Analyzing urban growth and land cover change scenario in Lagos, Nigeria using multi-temporal remote sensing data and GIS to mitigate flooding

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ABSTRACT
Lagos, Nigeria’s economic hub and one of Africa’s fastest-growing cities, has experienced remarkable urban growth due to rapid urbanization. The city has recently faced persistent urban flooding due to unsustainable growth and inadequate data for proper planning. Therefore, we analyzed urban growth and land cover change in Lagos, Nigeria, using multi-temporal datasets downloaded from the United States Geological Survey (USGS) at an interval of 10 years from 1990–2020. We employed the maximum likelihood classification and post-classification change detection to analyze the city’s urban growth and change dynamics. The study revealed three phases of growth in Lagos and a substantial increase in the city’s built-up area from 496 km² in 1990 to approximately 860 km² in 2000. This area increased further to 1113 km² in 2010, and presently over 1256 km². The result also revealed a substantial decrease in the city’s vegetation, water bodies, and bare soil by approximately 398 km², 246 km², and 115 km², respectively, between 1990 and 2020. These changes contribute to urban flooding, the prominent natural and human-induced disaster in the city. Therefore, this study’s findings provided the historical and scientific data for the effective planning, management, and sustainable development of the city.

1. Introduction
Over the years, the world has witnessed unprecedented urbanization resulting in cities and urban centers (Eigenbrod et al. 2011; Shaw and Das 2018; Zhou et al. 2019). The UN-Habitat describes urbanization as the growth and development of towns and cities, leading to the gradual increase in urban population and a subsequent decrease in
the rural population (UN-HABITAT 2006). It is the shift from rural to urban centers and the process in which a large concentration of people reside in relatively small areas (Katjambo and Ngigi 2017). Urbanization is characterized by the growth and expansion of built-up areas due to the increasing urban population (Al Jarah et al. 2019; Guan et al. 2018). The United Nations Department of Economic and Social Affairs (2018) indicates the world urban population to have grown astronomically since the 1950s, with more than 55% currently living in urban areas and cities. The world urban population is projected to increase to 68% by 2050, with most of the growth concentrated in Asia and Africa. Nigeria, a country with Africa’s largest population, has undergone a dramatic urban transformation over the last few decades. The country’s urban population has rapidly increased from 29.7% in 1990 to 51.2% in 2019 (World Bank 2020). This is an increase of about 74.5 million urban inhabitants between 1990 and 2019. Nigeria’s urban population is further expected to increase to nearly 295 million inhabitants by 2050, making the country Africa’s next urban giant (World Bank 2020). Unprecedented growth in the urban population accelerates the spatial expansion of built-up areas in most urban centers globally (Mosammam et al. 2017). As the urban population increases, the demand for various urban activities also increases, resulting in remarkable urban growth.

Lagos, being the largest urban center in Nigeria, has witnessed tremendous development due to the socio-economic status of the city (Gandy 2006; Owoade 2007; Wang and Maduako 2018). The consequences of this growth have led to several land cover changes with persistent urban flooding due to various human induced activities. Urban flooding is a prominent natural and human-induced disaster in Lagos, mainly caused due to unsustainable urban development and inadequate historical land cover data for appropriate planning. The consequences of this natural disaster have resulted in various forms of destruction, which require the intervention of various stakeholders in achieving sustainable urban development (Ameen and Mourshed 2017; Duvernoy et al. 2018). Between 1988 and 1998, Lagos witnessed about 13 major flood incidences. This flooding was mainly attributed to the demographical increase in size, which led to the rapid growth and expansion of built-up areas and the emergence of informal settlements around the city’s fringes. These unplanned settlements usually sub-merged during the peak of the rainy season due to high rainfall and inadequate urban infrastructures, resulting in the displacement of more than 300,000 populace (Etuonovbe 2011). In 2011, Lagos experienced a devasting flood, which led to 25 deaths and affected more than 5,400 inhabitants (IFRC 2011). Public buildings such as schools and offices, road networks, bridges, and residential developments were flooded and destroyed with several vehicles swept away (Oladunjoye 2011). Areas within the city’s core that include Agege, Ebute Metta, Mushin, Oshodi-Isolo, Apapa, Surulere, Ikeja, Ajeromi-Ifelodun, and Alimosho have also recently witnessed similar cases of flooding due to increased urbanization, indiscrimate and unplanned urban development, inadequate stormwater drainage system, and lack of enforcement of planning laws and regulations (Adelekan 2016). This flooding’s economic consequences had resulted in Nigeria losing over 50 billion naira, which is approximately 250 million dollars (Wahab and Ojolowo 2018). Therefore, the problem of flooding due to the growth and expansion of built-up areas is presently rising issues of great
concern to the government of Lagos and its inhabitants. This underscores the urgent need to provide reliable and up-to-date data on the city’s growth for proper planning and flood mitigation.

