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MODELLING OF FUTURE LAND USE/LAND COVER CHANGE DYNAMICS IN LAGOS, NIGERIA USING CELLULAR AUTOMATA AND MARKOV CHAIN (CA-MARKOV) MODEL

Auwalu Faisal Koko[1], Wu Yue[2], Muhammed Bello[3] and Ghali Abdullahi Abubakar[4]
[1,2]College of Civil Engineering and Architecture, Zhejiang University, China
[3]Department of Architecture, Kaduna Polytechnic, Kaduna State, Nigeria
[4]College of Environmental and Resource Sciences, Zhejiang University, China

Many cities in developing countries have witnessed rapid urbanization, resulting in various land use/land cover (LULC) changes. However, few studies focus on the growth and development of African cities. As a result, this study aims to predict the future land use/land cover of Lagos, Nigeria, from 2020-2050 using a combination of cellular automata and the Markov Chain model (CA-Markov). The CA-Markov model utilises historical land cover data and transition probabilities to simulate future LULC patterns through Geographic Information System (GIS) techniques. In this study, the land use/land cover pattern of Lagos was modelled and validated using the city's historical maps. The maps were derived from satellite images using the maximum likelihood classification. The historical LULC indicates that Lagos had witnessed an increase and decrease in the city's different land-uses, comprising built-up areas, vegetation, barren land, and water bodies. Over the last 20 years, the city's built-up areas and barren land have increased by approximately 19.81 km2 and 3.13 km2 per annum, while vegetation and water bodies have decreased annually by 15.89 km2 and 7.06 km2, respectively. The Land Change Modeler (LCM) of TerrSet software was utilised in simulating the CA-Markov model to forecast the city's future land cover based on the historical LULC trends. The predicted result reveals that in 29 years, Lagos will experience a notable increase in built-up areas from 1255.91 km2 in 2020 to 1544.95 km2 in 2050, while barren land will expand by 257.62 km2. This change is expected to occur at the expense of vegetation, and water bodies, which will decline by approximately 314.76 km2, and 231.90 km2. Therefore, this study provides critical data useful to urban planners, policy, and decision-makers in formulating strategies and initiatives for a sustainable built environment in Africa's most populous city.

Keywords: CA Markov, Geographic Information Systems(GIS), land use/land cover change, LULC prediction, remotely sensed data

[1] 11812112@zju.edu.cn
[2] ywu100@zju.edu.cn
[3] mbello02@kadunapolytechnic.edu.ng
[4] ghaliaa@zju.edu.cn

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INTRODUCTION

The recent changes in land use/land cover have become an issue of utmost environmental concern globally due to their unprecedented impact on the ecosystem (Alawamy, Balasundram, Hanif, & Teh, 2020; Halmy, Gessler, Hicke, & Salem, 2015). The continuous trend of socio-economic development and increasing population in most regions of the world have contributed to the wide-ranging modification of the earth surfaces, particularly land use/land cover (Gong, Yuan, Fan, & Stott, 2015). Several studies have indicated significant changes among different land-uses due to human-induced activities (Shi et al., 2019; Song & Deng, 2017; Yang, Yang, Li, & Huang, 2021). The consequences of these alterations have impacted directly and indirectly to the environment and climate. Some of the adverse effects of these changes include loss of fertile land, water resources, and biodiversity, forest degradation, deforestation, depletion of the ozone layer, emission of greenhouse gases (GHG), and urban heat island development (Al-sharif & Pradhan, 2014; Gogoi et al., 2019; Xu, Xie, Qi, Luo, & Wang, 2018; Zhong et al., 2017). Therefore, examining spatiotemporal temporal changes in LULC plays a crucial role in formatting policies on managing the built environment and natural resources. It is appropriate to analyse LULC changes and forecast the possible future changes for effective and long-term planning (Du et al., 2019; Haque & Basak, 2017). Such studies envisaging environmental alterations are of utmost importance in cities of developing countries such as Nigeria, having rapid urbanization with associated change in land-uses.

