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Spatio-Temporal Analysis of Urban Growth Using Integrated Remote Sensing and GIS Techniques in Nigeria, Lagos State as a Case Study

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Abstract— *The rapid expansion of urban areas as a result of population growth and economic prosperity is causing land use and land cover (LULC) changes in cities all over the world. Lagos state Nigeria is no exception to this trend, as one of Africa's fastest-growing cities, which experienced remarkable urban growth due to rapid urbanization. Consequently, a large population will burden the already fragile ecosystems that characterize the urban landscape. Thus, the objective of this study was to analyze land use and land cover changes in Lagos state Nigeria by applying geospatial and land use change modeling tools such as geographic information system (GIS) and remote sensing technologies. Therefore, understanding and quantifying the spatiotemporal dynamics of urban land use and land cover changes and its driving factors is essential to put forward the right policies and monitoring mechanisms on urban growth for decision making. In order to achieve this, satellite data of Landsat TM for year 2000 and ETM for year 2020 have been obtained and preprocessed using QGIS applications. The Maximum Likelihood Algorithm of Supervised Classification has been used to generate land cover maps. For the accuracy of classified land cover maps, a confusion matrix was used to derive overall accuracy and results were above the minimum and acceptable threshold level. Generally, the results of this study have shown that there was an increased expansion of built-up areas in last 20 years from 50% in 2000 to 57 % in 2020 and 5% in 2000 at the expense of bare soil areas to 8% in 2020, that is the temporal period between2000 and 2020 showed the highest conversion of vegetation and water area to urban areas. The spatial trend of built-up areas also showed that there was a growing trend in the western part of Lagos state relative to other directions.*

Keywords— *Land use/land cover change, Change detection, Remote sensing, Geographic information systems, Urbanization, Image classification.*

I. INTRODUCTION

Urbanization has been a universal and important social and economic phenomenon taking place all around the world. This process with no sign of slowing down, could be the most powerful and visible anthropogenic force that has brought about fundamental changes inland cover and landscape pattern around the globe. Rapid urbanization and urban expansion especially in the developing world are continuing to be one of the crucial issues of global change in 21st century affecting the physical dimensions cities (Jimoh et al., 2018).

Due to the African situation, currently urban growth is one of the most important issues in Africa. In 1950, only two African cities were accommodated by more than 1 million residents. By 2010, this number has reached 48 cities, and it is predicted to increase to 68 cities by 2025. Presently, urban growth in Africa is driven by both high natural growth rates and the concurrent rural-urban migration (Wang & Maduako, 2018).

Coastal cities in many parts of the world experience a relatively higher population densities and urban growth rates than the national average trends. Three of the megacities (with population > 10 million) to emerge in Africa by 2030, - Lagos, Luanda, and Dar es Salam - are coastal (Idowu et al., 2020). According to WHO (2010) in a century ago, only 20% of the global population resided are in urban areas, but this is projected to reach 70% by year 2050. Globally, the most extensive urban growths between 2014 and 2050 will occur in developing countries, and the leading country among these three megacities 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 (Nations, 2014) a double-fold increase from slightly over 100 million in 2019. According to (Idowu et al., 2020) the population increase experienced by these coastal cities, coupled with climate change-related events aggravate coastal challenges like seawater intrusion and groundwater contamination, coastal flash floods, urban sprawls, land subsidence, among others. These challenges necessitate deliberate and proactive management plans for sustainable development (Idowu et al., 2020).

II. MATERIALS AND METHOD

Study Area

Lagos state, known as Nigeria's 'Centre of Excellence', was created on 27th of May 1967 under its states decree no. 14, Lagos state government (2020). It has a complicated administrative structure. Lagos refers to both a city and a state, the state is geographically located on the West Coast of Africa in the South-western geopolitical zone of Nigeria, at altitude of 645 m above sea level (Sojobi et al. 2015) (figure1).

