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Land Use/Land Cover Changes Detection in Lagos City of Nigeria Using Remote Sensing and GIS

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Abstract

The rapid urbanization and population growth of Lagos City, Nigeria, have led to a significant change in land use and cover over the past two decades. The primary objective of this research was to assess the changes in land use and cover and forecast future trends in Lagos for the sustainable development of urbanization. The study utilized remote sensing and GIS technologies to monitor and identify the land use and cover of Lagos from 2000 to 2020. The CA Markov artificial neural network technique for cellular automata was employed to predict changes in land use and cover from 2020 to 2030. In addition, the post-classification comparison method was used to detect changes in classified classes in land use and cover. The study classified satellite images for 2000, 2010, and 2020 to develop land use and cover maps using ERDAS Imagine. The classification was based on six categories, namely 1) water bodies, 2) built-up, 3) bare land, 4) forest, 5) vegetation, and 6) wetlands. The results showed that: 1) the vegetation cover, wetlands, built-up areas, forests, and bare land have undergone significant changes over the past two decades. Built-up areas, wetlands, and forests have increased by 33.57%, 1.01%, and 21.37%, respectively, while vegetation, bare land, and water have decreased by 21.77%, 5.14%, and 17.13%, respectively. 2) Moreover, during 2020-2030, it is projected that 19.18% of forests and 16% of vegetation will decline, while 5.27% of barren land, 0.82% of wetlands, and 15.83% of water will increase. The urban area will be expanded by 42.44%. 3) The simulated results showed that the correction percentage was 82.43%, and the global kappa value was 0.85. The study found that the expansion of urban built-up areas due to population growth was the primary driver of the changes in land use and cover in Lagos. This research provides crucial insights that contribute to sustainable planning and management and helps us better understand the changes in land use and cover in Lagos.

Keywords

Urbanization, LU/LC Change, Remote Sensing, CA Markov, Sustainable Development

1. Introduction

A process of detecting land use/land cover (LULC) alteration involves identifying changes to the features or phenomenon over time [1], and it is key to controlling environmental change [2]. Global anthropogenic activities increase considerably and lead to large-scale modifications to the earth's surface, affecting the effectiveness of global systems. Consequently, the swift changes in LULC, specifically in low-income countries, have reduced important resources, such as water, soil, and vegetation [3]. Due to their magnitude, they have become global critical implications, and it is alarming that those changing steps are increasing locally, regionally, nationally, and worldwide, and this may significantly impact the environment on a different level [4] [5]. Satellite images are the most basic data for detecting, quantifying, and mapping LULC changes because of their repetitive acquisition, and their digital format is suitable for computer processing with a precise geo-reference procedure [6]. For the LULC, change detection and monitoring by ERDAS imagine involves using numerous datasets of images to assess the alterations occurring in LULC between the different acquisition dates of images due to several environmental conditions and human action [7]. The technique requires an adequate understanding of landscape features, imaging systems, and methodology involved [8]. Lagos has experienced significant urban growth and has become one of Africa's continent largest and most rapidly growing cities. In recent decades, there has been an unmatched level of urban expansion in Lagos, making it a unique case in West Africa [9]. Lagos is the economic center of Nigeria and the West African sub-region. As such, it has attracted a high volume of domestic and international migrants, resulting in an intense settlement in the region [10]. However, the deficiency of updated and accurate data on the place, the spatial extent, the rate, and triggering factors of city development has always been a major obstacle to implementing adequate and effective urban planning and governance policies in major cities in developing countries like Lagos [11]. Because urban development involves a dynamic spatial-temporal variation process, modeling, simulation, and prediction can be useful planning tools for understanding the interaction between the natural and anthropogenic environment and problems resulting from rapid urban growth. Paul *et al.* [12] pointed out that changing detection has become essential in RS for examining urban development and LULC changes. Various methods and remote sensing data have been used for monitoring LULC [13]. Among these methods, the Post Classification Comparison (PCC) and different complex images are frequently used, particularly for planning LULC change over time [14].