The use of remote sensing techniques has provided numerous ways of producing land use/land cover maps of a given area and generating statistical data for analyzing LULC change dynamics (Ayele et al., 2018; Koko, Yue, Abubakar, Hamed, & Alabsi, 2020). Butt, Shabbir, Ahmad, and Aziz (2015) opine that the availability of remotely sensed data and their advantages of high-resolution spatiotemporal images, when incorporated with GIS techniques, has provided a potential means of detecting land cover change scenarios on the earth's surface. The increase in satellite platforms has contributed to faster, continuous, and regular images, which help manage and forecast changes in various environmental studies (Abubakar et al., 2020). Such data assist in planning and remedying the negative effects associated with the alteration of land-uses. Previous studies have identified several models for detecting and predicting changes in LULC. Such models include empirical models (Cromley & Hanink, 1999; Veldkamp & Fresco, 1996), agent-based models (Rouchier, Bousquet, Requier-Desjardins, & Antona, 2001), evolutionary models (Sahebgharani, 2016), Cellular automata (CA), and Markov chain model (Abdulrahman & Ameen, 2020; Liping, Yujun, & Saeed, 2018). However, the integration of Cellular automata and Markov chain models are the most widely used methods for the LULC change prediction due to its spatiotemporal consideration of land use/land cover (Aneesha Satya, Shashi, & Deva, 2020).

Several studies have analysed spatiotemporal land use/land cover changes using various satellite data and GIS techniques while employing the CA-Markov model to predict the future LULC. A comprehensive review of the Cellular Automata and Markov chain modelling techniques for geospatial environment simulation can be found in Ghosh et al. (2017). In a recent study carried out by Koko et al. (2020), the

future land use/land cover pattern of Zaria city, Nigeria, was predicted using an integrated CA-Markov chain model. Similarly, Aneesha Satya et al. (2020) used open-source GIS methods to simulated the future land cover scenario in Warangal city, India. Wang and Maduako (2018) studied the spatio-temporal urban growth dynamics of the Lagos Metropolitan Region in Nigeria using a Hybrid approach for land cover modelling and prediction. Liping et al. (2018) analysed and predicted the LULC changes in the hilly region of Jiangle county, China, using remote sensing and GIS techniques. Gidey, Dikinya, Sebego, Segosebe, and Zenebe (2017), used the Cellular Automata and Markov Chain in predicting the future LULC scenarios in Raya, Northern Ethiopia. The integrated CA-Markov model has also been utilised in projecting the land cover changes in the urban renewal areas of Hong Kong (Zheng, Shen, Wang, & Hong, 2015). The result of these studies have demonstrated the efficiency of the integrated modelling approach for LULC prediction and provided credible data for informed decision-making on the management of land uses and natural resources.

Although numerous land use/land cover studies have been carried out on cities in different geographical regions, very few studies monitored and predicted the land use/land cover dynamics of rapidly growing cities in Africa, particularly Lagos, which is Nigeria's most populous city. The focus of such studies has always been the metropolitan area of the city, without any studies covering the entire city of Lagos. Therefore, to fill this existing research gap, the present study detected and modelled the future land use/land cover of Lagos, Nigeria, using an integrated modelling method, i.e., CA-Markov. To achieve this, the study; (i) derived and analysed the historical LULC data of Lagos city using remotely sensed images and GIS techniques, (ii) modelled and validated the simulated LULC pattern of Lagos in 2020, (iii) utilised the transition area matrix and transition probability matrix generated for the period between 2010 and 2020 to predict Lagos city's future LULC pattern in 2050. The findings of this paper provided the essential land use/land cover information that could be used as scientific data with a view of comprehensively understanding and planning the entire city of Lagos through environmental and developmental programs that are crucial to achieving sustainable development of the city.

MATERIALS AND METHODS

Study area

Lagos is located in a low-lying area in Nigeria's south-western zone, stretching over a landmass of approximately 3,577 square kilometers (Lagos State Government, 2020). The city has a latitudinal extent between 6° 15′ and 6° 45′ N, and a longitudinal coverage between 2°45´ and 4°15´ E as shown in Figure 1. It borders the Atlantic Ocean to the south, the Benin Republic to the west, and Ogun state to the north and east. Lagos has tropical rainforest climatic conditions, similar to other southern regions of Nigeria, with high temperatures and humidity throughout the year. It has an average annual precipitation of 1600mm and an average yearly temperature of 25°C (Jimoh et al., 2018). Lagos has two main seasons: a wet season, which occurs from April to October, and a dry season witnessed from November to March. These distinct seasons are often accompanied by dry Harmattan winds between December and February.