The city stretches over 180 kilometers along the Gulf of Guinea on the Atlantic Ocean on a vast lowland and island, having about 220.6 km^2 made up of water bodies, mangrove swamps, and wetlands (Lagos State Government 2013). Lagos, together with its adjoining metropolis, has the smallest land area in Nigeria (3,577 km^2). It is currently the second most populous city on the continent (after Cairo) with a population

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growth rate of 6 – 8% per annum which is more than twice the national average of 2.6% per annum (in year 2000 is 7,281,000, while by year 2020 is 14,368,000). Urbanization expressed as the outward expansion of built-up areas and the conversion of primary agricultural and forestlands into industrial and residential uses, and land reclamation activities are visibly evident in Lagos Nigeria (Idowu et al., 2020).

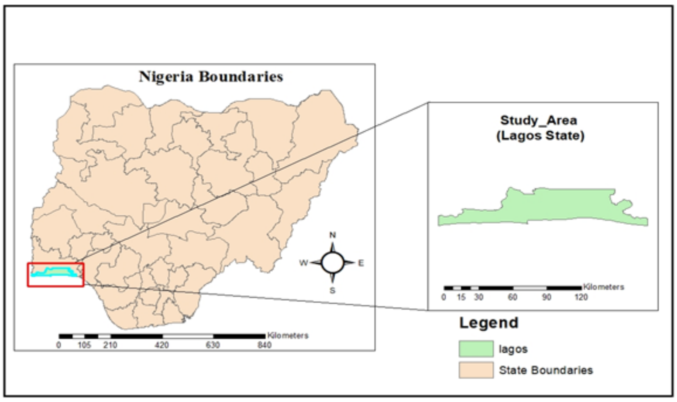

Figure 1. Nigeria map with the study area.

Acquisition of multi-temporal satellite data

To achieve the objectives of this study; Landsat 7 Enhanced Thematic Mapper Plus (ETMP), and Landsat 8 Operational Land Imager (OLI) images, with a cloud cover less than 20% were downloaded from the earth explorer porta l(https://earthexplorer.usgs.gov) for the years 2000, and 2020. The downloaded images had standard radiometric; therefore, it was processed geometrically with three infrared and three visible bands of spectral characteristics suitable for analyzing land cover change (Koko, 2021)

Method

The methodology of this study is based on the evaluation of land use land cover (LU LC) changes, land use land cover (LU LC) analysis, land use land cover (LU LC) change potential modeling and Metropolitan Region using remote-sensing data analysis, remote sensing image classification techniques as well as spatial-temporal analysis. Where two multi-temporal sets of Landsat images (ETM+ 2000, and OLI 2020) covering the entire study area, are used to create the land cover map using the maximum likelihood classification algorithm in QGIS applications, Post-classification comparison is used to produce expansion/change map, where the classified images are overlaid on top of each other in QGIS applications using different spatial analyst tools.

Image pre-processing and LULC classification

In this study, digital remote-sensing data of the Landsat series satellites were used to map various land use land cover (LU LC) classes in Lagos Metropolitan Region, Nigeria. Before analysis change, satellite image pre-processing is crucial in establishing a proper relationship between the acquired satellite data and various biophysical conditions (El-Kawy, 2011). This is vital in rectifying and removing various atmospheric conditions from satellite images, the satellite images were geometrically corrected to UTM zone31 N, datum WGS 1984, and a 30 m spatial resolution to compare the downloaded images with existing maps and other satellite images. Radiometric calibration, atmospheric corrections, layer stacking, mosaicking, and picture sub-setting are just a few of the different pre-processing techniques used. These procedures were performed in QGIS applications to remove numerous radiometric and atmospheric effects due to scattering, absorption, and reflectance. The final images of the study area were further processed in QGIS applications for image enhancements and contrast adjustments using the best bands composite selection to increase the visual interpretability of the images. Figure 2 illustrates the methodology flowchart of the study.

Land Cover Classification

Classification is the process of assigning pixels to informational classes of interest (Campbell and Wynne 2011). The classification process involves spectral or pattern recognition in order to create a cluster of classes from multispectral images.