Studies have shown that available data and information regarding cities’ urban growth in Nigeria are grossly inadequate and unreliable for appropriate decision-making (Gandy 2006; Owoade 2007). Cities such as Lagos lack timely and up-to-date data on the city’s extent of urban expansion. This serves as an obstacle to sustainable urban development. Therefore, analyzing the urban growth and land cover change of Lagos is crucial in overcoming the city’s challenge of uncontrolled and haphazard development, deteriorating environmental quality, destruction of agricultural lands, and persistent flooding. Historical land cover data are of the utmost importance in mitigating the city’s environmental challenges and natural disasters. Planners, decision-makers, and other relevant stakeholders require such data for policymaking, city management, and sustainable urban planning (Ahmad et al. 2017; El-Hattab 2016; Fenta et al. 2017). It is within this context that this study seeks to provide historical data on urban growth and land cover change in Lagos, Nigeria, to mitigate flooding.

Monitoring and analyzing urban growth has become a significant usage of data from satellite remote sensing and Geographical Information Systems (GIS). It involves identifying and describing changes in land cover patterns using remote sensing techniques. Remote sensing techniques have been widely adopted and used in various studies to monitor and analyze growth (Mosammam et al. 2017; Shaw and Das 2018; Toure et al. 2018; Yang and Liu 2005). Satellite remote sensing provides timely, high, and medium-resolution images suitable for visual and quantitative assessment of urban growth and land cover change dynamics (Keshtkar et al. 2017). The use of GIS facilitates urban planning by providing a suitable environment for displaying, storing, and analyzing digital maps necessary for detecting land-cover change.

Change detection has emerged in remote sensing as a vital process of analyzing urban growth and land cover changes due to its quantitative distribution of land cover classes (An et al. 2018). Several change detection methods have been developed and utilized in monitoring land cover changes using remotely sensed data. However, the Post-Classification Comparison (PCC) and the multi-date composite image change are the most widely used change detection methods, notably in planning due to their representation of LULC change over time (Hassan et al. 2016). The post-classification comparison analyses land cover changes by comparing the classification of independently produced satellite images of different years (Jensen and Cowen 1999; D. Yuan et al. 1999; F. Yuan et al. 2005). It demonstrates the nature of LULC change. The use of the PCC technique minimizes the problems associated with satellite images due to the differences in atmospheric and environmental conditions. Therefore, this study employed the post-classification comparison for change detection to analyze Lagos’ urban growth and land cover change from 1990 to 2020 using Multi-temporal Landsat Imagery and GIS.