The PCC approaches analyze land cover changes by comparing satellite images produced in different years [15]. It proves the nature of LULC change and helps to minimize the issues associated with satellite image variations. Therefore, the current study utilized the PCC method for examining the LULC change in Lagos from 2000-2020 using various Landsat imagery, remote sensing, and Geographic Information Systems. This study focuses on forecasting land use/land cover changes in Lagos, Nigeria, using the CA Markov artificial neural network technique and multiple Landsat imagery datasets. The study compares the urbanization of Lagos and Shanghai, two cities known for high population density. As a developed city, Shanghai has avoided slums, while Lagos is still advancing in infrastructure and economy. The findings of this study provide valuable insights into sustainable urban development strategies in Lagos. Moreover, the study's results can serve as a guide for other low-income countries facing similar challenges. By offering a comprehensive analysis of Lagos's urbanization process, the study fills the data gap crucial to effective urban planning and governance policies in burgeoning cities like Lagos.

2. Material and Methods

2.1. Study Area

Positioned in the southwest portion of Nigerian Federation **Figure 1**, Lagos is the most urbanized metropolis in Nigeria, the most populated nation in Africa,

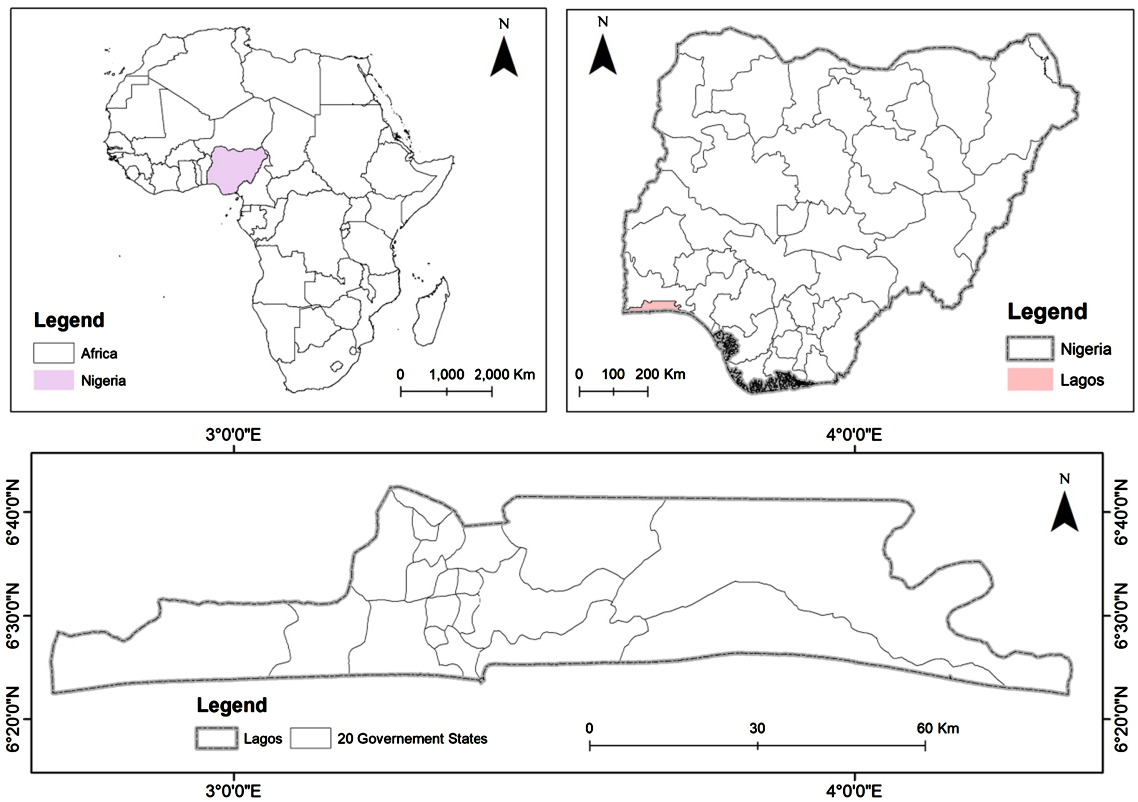

Figure 1. The location of Lagos city on Africa map.

and one of the cities experiencing the most rapid expansion on a global scale in terms of its urban population. It stretches 180 km across the Guinea shoreline of the Gulf of Benin on the Atlantic Sea. Moreover, it is roughly located on latitudes and longitudes of (6˚22' to 6˚42') N and (2˚45' to 4˚20') E, in the order mentioned, and situated at a height of 645 meters relative to sea level [16]. Its geographic scope and political authority extend to Lagos, with four administrative regions of Ikeja, Ikorodu, Epe, and Badagry, also known as IBILE, is a region in Nigeria that covers 3577 km^2, or 0.4% of the country's total land area (923,773 km^2).