The satellite image classification was done based on the supervised classification using the maximum likelihood classification algorithm. The Maximum likelihood classification (MLC) is the most adopted parametric algorithm for land cover classification due to its minimal miscalculation probability(Koko, 2021). It computes the probability of each pixel belonging to a particular land cover class. In each satellite image, training samples are chosen by drawing polygons around the typical regions of each land cover class. The training sites were established by the visual interpretation of the different satellite images based on Google Earth information, study area familiarity. The pixels were assigned using the maximum likelihood classifier's assumption that they belong to a particular class, which was used to construct spectral signatures. Each pixel was categorized into one of the following four classes as described in Table 1. To enhance the outcomes and lower misclassifications, a post classification sorting was carried out after the supervised classification. The area coverage of the different classes of multispectral images were then compared to determine changes that have taken place between the dates under study.

Assessment of classification accuracy

Analyzing land cover changes requires assessing the classification accuracy. The study employed the confusion matrix technique, which assesses the overall accuracy of the land use land cover (LU LC) map classification. This technique relies on a set of ground truth data, a classification and sampling scheme, a spatial auto-correlation, and sample size. The overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and kappa value are the components of the confusion matrix (Shao et al. 2019). The overall accuracy compares the classified pixels on each map with the actual land cover (LC) condition obtained using ground truth data. It is computed by dividing the diagonal entries sum by the number of pixels in each confusion matrix (Congalton 1991).