2. Study area

Lagos, known as Nigeria’s ‘Centre of Excellence’, was created on the 27th of May 1967 under its states decree no. 14 (Lagos State Government 2020). It is the most
urbanized city in Africa’s most populous country, Nigeria, and one of the world’s fastest-growing urban centers (PWC 2015). The city is geographically located on the West Coast of Africa in the South-western geopolitical zone of Nigeria. It lies between latitudes 6°22’ North to 6°42’ North and longitude 2°45’ East to 4°20’ East at an altitude of 645 m above sea level (Sojobi et al. 2015) as displayed in Figure 1. 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 km² 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. It occupies about 3,577 square kilometers, approximately 0.4 percent of Nigeria’s landmass (Lagos State Government 2020). The city is estimated to have approximately 22 million populace, with a significant percentage of its population residing in urban areas (UNDESA 2019). Lagos’ vegetation is dominated by freshwater and mangrove swamp forests, having a wet equatorial climatic condition due to its proximity to the Gulf of Guinea.
along the Atlantic ocean (Meteoblue 2020). The city experiences two climatic seasons, the dry season having dry and cold climatic conditions experienced from November to March, and the wet season having warm and humid climatic conditions experienced from April to October. The city also has an average annual precipitation of about 1000 mm and an average annual temperature of between 23 to 34 degrees Celsius (Lagos State Government 2020).

3. Materials and methods

3.1. Data collection

The data collected were broadly categorized as satellite data and ancillary data. These data were used to analyze the historical land cover change and produced a thematic map of the study area over the last 30 years. Multi-temporal satellite data were downloaded freely in Geostationary Earth Orbit Tagged Image File (GeoTIFF) and were used to produce the land cover maps of Lagos. Ancillary data, which comprises of Ground Control Points (GCP), topographic maps, Google Earth images, and a combination of historical land use plans and digital maps covering the study area were obtained from the Lagos State Ministry of Lands and Survey for analyzing and validating our result. Also, the study area’s historical aerial photographs were utilized to identify the different areas subjected to various land cover changes. Ground reference data were collected using points during field surveys with a handheld Geographical Positioning System (GPS) device. These points were integrated into ArcGIS 10.7 image processing software for onscreen digitization as used in Abubakar et al. (2020). We divided the reference data and utilized 70 percent as the training samples and 30 percent for validation. The training samples were used to classify land cover, while the validation samples were used to assess LULC classification accuracy.

3.2. Multi-temporal satellite data

The study employed the use of Landsat 4 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) images. The use of Landsat satellite images has been recognized as one of the most reliable and efficient ways of quantifying, mapping, and detecting Land-use/Land cover (LULC) changes over the years due to its spatial resolution and frequency of data collections (Kusetogullari and Yavariabdi 2018; Tewolde and Cabral 2011; Y. Wang et al. 2020). Therefore, Landsat Level 1 datasets of the study area (Lagos, Nigeria) with a cloud cover less than 20% were downloaded from the earth explorer portal (https://earthexplorer.usgs.gov/) of the USGS (United States Geological Survey (USGS), 2020) as presented in Table 1, according to their year and date of acquisition. These comprise satellite images of 1990, 2000, 2010, and 2020. Other information of each satellite image includes the satellite number, sensor type, Worldwide Reference System (WRS) path and row, Universal Transverse Mercator (UTM) zone, datum, and spatial resolution. The downloaded images had standard radiometric. Therefore were processed geometrically with three infrared and three visible bands of spectral characteristics suitable for analyzing land cover change (Wulder et al. 2012;
Thirteen (13) satellite images were downloaded for the study, with an average of three to four scenes per 10-year interval. No satellite image was obtained during the wet season between April and October to acquire images with cloud-free or limited cloud cover.

### 3.3. Pre-processing of satellite data

Although, the USGS had radiometrically calibrated and geometrically corrected all of the acquired level 1-satellite images. Various studies indicate that satellite images or aircraft remotely sensed data are often distorted geometrically due to numerous acquisition systems or platform movements (Hassan et al. 2016; Mohamed and Hassan 2019; Patel and Thakkar 2016; Santhosh and Devi 2011). This may result in difficulties during the processing of polygon-based mosaic classification (Al-Fares