According to the United Nations, globally, Lagos is classified as the urban region's most densely inhabited and rapidly developing region [17]. Moreover, it has many administrative, commercial, and industrial activities in Nigeria. As an urban conglomerate, Lagos extends towards the interior, creating an urban corridor connecting Lagos with other hinterland cities, such as Ibadan. The city is believed to have around 22 million inhabitants, and many live in urban regions.

2.2. Data Source

Landsat images were utilized to determine LULC distribution and alterations over time. To complete the objective, the task required acquiring three sets of image datasets with a resolution of 30 meters. These datasets were obtained from the USGS Earth Explorer and correspond to the years 2000, 2010, and 2020. Specifically, Landsat 5, 7, and 8 were used to collect the respective datasets for each of these years. The software packages ERDAS Imagine 2022, ArcGIS Pro 3, Excel, and Google Earth Pro were actively used in different analysis phases. **Table 1** describes distinct categories of LULC.

Table 1. Classification of LULC of Lagos.

LULC Class	General explanation
Vegetation	Includes natural or planted vegetation, such as grasslands, shrubs, trees, and cropland.
Forest	Includes dense trees and undergrowth, usually the areas covered with vegetation.
Built-up	This class includes buildings, roads, and other artificial structures. In Lagos, built-up is highly concentrated in urban centers.
Bare land	This class refers to areas with no vegetation or human-made structures. In Lagos, bare land can be found in areas undergoing development, abandoned properties, and areas where natural conditions make it difficult for vegetation to grow.
Water	This class includes all bodies of water, such as rivers, lakes, and lagoons.
Wetland	Wetlands are areas where the land is filled with water, whether it be on a permanent or seasonal basis. In Lagos, wetlands can be found in coastal areas and places with poor drainage.

2.3. Data Processing and Data Analysis

The overall methodology used in this research is schematically represented in Figure 2.

2.4. Supervised Classification

Classifying images in a supervised manner is one of the best approaches with highly precise. An operator identifies sample areas (training areas). It requires familiarity with the area of interest using Google Earth with high spatial resolution. ERDAS IMAGINE 2022 is software used for Landsat image processing. Precisely, training samples for the specified LULC types have been chosen by demarcating polygons around indicative sites, with pixels surrounded by these polygons and spectral signatures for the corresponding land cover types collected by satellite images [2]. Incorporated the spectral signature into the classification procedure once it was tried satisfactorily. As one of the familiar parametric classifiers applied for supervised classification, the maximum likelihood technique as a classification method was chosen. According to Mugiraneza *et al.* [18], the process of calculating the likelihood D or weighted distance of the unknown measurement vector X falls into a specific category known as M_c, and it serves as a fundamental component of the Bayesian equation.

$$D = \ln(a_c) - 0.5\ln(|cov_c|) - 0.5(X - M_c)T(cov_c - 1)(X - M_c) \quad (1)$$

The MLC has the advantage of considering variance and covariance within the ranges as a parameterization classifier, and it works better than other recognized parametric classifiers for normal distribution data [9]. However, if the data provided has a non-normal distribution, it may be necessary to enhance the accuracy