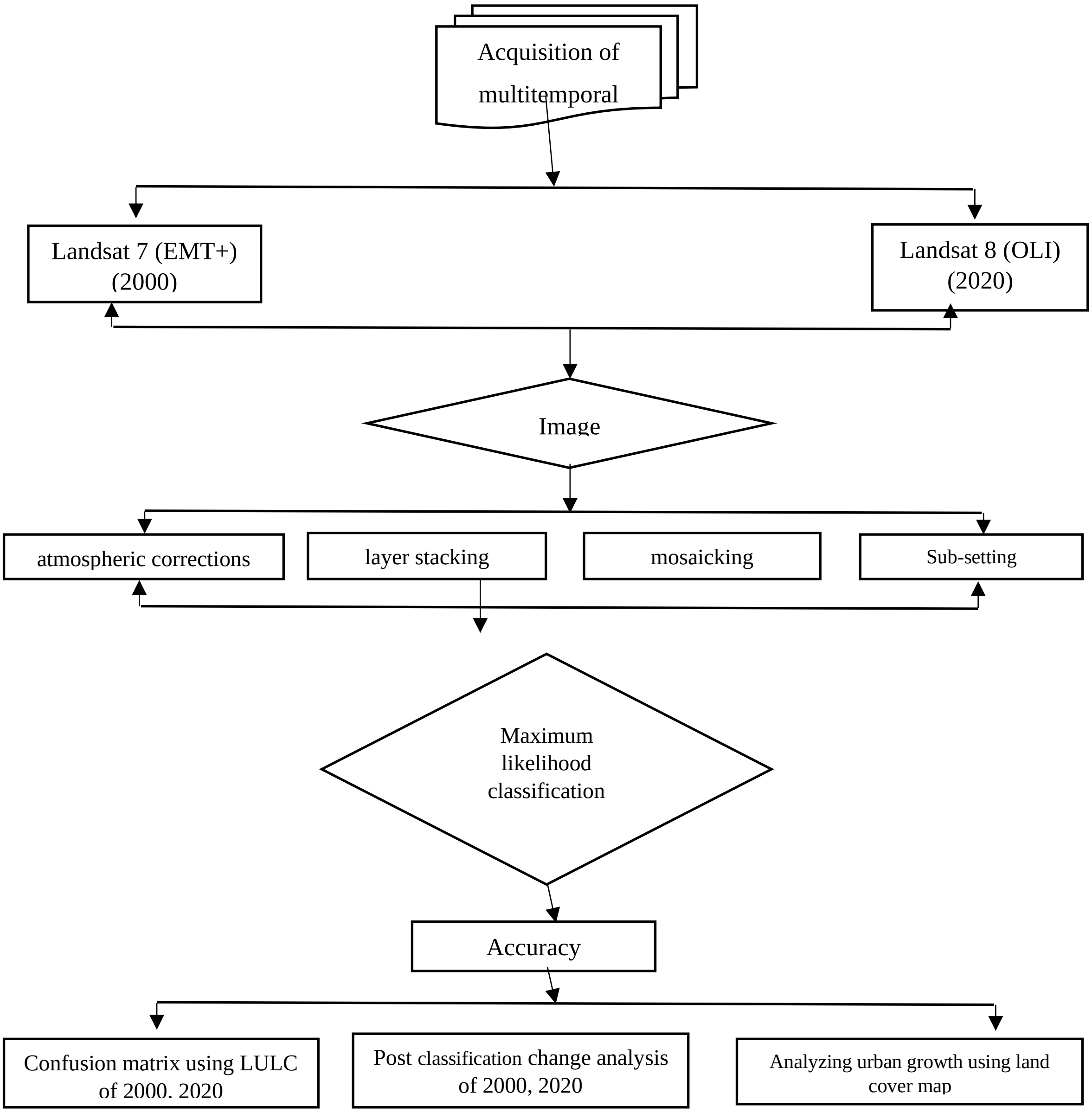

Figure 2: showing the methodology flowchart

TABLE 1: The four-classes of Lagos city-Nigeria

No	Land cover classes	Class description
1	Built-up/Urban area	Land covered with buildings, structures, and facilities for residential, commercial, industrial, and mixed-use areas.
2	Vegetation	Areas that include agricultural lands, scrublands, evergreen, deciduous, mixed forest areas, recreational areas, artificial and natural landscapes
3	Water bodies	Areas persistently covered with various water bodies that include rivers, canals, lakes, water reservoirs, streams, swamps, or ocean
4	Bare soil	Areas that comprise of non-vegetated lands, beaches, sandy areas, bare rocks, gravel pits, and quarries

III. Results and Discussion

Two thematic land cover maps were produced from the various pre-processing operations conducted alongside the supervised classification using the maximum-likelihood algorithm of the satellite images in 2000, and 2020 as shown in table 2 and figures 3. These maps provided the land use land cover (LU LC) classification of the study area comprising the four distinct classes: the red color on the map signifies the built-up area, the green color shows the vegetation cover, the blue color signifies water bodies, while the yellow color signifies the bare soil.

TABLE 2. Land cover statistics of Lagos from 2000 to 2020

Year Land cover classes	2000 Area(km^2)	2000 area (%)	2020 Area(km^2)	2020 area (%)
Water bodies	72.35	23	70.64	22
Vegetation	70.32	22	42.43	13
Built up/Urban area	156.50	50	178.75	57
Bare soil	16.77	5	24.09	8
Total	315.95	100	315.92	100