| Year   | Date of acquisition | Satellite number | Sensor type | WRS path/Row | UTM zone | Datum   | Spatial resolution (m) |
|--------|---------------------|------------------|-------------|--------------|----------|---------|------------------------|
| 1990   | 20/Dec/1990         | Landsat 4        | TM          | 190/55       | 31N      | WGS84   | 30                     |
|        |                     |                  |             | 190/56       |          |         |                        |
|        |                     |                  |             | 191/55       |          |         |                        |
|        |                     |                  |             | 191/56       |          |         |                        |
| 2000   | 06/Feb/2000         | Landsat 7        | ETM +       | 190/55       | 31N      | WGS84   | 30                     |
|        |                     |                  |             | 191/55       |          |         |                        |
|        |                     |                  |             | 191/56       |          |         |                        |
| 2010   | 15/Feb/2000         | Landsat 7        | ETM +       | 190/56       | 31N      | WGS84   | 30                     |
|        |                     |                  |             | 191/55       |          |         |                        |
|        |                     |                  |             | 191/56       |          |         |                        |
| 2020   | 01/Feb/2010         | Landsat 8        | OLI         | 190/56       | 31N      | WGS84   | 30                     |
|        |                     |                  |             | 191/55       |          |         |                        |
|        |                     |                  |             | 191/56       |          |         |                        |
|        |                     |                  |             | 190/56       |          |         |                        |

![Research methodological flowchart.](image)
2013; Roy et al. 2016; Shi et al. 2014). Therefore, before change analysis, satellite images’ pre-processing is crucial in establishing a proper relationship between the acquired satellite data and various biophysical conditions (Abd El-Kawy, Rød, Ismail, & Suliman, 2011; Coppin et al. 2004). This is vital in rectifying and removing various atmospheric conditions from satellite images. An appropriate image processing of satellite images is vital for successive land cover mapping and change detection analysis (Hassan et al. 2016). We geometrically corrected the satellite images to UTM zone 31 N, datum WGS 1984, and a 30 m spatial resolution to compare the downloaded images with existing maps and other satellite images. The various procedures adopted for the pre-processing operation includes radiometric calibration, atmospheric corrections, layer stacking, mosaicking, and sub-setting of images. These procedures were performed using ENVI 5.3 software to remove numerous radiometric and atmospheric effects due to scattering, absorption, and reflectance (Czapla-Myers et al. 2015; Shen et al. 2011). The final images of the study area were further processed in ArcGIS 10.7.1 for image enhancements and contrast adjustments using the best bands composite selection to increase the visual interpretability of the images. Figure 2 illustrates the methodological flowchart of the study.

3.4. Land use/land cover classification

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 (Currit 2005; Pal and Mather 2003; Shafri et al. 2007; Sisodia et al. 2014; Soheili Majd et al. 2011). It computes the probability of each pixel belonging to a particular land cover class. The process involves selecting training samples in each satellite image by outlining polygons around each land cover class’s representative areas. The training sites were established by the visual interpretation of the different satellite images based on ground truth data, Google Earth information, field observation, study area familiarity, and historical data derived from local authorities. The maximum likelihood classifier was utilized to create spectral signatures and assign pixels based on its assumption of belonging to a specific class. Each pixel was categorized into one of the following four (4) classes: built-up/urban area, vegetation, water bodies, and bare soil, as described in Table 2. A post-classification sorting was performed after the supervised classification to improve the results and reduce misclassifications (Thakkar et al. 2017). The classified images were sieved and filtered in ENVI 5.3 image processing software before producing the final LULC maps used for further analysis.

3.5. Assessment of classification accuracy

Assessment of classification accuracy is an essential process in analyzing land cover changes. The study employed the confusion matrix technique, which assesses the overall accuracy of the LULC map classification. This technique relies on a set of ground truth data, a classification and sampling scheme, a spatial auto-correlation,
Table 2. Description of land cover classes used in the study.