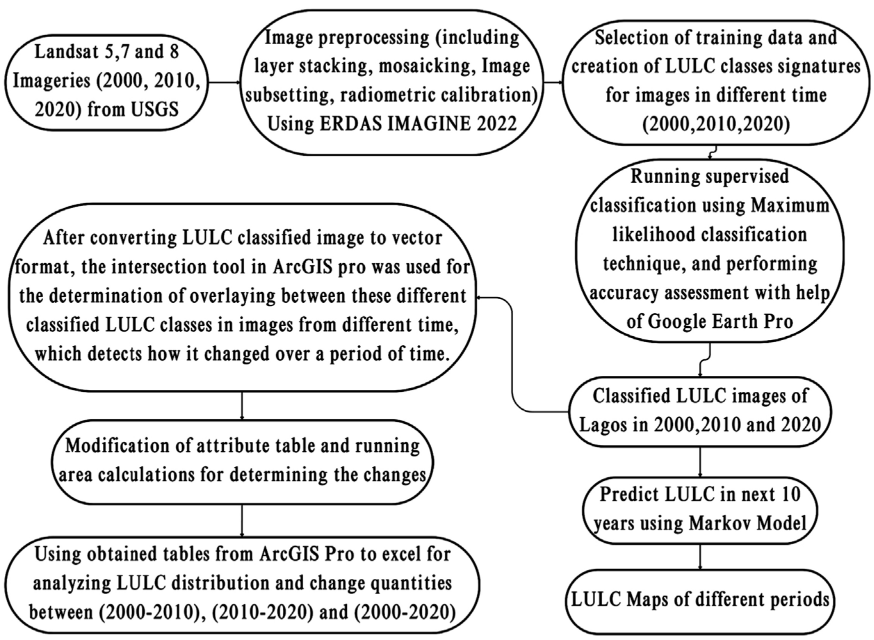

Figure 2. Flow chart.

of the results [19]. The post-classification threshold was set using a thematic layer and distance files output from supervised classification, and three initial LULC maps were created.

2.5. Accuracy Assessment

This study tested the accuracy of the LULC map and the change detection results by comparing them with surface reality by randomly choosing ground truth points as references. It has been performed for all results. However, an error matrix and simple descriptive statistics were used to determine approval and disapproval of all images regarding classification. An error matrix is a grid of numerical values arranged in both rows and columns that displays a count of sample elements, such as pixels, that are allocated to a specific group compared with those assigned according to a referenced dataset [20]. The Kappa coefficient was also computed to measure how accurate the results are. It is a commonly used metric for evaluating accuracy and is a method for analyzing discrete multivariate data [21]. More generally, the Kappa coefficient is the percentage of agreement minus what we would expect by chance [22] [23] [24]. The calculation of Kappa, as outlined by Jensen and Cowen, in addition, is determined using the next equation:

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i+} \times x_{+i}\right)}{N^2 - \sum_{i=1}^{r}\left(x_i \times x_{+i}\right)} \quad (2)$$

Let N represent the overall count of sites within the matrix, r denotes the number of rows present in the matrix, x_{ii} signify the value found at the intersection of row i and column i. x_{+i} indicates the sum of values within row i, while x_{i+} represents the sum of values within column i [24]. The LULC map result has a Kappa statistic estimated to be greater than 0.85. The Kappa coefficient expresses the proportionate reduction of a classification process's errors compared to a random classification error [25]. A Kappa value of one implies true agreement, whereas a value greater than 0.85 shows that the resulting LULC map avoided more than 85% of errors. Remote sensing professionals and GIS practitioners widely acknowledged the accuracy of the LULC map of the research area [26].

2.6. Change Detection

Change detection analysis determines the nature, magnitude, and level of land cover changes over spatial-temporal variations [13]. Land managers may use the results delivered by LULC change detection by linking different variables such as urban sprawl, water resource management, deforestation, and land degradation [27] [28]. Change detection is performed by deducting images from two different periods of the same location [29] [30].

The distinction between images for two or more dates indicates an increase or decrease in specific LULC categories and variation in their spatial distribution. Many indices have been well-known and used to detect changes in various environmental states worldwide. The normalized difference water index (NDWI) and the normalized difference vegetation index (NDVI) are extensively used time series indices. Different satellite images are routinely used to identify and monitor water and vegetation cover changes across time [30]. The following equation has been modified to calculate changes in land cover.

$$K_{gain} = S_b - S_a \tag{3}$$

$$K_0 = S_{bi} = S_{ai} \tag{4}$$

$$K_{loss} = S_a - K_0 \tag{5}$$

where S_a and S_b mean land cover types at the starting and end year (time) in an expected period (10 years), respectively. S_{ai} and S_{bi} represent land cover types.