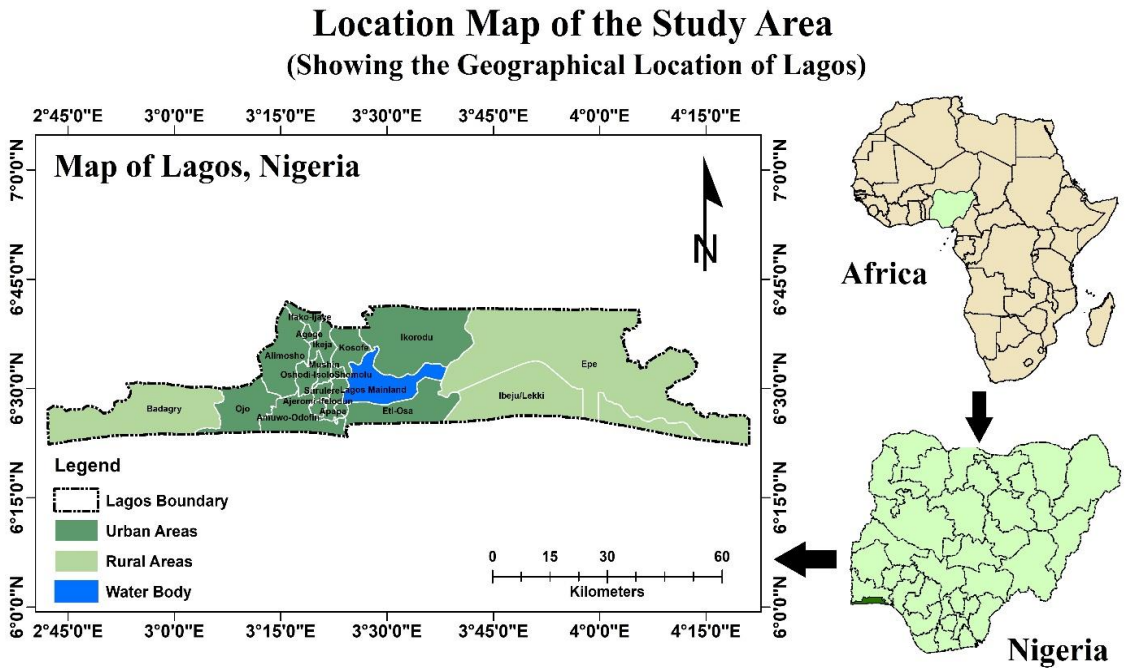


Figure 1: Geographical location of Lagos, Nigeria

Like many other rapidly growly urban centers, Lagos has witnessed increased urban development and expansion due to rapid urbanization. This development has altered the city's land-use/land cover and transformed Lagos from a port city to Nigeria's most vibrant socio-economic hub, contributing over 30% of its Gross Domestic Product (GDP). The city of Lagos is a crucial contributor to Nigeria's non-oil sector, with over 60% of Nigeria's commercial and industrial activities (Lagos State Government, 2020). The availability of urban infrastructures has contributed immensely to the migration of the people to the city. Lagos having nearly 80% of Nigeria's international fight traffic and over 70% of Nigeria's cargo freight, has helped connect the city to different parts of the world. Lagos city's population had rapidly increased from about 4.8 million in 1990 to approximately 14.4 million in 2020. The city is projected to have approximately 24.4 million inhabitants by 2035, which is expected to increase twice by 2050, making the city one of the world's top three largest cities (Population Stat, 2020). Hence, the motivation for selecting Lagos as the study area mainly emanated from the city's rapid urbanization and increased population, which contributes to the numerous environmental challenges that affect the city.

METHODS

To achieve the study's aim. The procedures were divided into two main steps: i) the generation of spatiotemporal land-use/land cover data from remotely sensed satellite images and ii) using the acquired LULC data to forecast the future changes in LULC patterns. For the generation of spatiotemporal LULC data, Landsat (level 1) satellite images of the study area were acquired without any cost from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/) for 2000, 2010, and 2020. The images were obtained during the dry season between October and February to acquire cloud-free images and avoid atmospheric distortions. The satellite data comprises Landsat ETM+ for 2000 and 2010 and Landsat OLI for 2020.

Google earth images of the study area were also obtained to ascertain the actual ground conditions during the study's different time nodes.

The methodological flowchart of the study is illustrated in Figure 2. It consists of two (2) main sections. Section (a) demonstrates the various steps involved in the classification of LULC and its accuracy assessment, while section (b) illustrates the procedure utilised for modelling the future LULC pattern of the study area. The various processes utilised are further discussed below.

