land will increase from 1393.98 km\(^2\) to 2005.68 km\(^2\) between 2015 and 2030. The non-built-up land will decrease from 2607.95 km\(^2\) to 2027.17 km\(^2\) between 2015 and 2030. The waterbodies will also decrease from 802.86 km\(^2\) to 771.95 km\(^2\) between 2015 and 2030. For the prediction of 2050, it is found that built-up land will increase from 1393.98 km\(^2\) in 2015 to 2601.88 km\(^2\) in 2050. The non-built-up land will decrease from 2607.95 km\(^2\) in 2015 to 1485.23 km\(^2\) in 2050. The waterbodies will also decrease from 802.86 km\(^2\) in 2015 to 717.69 km\(^2\) in 2050. Unfortunately, the increasing rate of built-up area will occur at the cost of the decreasing changes in non-built-up land such as agricultural land and vegetation area.

![Figure 8. Predicted LULC maps and transition potential maps for 2030 and 2050.](image-url)
The prediction of LULC distribution in Lagos metropolitan region shows that, among 611.7 km² built-up land growth from 2015 to 2030, about 164.26 km² (26.15%) will occur in Lagos State, and 447.44 km² (73.15%) will be located in Ogun State. Similarly, from 2015 to 2050, 292.24 km² (24.19%) of 1207.90 km² built-up land growth will be located in Lagos State, and 915.66 km² (75.81%) will be in Ogun State (Table 7). According to the forecast, from 2015 to 2050, more than three quarters of spatial growth in Lagos metropolitan region will happen beyond the administrative boundary of Lagos State. Accordingly, more than three quarters of LULC losses in waterbodies and non-built-up land are predicted to occur in Ogun state.

### Conclusion

This study revealed the changes in LULC during the period of 1984–2015 with a combined approach of remote-sensing, GIS and artificial neural network algorithms. To conduct the study, a supervised maximum likelihood classification methods was used to produce LULC maps by using Landsat TM/ETM+/OLI satellite images of 1984, 2000 and 2015. An integrated MLP-MCA method was applied to predict future LULC changes in Lagos Metropolitan Region. The accuracy of predicted LULC map for 2015 was evaluated using kappa index statistic and ROC. After that, the future LULC change scenarios for 2030 and 2050 were predicted using MLP-MCA method. The result shows a clear understanding about the amount and location of probable changes spatially and quantitatively. The predictions of future LULC are based on the continuity of observed past trends of 2000–2015, a hard-predicted scenario map and a soft predicted vulnerability map were produced for the years 2030 and 2050, respectively.

The study indicated significant changes in LULC from 1984 to 2015. The built-up area of Lagos metropolitan region increased from 367.99 km² in 1984 to 625.29 km² in 2000, to reach 1393.98 km² in 2015. According to the prediction for future LULC, the built-up land will attain 2055.68 km² by 2030 and 2601.88 km² in 2050. An increase of 611.70 km² in built-up land and a decrease of 580.78 km² in non-built-up land were predicted between 2015 and 2050. The waterbodies were predicted to lose by 30.91 km² and 17.17 km² in non-built-up land were estimated between 2015 and 2030; notably, a gain of 1207.90 km² in built-up land and a loss of 1122.72 km² in non-built-up land were predicted between 2015 and 2050. The waterbodies were predicted to lose by 30.91 km² and 85.17 km² during 2015–2030 and 2015–2050, respectively. The LULC change analysis of the study period demonstrated enormous gains in built-up land at the cost of massive losses of non-built-up land.

It is noticed that since 2000, the growth of Lagos metropolitan region has fully gone beyond the administrative boundary of Lagos State, spreading into the neighbouring Ogun State. The rapid urban growth has annexed and integrated several adjacent towns and settlements of Ogun State into the continuous sprawling urban fabric. In fact, nearly 50% of the built-up land growth was located in the territory of Ogun State during the period of 2000–2015. It is remarkable to mention that, during the periods of 2015–2030 and 2015–2050, about three quarters of new built-up lands in Lagos metropolitan region will take place beyond the administrative boundary of Lagos State (73.15% and 75.81%, respectively).

With its powerful economic dynamics at regional and sub-regional level, the influence of Lagos metropolis has gone far beyond Lagos State, stretching into its vast hinterland, even as far as Nigeria’s northern boundary with Niger. The massive physical growth across the border of Lagos State as described above is just the prelude of an emerging super-metropolitan region. Given the fact that there is no comprehensive or master plan cover, the whole Lagos metropolitan region and its surrounding areas in both states, more land expansion will continue to grow in an ad hoc and unordered way beyond the jurisdiction of Lagos State planning authorities. It is clear that the growth...
of Lagos metropolitan region is not only a matter of Lagos State, and the solution to deal with the challenges of urban growth requires a strong regional planning framework and a consistent collaboration of Lagos State, Ogun State and other potential regional stakeholders.

The study demonstrated the efficiency of remote-sensing data and GIS integration for LULC change analysis and prediction of future LULC scenarios. Besides, the research also provides the potential to contribute toward the sustainable development at local and regional level. The predicted LULC situations in 2030 and 2050 reveal an alarming faster loss of non-built-up land and high increasing rate of built-up land which needs great attention from policy makers and town planners for urban growth management of the Lagos metropolitan region. The rapid urban expansion will further increase the pressure on non-built-up land and natural resources in the study area, which will also contribute to the local and global climate change.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

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