The intersection tool in ArcGIS Pro, which is a spatial analysis tool that overlays two or more layers to create a new layer with only the features that overlap, was used to detect LULC change for 20 years (2000, 2010, and 2020). Areas where changes have occurred were identified by overlaying the LULC data for each period. In vector data format, the resulting output from the intersection tool allows for further analysis and visualization of the changes over time. It is extensively utilized in diverse domains such as urban planning, natural resource management, and environmental monitoring.

2.7. Driving Factors for LULC Change

In the context of (LULC) change, elevation has been identified as a major factor influencing the transformation of undeveloped land to developed land. This is possible because places at higher altitudes are better suited for settlement. After all, Lagos is located on low-lying land susceptible to flooding. Distance from the water bodies is a vital spatial factor that influences urban development. In addition, proximity to the town center plays a significant role in LULC change; areas nearer the urban center are more likely to be developed into built-up areas. It is because the city infrastructure, employment opportunities, and other socioeconomic resources are concentrated in the downtown area, making them more accessible to people living close to the town center. In contrast, the slope is not observed to impact urban growth in Lagos significantly. However, it could be attributed to the flat topography of Lagos, where slope-related constraints are less pronounced than in mountainous regions. As a result of Lagos' rapid population growth, there has been pressure on various types of land use, which has led to the conversion and modification of land LULC in the city. LULC changes and population growth are significantly related during the observed period. LULC in the Lagos city region changed rapidly from 2000 to 2010. Urbanization is primarily caused by the migration of rural residents to urban areas. Furthermore, more reliable population data is needed to make land use policy for planning and implementation easier. This is one of the primary issues that has rendered successive governments' execution of land use plans to handle population growth in an orderly and planned manner a failure. The expanding population's demand for shelter and other facilities resulted in unprecedented urban expansion (spatial). The influx of people to Lagos led to the formation of shanty towns and villages, which deteriorated into slums in modern Lagos.

3. Results

3.1. LULC Distribution in 2000, 2010, and 2020

In order to test the validity of satellite image classification results, we wanted to compare them with reference data or ground truth. An error matrix is commonly used to assess classification accuracy for remote sensing applications [31]. LULC maps resulting from visual interpretation and classification were evaluated using an error matrix. The following are classified image maps, their accuracy assessment reports, and the area and percentages for each class. Figure 3 indicates the LULC maps of Lagos in 2000, 2010, and 2020, and Table 2 shows the area with the corresponding percentage of each LULC type. Figure 3 shows that between 2000 and 2020, there were considerable changes in the LULC in Lagos, Nigeria. The most notable change was the increase in the build-up area, which grew from 598.426 km^2 in 2000 to 1271.286 km^2 in 2020, as shown in Table 2.