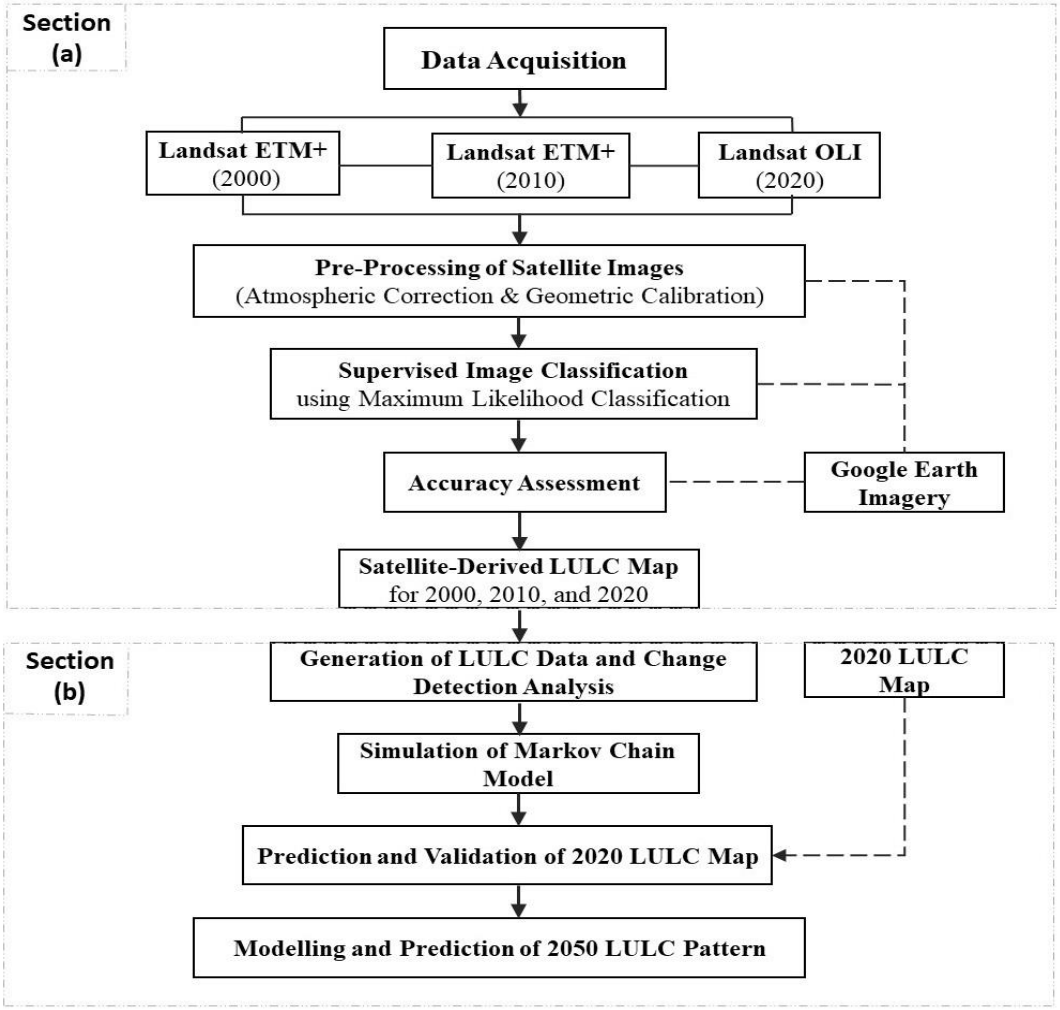


Figure 2: Methodological flowchart of the study comprising (a) LULC classification procedure and (b) LULC modelling steps.

Image pre-processing and classification

The study utilised Landsat Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) to derive the LULC data and model the study area's future change dynamics. It acquired full scenes of datasets for three different periods (i.e., 2000, 2010, and 2020). The images were downloaded at a spatial resolution of 30m having the visible, near-infrared (NIR), and mid-infrared (MIR). However, processing these satellite images or remotely sensed data could be challenging due to few distortions in acquiring systems or sensors (Koko et al., 2020). Therefore, prior to image classification, satellite images 'pre-processing is vital in minimizing errors and building a more reliable connection between the actual ground condition and satellite data (Coppin, Jonckheere, Nackaerts, Muys,

& Lambin, 2010). The study utilised pre-processing operations that included gap filling, sub-setting, radiometric, atmospheric, and geometric corrections. These operations were performed in ArcGIS 10.7.1 and ENVI 5.3 image processing software. All the images were mapped using WGS84 ellipsoid and georeferenced to the Universal Transverse Mercator (UTM) Zone 31N. The classification of images aided in cataloguing the entire pixels of the individual satellite images into land use/land cover classes using thematic maps. It assigns spectral signatures to land-use categories based on the diverse LULC classes 'reflectance attributes (Cheruto, Kauti, Kisangau, & Kariuki, 2016). The Maximum Likelihood Classifier (MLC) algorithm was used for the classification of images. The images were classified into four broad classes comprising the built-up/urban area, vegetation, bare soil/barren land, and water bodies. The description of each LULC class is presented in Table 1.

Table 1: Description of various LULC classes adopted in this study.