| S/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. |

and sample size. The confusion matrix comprises the overall accuracy (OA), producer’s accuracy (PA), user’s accuracy (UA), and kappa value (Shao et al. 2019). The overall accuracy compares the classified pixels on each map with the actual LULC 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). Producer accuracy is the probability of classifying a reference pixel correctly, while user accuracy is the probability of each classified pixel representing the actual class on the ground or real-world location (Campbell 2007; Jensen 2005). The kappa value is the overall measurement of the statistical agreement of the confusion matrix. It accounted for the non-diagonal entries and considered one of the most appropriate single error matrix evaluation methods (Kim 2016). The validation samples used to assess classification accuracy were generated using stratified random points in ArcGIS 10.7. It involved the use of a probability sampling design to produce a statistically rigorous LULC map assessment. A minimum of 50 validation samples was generated for each land cover class. The formulas for various accuracies are defined in Eqs. (1)–(4).

$$\text{OA} = \frac{\text{DP}}{\text{TRP}}$$  \hspace{1cm} (1)

where OA is overall accuracy, DP is the total number of diagonal pixels that are correctly classified. TRP is the total number of referenced points.

$$\text{PA} = \frac{\text{PC}}{\text{TPC}}$$  \hspace{1cm} (2)

where PA is producer accuracy, PC is the total number of pixels correctly classified in each column class. TPC is the total number of pixels classified in the same column class.
where \( UA \) is user accuracy, \( PR \) is the number of pixels correctly classified in each row class. \( TPR \) is the total number of pixels classified in the same row class.

\[
UA = \frac{PR}{TPR}
\]  

where \( KC \) is the value of the kappa coefficient. An overall accuracy above 70% is considered an acceptable classification accuracy (Zheng et al. 2015). Kappa value above 0.75 signifies an excellent agreement between two maps, coefficients between 0.40–0.75 indicates a fair or good agreement, and coefficients below 0.40 are regarded as a poor agreement (Fleiss et al. 2003).

**3.6. Change detection using post-classification comparison**

The Post-Classification Comparison (PCC) involves the classification of satellite images to produce thematic maps. These maps are used in analyzing land cover changes and generating tables based on pixel comparison. The PCC is an effective method of change detection in an urban environment due to its advantage of (i) minimizing environmental and atmospheric differences between independently classified images, (ii) providing detailed information on the LULC change matrix, and (iii) quantifying the magnitude and rate of land cover change (Mallupattu and Sreenivasula Reddy 2013). Many studies have efficiently utilized the post-classification
comparison for detecting land cover changes in different parts of the world (Toure et al. 2018; Wang and Maduako 2018). Such studies have successfully achieved high results accuracies. Therefore, we employed PCC conducted using cross-tabulation to

Figure 4. Land cover map of Lagos produced from the supervised classification of Landsat ETM+ image of 2000.

Figure 5. Land cover map of Lagos produced from the supervised classification of Landsat ETM+ image of 2010.
quantify urban growth and analyze the change transitions from a particular land cover class to another. This was done by classifying individual images of the study area independently and comparing each image’s corresponding pixels with that of the

Figure 6. Land cover map of Lagos produced from the supervised classification of Landsat OLI image of 2020.

Figure 7. Land cover statistics of Lagos in 1990, 2000, 2010 and 2020.
different years. The pixel comparison was used to determine the multi-date transition of land cover classes using the different classified maps. The areas of the different land cover classes were obtained by multiplying each land cover class’s image pixels
by the spatial resolution (i.e. 30 m × 30 m) and converting the areas into square kilometers (km²). New thematic maps and matrices were created from the four-time series maps using the overlay procedure to highlight the magnitude of urban growth and land cover changes. The change magnitude (CM), change percentage (CP), and the annual change rate (ACR) for the individual land cover class in each period were calculated using Eqs. (5)–(7).

\[
CM = AL_1 - AL_2 \tag{5}
\]

\[
CP = \frac{AL_1 - AL_2}{AL_1} \times 100\% \tag{6}
\]

\[
ACR = \left( \frac{AL_1 - AL_2}{AL_1 \times N} \right) \times 100\% \tag{7}
\]

Table 5. Area and percentage change of LULC in Lagos during the different periods.