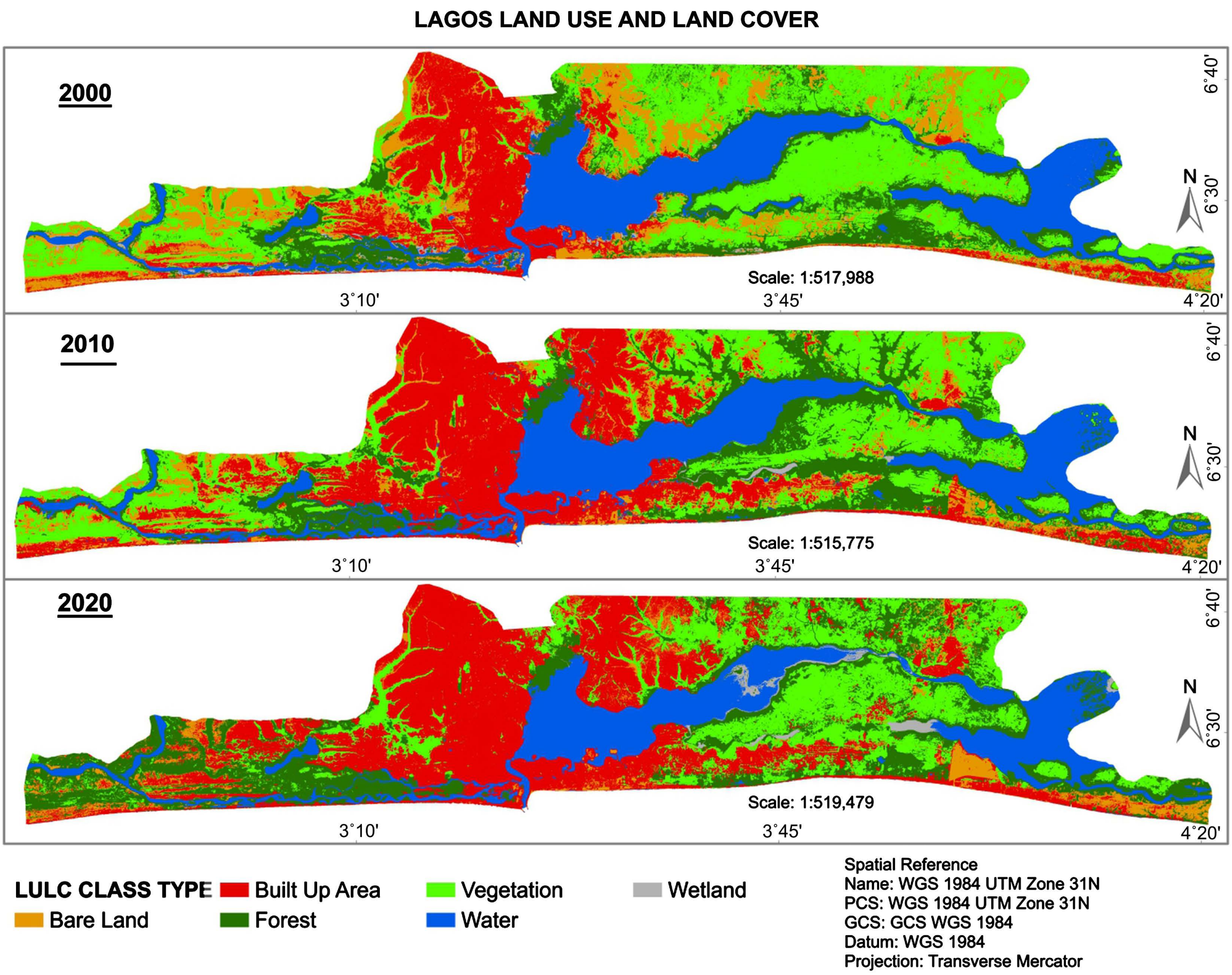

Figure 3. Lagos LULC change of different period.

Table 2. Overall LULC distribution (2000-2020) in the study area.

LULC Class	2000		2010		2020	
	Area in km^2	Percentage	Area in km^2	Percentage	Area in km^2	Percentage
Bare Land	631.383	16.67%	345.280	9.12%	194.643	5.14%
Built-up	598.426	15.80%	1083.654	28.61%	1271.286	33.57%
Forest	574.335	15.16%	693.595	18.31%	809.944	21.39%
Vegetation	1200.728	31.70%	887.113	23.42%	824.428	21.77%
Water	746.997	19.72%	770.434	20.34%	648.795	17.13%
Wetland	35.535	0.94%	7.328	0.19%	38.307	1.01%
Total	3787.404	100.00%	3787.404	100.00%	3787.404	100.00%

This represents a 112.2% rise in built-up, indicating that Lagos has experienced rapid urbanization over the past two decades. The increase in the built-up area was accompanied by a decline in vegetation, which decreased by 376.3 km^2 during the same period. Thus, vegetation reduction has been considered a triggering factor for several environmental-related issues, including soil erosion, decreased air quality, and reduced biodiversity.