S/No.	Broad LULC Classification	Description
1.	Urban/Built-Up Area	Areas covered by buildings and other human-made structures having residential, commercial, mixed-use, and industrial facilities/services
2.	Vegetation	It includes areas covering various shrubland, mixed forests, agricultural land, farmlands, crop fields, and other plantations.
3.	Bare Soil	Comprises areas having no vegetation cover. Such lands include bare ground, exposed soil and rock surfaces, quarries, construction, and excavation site.
4.	Water Bodies	Includes areas such as swamps, lakes, streams, rivers, reservoirs, and ponds

Accuracy assessment of classified images

Accuracy assessment is a vital process in land use/land cover classification. It evaluates the reliability of classified LULC maps derived from satellite images. Satellite images are usually compared with ground truth data using land-use maps, field observations, and other high-resolution satellite images such as google earth imagery. In this study, the accuracy assessment was conducted using high-resolution satellite imagery retrieved from Google Earth Pro (Version 7.3.3.). The satellite images of 28th January 2010 and 7th January 2020 were used to validate the classified LULC maps. The study employed a random sampling method to generate validation points for each LULC category. A total of 200 reference points were randomly created, having approximately 50 sample points per LULC class as suggested by Congalton (1991). The reference points were compared with the classified land use/land cover map of 2010 and 2020 to produce an error matrix. The LULC classification accuracy was evaluated using various measures obtained from the error matrix, which mainly includes the overall accuracy and kappa coefficient (k). An overall accuracy above 80% is often considered an acceptable land use/land cover classification (Rwanga & Ndambuki, 2017). A kappa coefficient above 0.8 signifies an excellent agreement. 'k 'values between 0.4 and 0.6 represent a good agreement, whereas values less than 0.4 signifying a poor agreement (Foody, 2004).

Modelling of future LULC pattern

The spatiotemporal modelling of the future LULC distribution was carried out using Lagos 'historical land use/land cover data between 2010 and 2020. During this

period, Lagos had witnessed significant LULC alterations due to rapid urbanization. Therefore, to predict the city's future land use/land cover of 2050, this period's LULC transition was considered. The study employed the Land Change Modeller (LCM) of TerrSet (Version 18.31) geospatial monitoring and modelling software to predict the city's future LULC. The modelling system is suitable for simulating land use/land cover changes, mainly when physical mapping is time-consuming and difficult. It utilises the combination of Markov chain and cellular automata models. The Markov chain model has been widely used in modelling changes in land use/land cover conditions due to its advantages for predicting land cover conditions through transition probabilities. However, the model lacks the ability to simulate the various alterations in spatial trends of land use/land cover classes. Therefore, the integrated CA-Markov model is considered in urban planning as an effective and robust simulation model that helps improve the efficiency of spatiotemporal land-use/land cover prediction. It computes transition matrixes based on the number of temporal changes among the different LULC classes. The CA-Markov helps simulate spatial variation by utilizing remotely sensed datasets and GIS techniques (Cunha, Santos, Silva, Bacani, & Pott, 2021). It is also a model that considers the suitability of changes in land use/land cover categories and the effect of natural, societal, and economic factors on LULC change dynamics (Sang, Zhang, Yang, Zhu, & Yun, 2011). In our present study, the modelling of the LULC changes was therefore conducted using the CA-Markov model due to the numerous advantages of the model for forecasting land use/land cover conditions. The CA-Markov model was trained in the land change modeler by combining the Markov chain processes and cellular automata filter functions. The simulation model utilised the transition probability matrix, transition areas matrix, and transition probability map of the simulated and validated period, i.e. the year 2020 to predict the changes in land use/land cover of Lagos in the forecasted period i.e. year 2050. The procedures involved for the land use/land cover simulation include; (i) analyzing the historical LULC data, (ii) modelling and validation of simulated LULC of 2020, and (iii) modelling the city's 2050 LULC pattern.

RESULTS AND DISCUSSION

Historical LULC distribution and its changes

The mapping of Lagos 'historical LULC pattern for the years 2000, 2010, and 2020 are illustrated in Figure 3, with the area statistics and its changes presented in Table 2. The result revealed significant growth in built-up areas from 23.43% in 2000 to 34.23% in 2020, increasing 10.8% over the last 20 years. The result shows that vegetation areas declined from 49.74% in 2000 to 45.29% in 2020. Water bodies declined from 22.90% in 2000 to 19.05% in 2020, while the bare soil increased from 3.93% in 2000 to 5.64% in 2020. The outcome signifies an increase and decrease in the different LULC patterns of Lagos, which can be attributed to the city's increased socio-economic activities that continuously alter land-use/land cover distribution (Auwalu, Wu, Ghali, Roknisadeh, & Akram Ahmed, 2021). Therefore, analyzing the historical LULC changes and forecasting future land-uses could help manage the city's built environment and drive policy interventions in areas needed.