| Period          | Land cover classes | (1990–2000) | (2000–2010) | (2010–2020) | (1990–2020) |
|-----------------|-------------------|-------------|-------------|-------------|-------------|
|                 | km²               | %           | km²         | %           | km²         | %           | km²         | %           |
| Built-up        | 363.71            | 9.91        | 253.22      | 6.90        | 143.07      | 3.90        | 760.00      | 20.71       | 25.33       |
| Vegetation      | –80.41            | –2.19       | –163.31     | –4.45       | –154.41     | –4.21       | –398.13     | –10.85      | –13.27      |
| Water bodies    | –105.38           | –2.87       | –21.46      | –0.59       | –119.77     | –3.26       | –246.61     | –6.72       | –8.22       |
| Bare soil       | –177.92           | –4.85       | –68.45      | –1.86       | 131.11      | 3.57        | –115.26     | –3.14       | –3.84       |

Figure 8. Land cover change of Lagos from 1990 to 2020.
where $\text{AL}_1$ is the area of land cover class at the initial time, $\text{AL}_2$ is the area of land cover class in final time, and $N$ is the number of years between the periods.

### 4. Results and discussion

#### 4.1. Land cover classification

The study produced four thematic land cover maps from the various pre-processing operations conducted alongside the supervised classification using the maximum-likelihood algorithm of the satellite images in 1990, 2000, 2010, and 2020 as shown in Figures 3–6. These maps provided the land cover classification of the study area comprising four distinct classes: built-up/urban areas, vegetation, water bodies, and bare soil. The red color on the map signifies the built-up area; the dark green color shows the vegetation cover, the blue color signifies water bodies, while the yellow color signifies the bare soil.

The spatial distribution of each land cover class was extracted from the individual classified map, and the result was quantified in Table 3. It shows vegetation as the

| S/No | Year | Built-up area (km²) | Annual growth (%) |
|------|------|---------------------|-------------------|
| 1.   | 1990 | 495.91              | –                 |
| 2.   | 2000 | 859.62              | 7.33              |
| 3.   | 2010 | 1112.84             | 2.95              |
| 4.   | 2020 | 1255.91             | 1.29              |

Figure 9. The growth and expansion of built-up areas in Lagos from 1990–2020.
dominant land cover class in Lagos. The vegetation-covered an area of 1905.34 km² in 1990 and gradually decreased to 1507.2 km² in 2020. This indicates a decrease from 51.93% of Lagos’ total land cover in 1990 to 41.08% in 2020. For other land cover classes, the results have shown that the built-up area had rapidly increased from 495.91 km² in 1990 to approximately 1255.91 km² in 2020. This indicates an urban area increase from 13.52% to 34.24% of Lagos’ total land cover over the last 30 years. The area of the water bodies decreased significantly from 945.54 km² in 1990 to about 698.93 km² in 2020. This indicates a decrease from 25.77% to 19.05% between 1990 and 2020. During the same period, Lagos’ bare soil decreased slightly from 322.15 km² in 1990 to 206.89 km² in 2020. This suggests a decline from 8.78% to 5.64% of the city’s total land cover from 1990 to 2020. The classification result established significant changes in the different land cover classes in Lagos between 1990 and 2020. A remarkable increase in built-up areas was observed, and a considerable decrease in area covered by vegetation, water bodies, and bare soil, as shown in Figure 7.

4.2. Accuracy assessment

The confusion matrix assessment was utilized to evaluate the accuracy of classified maps. Each classified map’s overall accuracy was computed by dividing the sum of the diagonal entries by the total entries in the confusion matrix. The overall accuracy and Kappa values for all the classified maps were between 85% to 95% and 0.76 to 0.93, respectively as presented in Table 4. This result shows that all the overall accuracies are above 85%, signifying an effective image processing approach used in the study. It also produced kappa values above 0.75, signifying a substantial and almost perfect kappa coefficient, indicating an unbiased classification assessment.