Another significant change observed in Lagos was the decline in bare land, which decreased by 436.739 km^2 between 2000 and 2020 (**Table 2**). This change was due to the alteration of bare land into built-up. However, this decline in bare land may also have negative implications for the region's hydrology, as bare land is important for groundwater recharge and infiltration. On the other hand, the wetlands showed a minor increase of 2.772 km^2 from 2000 to 2020, as shown in **Table 2**. This increase is attributed to the government's efforts to preserve wetlands for flood mitigation purposes. Previous studies have highlighted the challenges of urbanization in Lagos, with a growing population and rapid expansion leading to various environmental, social, and economic problems. One of the most significant challenges is flooding, which has become a recurrent problem in the region. This study provides valuable information for flood mitigation efforts. The development in built-up areas may contribute to the flooding problem, as it can reduce the permeability of the soil, resulting in increased surface runoff. Therefore, sustainable land use planning is a need in Lagos to balance the needs of urban development with the conservation of natural resources and the protection of vulnerable ecosystems [32].

3.2. LULC Accuracy Determination

Assessing the accuracy of the classification result is a vital requirement for analyzing LULC changes. Classification results presented that the total accuracy was 95%, 92%, and 93% for 2000, 2010, and 2020, respectively, and the kappa coefficient values were 94%, 90%, and 91% for 2000, 2010, and 2020, respectively (**Table 3**). Further, the classification accuracy exceeded the acceptable threshold, indicating it could meet the LULC classification requirements.

Table 3. Overall LULC accuracy distribution and kappa coefficient (%).

LULC	2000		2010		2020	
	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy
Bare land	0.96	0.94	0.94	0.89	0.86	0.90
Built-up	0.94	0.94	0.84	0.87	0.94	0.93
Forest	0.96	0.96	0.96	0.95	0.92	0.96
Vegetation	0.94	0.94	0.96	0.94	0.96	0.89
Water	0.96	0.94	0.94	0.92	0.96	0.92
Wetland	0.92	0.96	0.88	0.96	0.92	0.96
Overall	0.95		0.92		0.93	
Kappa	0.94		0.90		0.91	

3.3. LULC Change Detection

The LULC change detection results have briefly been presented in **Tables 4-6** for the past two decades (2000-2010, 2010-2020, and 2000-2020). Meanwhile, **Figure 4** indicates the spatial distribution of LULC classes. In this study, the changes matrix was determined by applying the cross-tabulation technique to compare two maps of the different periods. Teferi *et al.* [33] net change refers to the disparity between the amount gained and the amount lost. The alterations in LULC throughout the research were assessed by comparing data from 2000, 2010, and 2020. The results, primarily displayed in **Table 7** as well as **Figures 5-7**, highlight the gains and losses.

From **Table 7**, the outcomes showed that the LULC in Lagos has undergone significant changes in the selected period. The built-up has augmented by 672.860 km^2, with a net increase of 485.228 (81.08%) km^2 between 2000 and 2010 and 187.632 (17.25%) km^2 between 2010 and 2020. On the other hand, the bare land has decreased by 436.739 km^2, with a net decrease of 286.103 km^2 between 2000 and 2010 and 150.636 km^2 between 2010 and 2020. Similarly, the forest area has increased by 235.609 km^2, with a net increase of 119.261 km^2 between 2000 and 2010 and 116.349 km^2 between 2010 and 2020. The vegetation area has shown a significant net decrease of 376.300 km^2 between 2000 and 2020, with a net decrease of 313.615 km^2 between 2000 and 2010 and 62.685 km^2 between 2010 and 2020. The water area has also decreased by 98.202 km^2 between 2000 and 2020, with a net increase of 23.436 km^2 between 2000 and 2010 and a net decrease of 121.638 km^2 between 2010 and 2020. The wetland area has slightly increased by 2.772 km^2 between 2000 and 2020, with a net decrease of 28.207 km^2 between 2000 and 2010 and a net increase of 30.979 km^2 between 2010 and 2020. In the next 10 years, it is predicted that the LULC will keep changing. A prediction map from 2020-2030 revealed a significant decreasing trend in (the forest, vegetation, bare land, wetlands, and water by 19.18%,