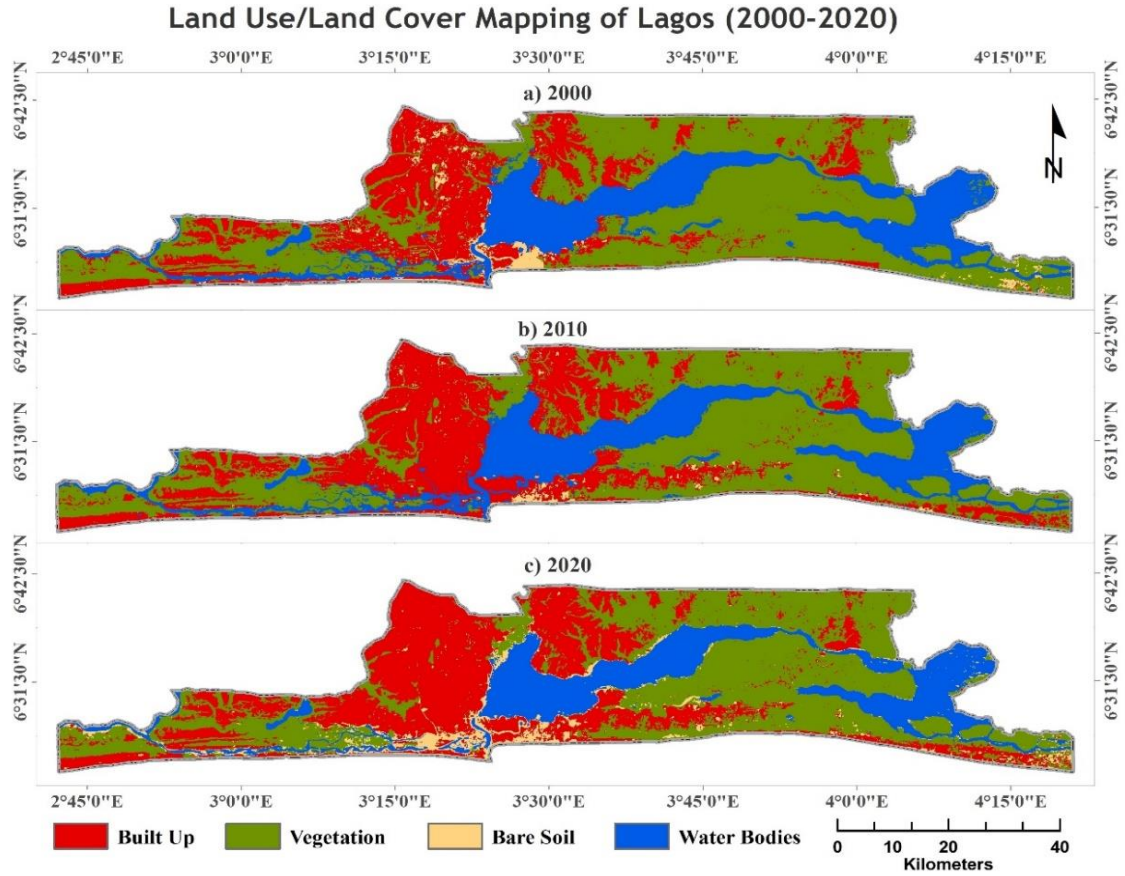


Figure 3: Land use/Land Cover Classification Mapping of Lagos in 2000, 2010, and 2020.

Table 2: LULC class distribution and its periodic changes.

LULC Categories	2000		2010		2020		Total Change in Area (2000-2010)		Total Change in Area (2010-2020)		Total Change in Area (2000-2020)	
	Area (km²)	Area (%)	Area (km²)	Area (%)	Area (km²)	Area (%)	(km²)	(%)	(km²)	(%)	(km²)	(%)
Built-Up	859.62	23.43	1112.84	30.33	1255.91	34.23	253.22	29.46	143.07	12.86	396.29	46.10
Vegetation	1824.93	49.74	1661.62	45.29	1507.21	41.08	-163.31	-8.95	-154.41	-9.29	-317.72	-17.41
Bare Soil	144.23	3.93	75.78	2.07	206.89	5.64	-68.45	-47.46	131.11	173.01	62.66	43.44
Waterbody	840.16	22.9	818.70	22.31	698.93	19.05	-21.46	-2.55	-119.77	-14.63	-141.23	-16.81