4.3. Historical land cover changes

The result clearly shows that the land cover classification of the study area has undergone continuous spatial changes over the past three decades based on the change detection results and land cover classification accuracy. Table 5 presents the changes in the land cover of Lagos city as categorized into three different periods. The first period from 1990 to 2000, the second period from 2000 to 2010, and the third period from 2010 to 2020. The result of the three different periods revealed substantial growth in only one land cover class, which is the built-up/urban area. The built-up area grew by 363.71 km² (9.91%) during the first period, 253.22 km² (6.9%) during the second period, and 143.07 km² (3.9%) during the third period. During the whole study period from 1990 to 2020, the built-up area expanded by 760 km² (20.71%) at an annual growth rate of 25.33 km² per annum. As the built area increases, the study result revealed a corresponding decrease in other land cover classes. It shows that vegetation lost 398.13 km² between 1990 and 2020, indicating a negative change of −10.85%. Water bodies lost 246.61 km² between 1990 and 2020, indicating a negative change of −6.72%. While, bare soil lost 115.26 km² between 1990 and 2020, indicating a negative change of −3.84%. The historical land cover change result suggests
both positive and negative changes observed among the different land cover classes in Lagos from 1990 to 2020, as shown in Figure 8.

4.4. Urban growth analysis (1990–2020)

The study utilized an annual growth rate to analyze the urban growth and the expansion of built-up areas in Lagos from 1990 to 2020. The annual growth rate (AGR) indicates the urbanization process over a period. The result presented the quantitative and spatial increase in the city’s built-up areas, as shown in Table 6 and Figure 9, which highlighted the urban growth of Lagos.

The urban growth and land cover changes in Lagos are influenced by various geographical and socio-economic factors that include urbanization, industrialization, and economic development (Wang and Maduako 2018). In most cases, the city’s urban growth and associated land cover changes result from the combination of these factors. Lagos’ population growth is also a dominant factor driving urban expansion and has undergone a tremendous increase over the last few decades. Data collected from UNDESA (2019) ranks the city as the 21st largest urban center globally and the largest urban center in Nigeria. It has over 22 million inhabitants, with a significant percentage living in the city’s urban areas (Demographia 2020). Lagos city’s population is increasing ten times faster than New York and Los Angeles; more than 32 African countries’ population put together (UN-HABITAT 2004). The growing population has led to the designation of the city as a leading megacity in Africa. The UN-HABITAT (2004) and Federal Government of Nigeria (2012) opined that with the present population growth in Lagos, the city is set to become the world’s third-largest megacity by 2050, after Tokyo in Japan and Bombay in India. The population of Lagos is expected to exceed 35 million inhabitants in the next 30 years. This growth
may be connected to the city’s socio-economic activities that have contributed immensely to the rapid increase in built-up areas.

This study shows that Lagos’ urban growth can be categorized into three (3) phases from 1990–2020. These phases include (i) the rapid growth phase from 1990 to 2000, (ii) the continuous growth phase from 2000 to 2010, and (iii) the steady growth phase from 2010 to 2020. During the first phase between 1990 and 2000, the city’s built-up area witnessed a rapid increase of approximately 36.37 km² per annum. Lagos experienced the highest annual urban growth rate of 7.33% during this period. This exceptional growth can be attributed to the city’s massive investment in infrastructural developments after Nigeria’s oil boom in the 1970s and 1980s. The urban expansion within this period can be described as a concentric and multiple nuclei growths mainly due to its occurrence away from the city’s metropolis or Central Business District (CBD). Areas in around the city’s water bodies began to experience early developments in 1990 and continued until 2000. The second growth phase stretched from 2000–2010. During this period, the city experienced a continuous urban expansion at a rate of 25.32 km² per annum. This continuous growth primarily occurred in coastal and low-lying areas of the city at an annual growth rate of 2.95% between 2000 and 2010. Such low-lying areas include Ikoyi and Victoria Island, which had experienced unanticipated flooding over the years (Kaoje and Ishiaku 2017). Lagos’ city experienced steady urban growth at an almost stabilized rate during the third phase from 2010–2020. During this period, the city expanded by 14.31 km² annually, with a growth rate of 1.29%. The steady growth occurred mainly within the coastal areas due to various urban amenities such as electricity, potable water supply, roads, and housing projects. This resulted in the development of Islands such as Eko Atlantic City, Orange, Diamond, and Gracefield Phoenix Islands. The study also produced a thematic map showing the city’s population density and areas that recently experienced flooding, as shown in Figure 10. The map suggests that urban growth areas are more vulnerable to flooding due to unsustainable growth.