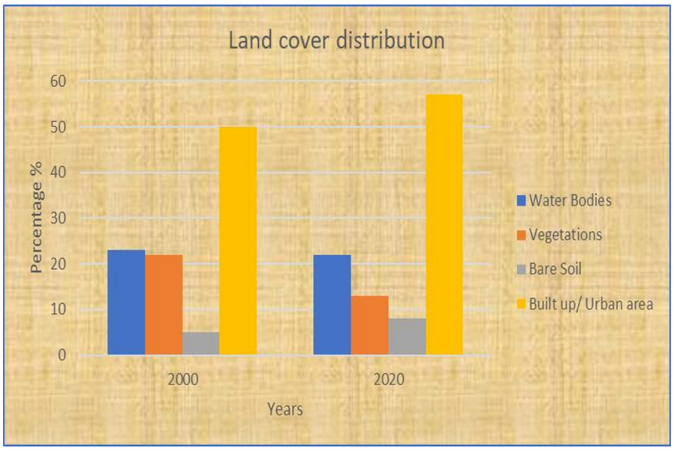

Figure 3: Land cover statistics of Lagos in 2000 and 2020

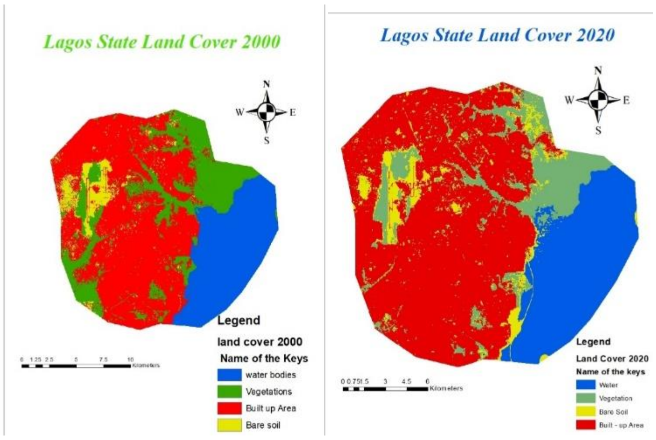

Figure 4: Land cover map of Lagos state 2000, Land cover map of Lagos state 2020

TABLE 3. Overall Accuracy of 2000 and 2020 land cover map

	Land cover map 2000			Land cover map 2020		
Classes	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Overall Accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Overall Accuracy (%)**
Water bodies	73.7	100		87.1	93.1	
Vegetation	79.6	79.6		88	98.5	
Built up/Urban area	78.7	84.1	76.4	90.1	94.1	87.7
Bare soil	67.9	52.8		81.5	55	

KC of year 2000 = 10466/15646 = 0.67 *100 = 66.9%
KC of year 2020 = 24694/29784 = 0.828 *100 = 82.8%

IV. Conclusions

Land use landcover change over time is the response of combined effect of the social, economic, demographic and environmental variables. Understanding the characteristics, extent and pattern of change in land use is vital element for efficient planning, managing and decision-making activities. In the absence of basic information about the current land use and landcover, it would be difficult to determine future improvements. This leads to suggest the need to provide up-to-date information about land-related resources to help planners in decision-making.

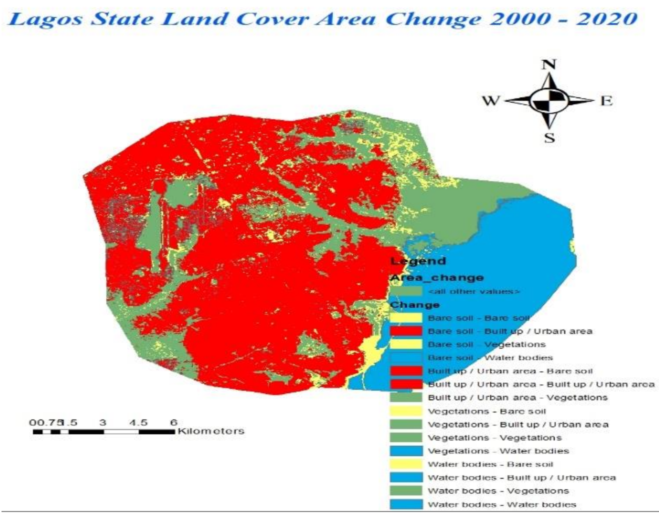

Figure 5: Land cover change map of period 2000 – 2020 of Lagos city

Analysis of Landsat images of 2000 and 2020 revealed that land use and land cover of the study area has changed over the study period. The greatest amount of change detected in the study area occurred in built up/Urban area.

A result from this study have shown that the urban expansion largely from Lagos metropolis have indeed in the past twenty years being sprawling into the nearby rural communities due to the uncontrolled and unauthorized acquisition and conversion of lands. This growth was attributed to people's continuous inflow due to socio-economic activities and massive investment in developmental and infrastructural projects, which took a big impact in changing the area and effect on the community

Therefore, this study conforms with the previous study that identified the various factors contributing to cities' growth in Nigeria. This study highlights the efficiency of remotely sensed data and the integration of various GIS techniques for analyzing urban growth and land cover changes.

The study results will aid urban planners, policy, and decision-makers in developing strategic frameworks and policies to mitigate disasters such as flooding, with relevant data that would enable them to promptly curtain the adverse effects. It will also greatly help preserve the city's ecological system and remedying the various environmental challenges that result from inappropriate planning due to inadequate data.

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