The study demonstrated the historical changes of the different LULC classes categorised into three different study periods, i.e., period one (2000-2010), period two (2010-2020), and period three (2000-2020). The analysis of the change detection result of the first period, i.e., 2000-2010, revealed an increase of 29.46% in Lagos city's built-up areas while the area of vegetation, water bodies, and bare soil declined by 8.95%, 2.55%, and 47.46%, respectively. During these ten years, the built-up area expanded rapidly by 253.22 km2 while a significant decrease of 163.31 km2, 21.46 km2, and 68.45 km2 was observed in vegetation, water bodies, and bare soil, respectively. These changes can be attributed to the city's socio-economic development that attracted a massive influx of people. In the second period between 2010 and 2020, the increase in the built-up areas was observed in Lagos city's central axis, precisely in urban areas around Ikeja, Mushin, Oshodi-

Isholo, and other adjourning areas. This period witnessed a lower growth magnitude in built-up areas having a decline of 16.6% compared with the earlier period between 2000 and 2010. Vegetation and water bodies also experienced a decreasing trend between 2010 and 2020, declining by 154.41 km2 and 119.77km2, respectively. However, bare soil observed a significant increase of 173.01%, approximately 131.11 km2, during this second period. During the third period between 2000 and 2020, the built-up area expanded by 396.29 km2, i.e., 46.10%, while vegetation and water bodies decreased by 317.72 km2 and 141.23 km2, respectively, signifying a decline in area of about 17.41% and 16.81%.

Accuracy assessment of classification

The study employed google earth images to evaluate the accuracy of classified land use/land cover maps. For this, the study compared the generated LULC maps of Lagos and the actual ground condition. It is an effective and reliable method of validating the accuracy of each LULC category. The result revealed an overall accuracy of 89.86% in 2000, 91.03% in 2010, and 95.12% in 2020. Also, it indicated a Kappa coefficient of approximately 0.85, 0.86, and 0.93 in 2000, 2010, and 2020. Anderson, Hardy, Roach, and Witmer (1976) specified 85% as the minimum level of accuracy for LULC class classification. In this study, the overall accuracies for all the periods under study were above 85%, indicating a reliable LULC classification (Congalton, 1991). Besides, a Kappa coefficient above 0.75 signifies good agreement between ground truth data and classified LULC categories.

Simulation and validation of 2020 LULC

The study compared the simulated land use/land cover map of 2020 with the satellite-derived LULC map of the study area in 2020, which served as the reference map representing the city's actual ground condition. The automated 2020 LULC map comparison validated the simulation model for the CA-Markov.

Table 3: Markov Transition probabilities for LULC change from 2010 to 2020.

LULC Classes		2020			
		Built-up	Vegetation	Bare Soil	Water Bodies
2010	Built-up	0.9110	0.0186	0.0704	0.0000
	Vegetation	0.1744	0.7624	0.0609	0.0022
	Bare Soil	0.5396	0.0045	0.4559	0.0000
	Water Bodies	0.0841	0.0042	0.2638	0.6479

The validation information of the specified period (i.e., the year 2020) was used in the study to evaluate the certainty of the CA-Markov model for future LULC prediction. The result revealed four Kappa coefficients comprising a Kno value of 0.86, Klocation value of 0.81, KlocationStrata value of 0.82, and Kstandard value of 0.79. The analysis of the result shows that the individual kappa coefficients 'values are all above 0.75, demonstrating a good and reliable simulation process (Landis & Koch, 1977). The validation result signifies that the simulation model along its composition is satisfactory for modelling future LULC changes. Thereafter, the model was employed to project the future land use/land cover of Lagos in 2050. The transitions in the various LULC classes during this period (i.e., (2010-2020) are presented in Table 3. The transitions indicate bare soil as the land cover class with the most significant probability of changing into built-up with a transition

probability of 0.5396, followed by vegetation with 0.1744 and then water bodies with 0.0841. Therefore, the study utilised the transition probability matrix between 2010 and 2020 to model the future land use/land cover of Lagos in 2050