The demographical shift in population and subsequent urban growth can significantly affect the ecological system and damage the environment through the increased concentration of populace and gradual loss of vegetation and natural habitat (Atta-ur-Rahman et al. 2016). Adelekan (2016) identified the high population density and the large concentration of residential, commercial, industrial, and urban infrastructure systems in Africa’s coastal megacity of Lagos to be a substantial factor increasing the city’s flooding. Other factors include the topography of the area, high precipitation, and land use/land cover changes due to human-induced activities (Okoye and Ojeh 2015). Lagos city’s growth and land cover changes have led to a complex and challenging relationship between natural and built environments. Studies suggest Low lying and highly populated areas having inadequate amenities as highly vulnerable to flood (Hallegatte et al. 2013; UN-Habitat 2011). Salami et al. (2017) believe that highly populated cities in Nigeria are frequently characterized by unplanned and haphazard development with inadequate basic infrastructural facilities. Echendu (2020) asserts that uncontrolled urbanization, poor or non-existent drainage systems, poor waste management, and weak planning regulations contribute to urban flooding in Lagos city. Similar scenarios exist in different parts of the world where urban flooding predominantly occurred
mainly in flood-prone and low lying areas of cities (Moftakhari et al. 2017). This, therefore, highlights the need to analyze the urban growth and understand the nature and rate of land cover changes to avert such a natural and human-induced disaster. The findings provide the historical data on urban growth and land cover change of Lagos over the past 30 years and suggest proper planning and consideration towards the fringes of the city’s center and in areas along the city’s coastal zones due to the increased urban developments as shown in this study.

5. Conclusion

The present study analyzed the urban growth and land cover change in Lagos, Nigeria, using multi-temporal remote sensing imageries and GIS obtained from 1990 to 2020. This study aimed to mitigate potential flooding and various environmental challenges due to the city’s growth in built-up areas. In this study, classified maps categorized into four (4) land cover classes were produced using the supervised maximum likelihood classification scheme of the satellite images of 1990, 2000, 2010, and 2020. The efficacy of the classified maps was achieved through rigorous operations to ensure accurate land cover change over time. The accuracy of these maps were further evaluated to ensure results obtained are reliable and fit for informed decision-making. The study results demonstrated significant changes in land cover patterns of Lagos and indicated the expansion of the built-areas with about 153.25% over the last 30 years. This growth was attributed to people’s continuous inflow due to socio-economic activities and massive investment in developmental and infrastructural projects. The result of this study aligns with a study that analyzed settlement expansion in Abuja, Nigeria, using remotely sensed data and other auxiliary datasets (Mahmoud et al. 2016). It established that Abuja’s urban growth results from the city’s population growth and available infrastructures that included public offices, residential facilities, commercial, and other industrial facilities. 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. 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. However, further research is required in understanding the city’s future urban expansion using a combination of optical and Synthetic Aperture Radar (SAR). This is with the hope of achieving sustainable urban growth in Lagos, Nigeria.

Data availability statement

Raw data were generated at the United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (https://earthexplorer.usgs.gov). Derived data supporting the findings of this study are available from the corresponding author W.Y on request.
Disclosure statement

No potential conflict of interest.

Funding

This study was supported by the National Natural Science Foundation of China (NSFC) with grant number 51778559 (2018/01–2021/12).

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