Predicted LULC pattern of 2050

The spatial distribution of LULC was mapped from 2020 to 2050. It relied on the result of the good validation process of the CA-Markov and utilised the simulation model for the prediction. The derived LULC maps of 2010 and 2020 were used to map Lagos 'future LULC distribution in 2050. The LULC map of 2020 was used as the base map for the CA Markov while incorporating the transition probability matrix for the period between 2010 and 2020 into the model. The modelling result of the LULC pattern of Lagos in 2050 is presented in Figure 4. Also, the comparison of the 2020 and 2050 LULC distribution obtained from the two LULC maps is presented in Table 4. It indicates both positive and negative changes in the different LULC classes. An analysis of the results revealed that in the next 29 years, Lagos built-up areas would increase from 1255.91 km2 in 2020 to 1544.95 km2 in 2050, indicating an increase of 289.04 km2. This increase will be likely attributed to the excessive use of natural land and the development of urban areas. The area comprising the city's bare soil is also expected to increase from 206.89 km2 in 2020 to 464.51 km2 in 2050. This indicates an increase of 257.62 km2. However, vegetation and water bodies showed a decreasing trend in the forecasted result. It indicated that the vegetation in Lagos would decline from 1507.21 km2 in 2020 to 1192.45 km2 in 2050, indicating a vegetation loss of 314.76 km2. The area covering the water bodies will also decline from 698.93 km2 in 2020 to 467.03 km2 in 2050, signifying a decline of 231.90 km2.

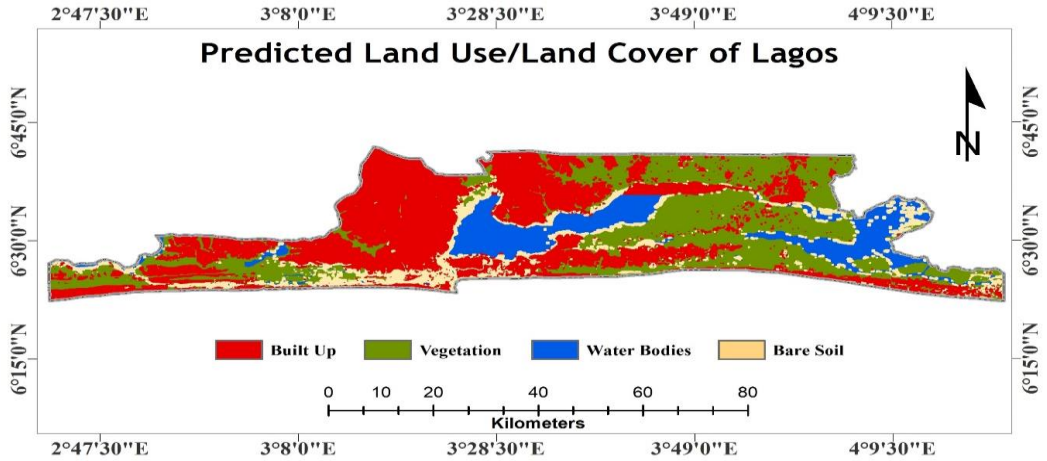


Figure 4: Predicted LULC Map of 2050

Table 4: Area of predicted LULC and its changes from 2020 to 2050.

LULC Classes	Area in 2020 (km^2)	Area in 2050 (km^2)	Total Change in Area (km^2)	Total Change (%)
Built-up	1255.91	1544.95	289.04	23.01
Vegetation	1507.21	1192.45	-314.76	-20.88
Bare Soil	206.89	464.51	257.62	124.52
Water Bodies	698.93	467.03	-231.90	-33.18

In summary, the prediction of the 2050 LULC pattern of Lagos indicates that the city's built-up area and bare soil will expand by approximately 23.01% and 124.52%, respectively, while vegetation and water bodies will decline by approximately 20.88% and 33.18% over the next 29 years. The anticipated alterations in the land use/land cover pattern of the study area, i.e., Lagos, can mainly be attributed to the socio-economic development in various sectors of the city that comprise manufacturing, construction, transportation, and many others. The forecasted LULC will significantly help manage the environmental consequences of rapid urbanization in Lagos.

CONCLUSIONS

The present study analysed the historical changes in land use/land cover of Lagos while aiming to model the city's future LULC over the next 29 years. Remotely sensed satellite images of the years 2010 and 2020 were employed to simulate the city's future LULC using an integrated CA-Markov model. The study validated the simulation model, and the outcome showed satisfactory kappa coefficients. The model was then used to project the future LULC pattern of Lagos in 2050. The results revealed that from 2020 to 2050, Lagos would witness a considerable increase in built-areas and bare soil while a significant decline is expected in the city's vegetated land and water bodies. The integration of the CA-Markov model, coupled with geospatial technology, has demonstrated its capabilities for predicting future land-uses. The study result depicts the usefulness of the modelling technique as a tool for providing reliable LULC data on the magnitude of future LULC changes. However, this study was limited to assuming uniform historical transition probabilities in the LULC simulation model. It is, therefore, necessary for future studies to consider the unprecedented influences of various factors that include socio-economic data, climate, government policies, and many others. Incorporating these variables to model future LULC changes will undoubtedly lead to a more accurate and reliable LULC prediction.

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