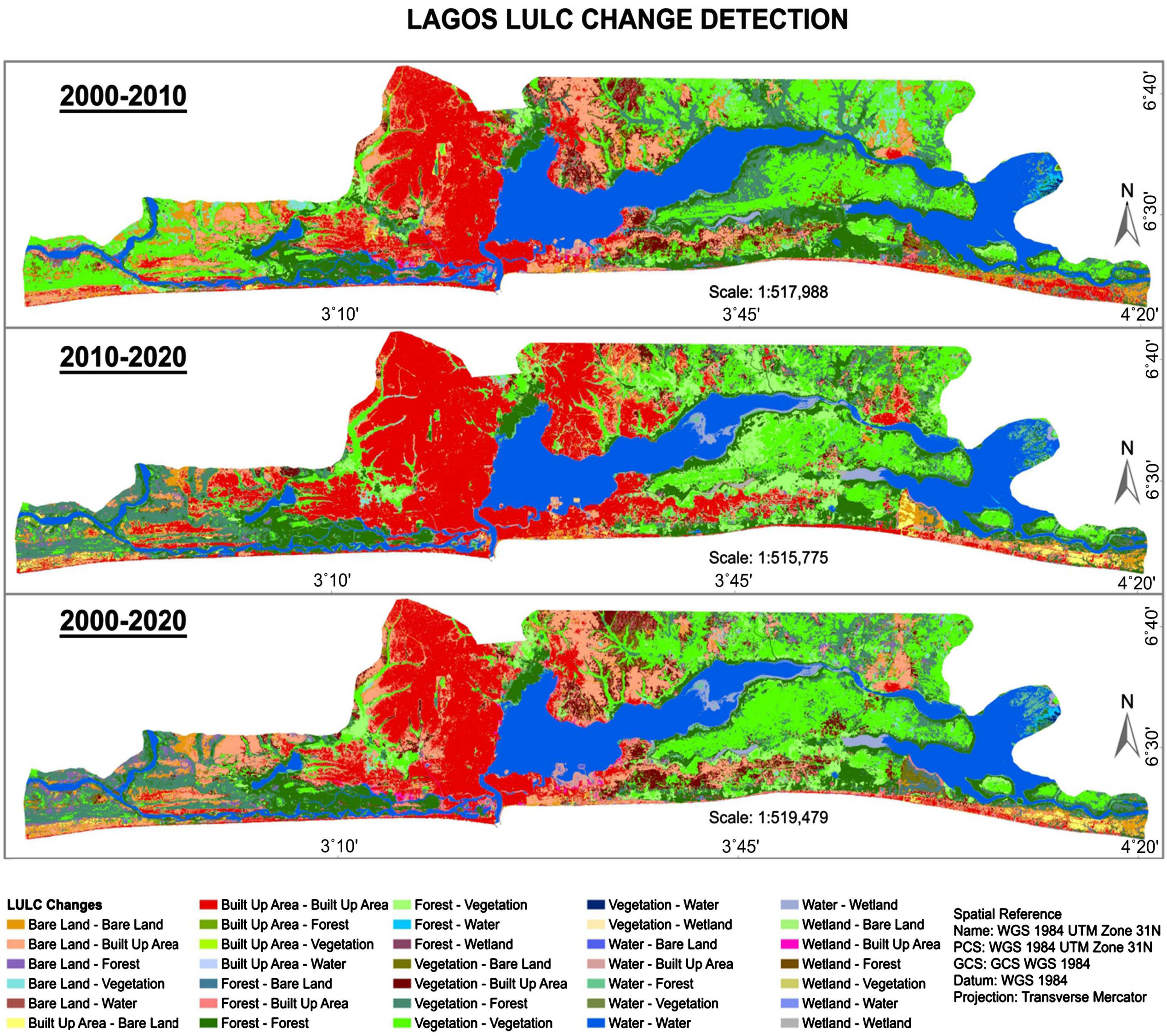

Figure 4. Lagos LULC change detection from 2000 to 2020.

Table 4. LULC changes matrix as detected from 2000 to 2010.

	LULC Classes	2010 Area in km²						
		Bare land	Built-up	Forest	Vegetation	Water	Wetland	Grand Total
2000 Area km²	Bare land	**162.0206601**	354.259417	21.61010673	87.00037156	6.466535778	0.025526332	631.383
	Built-up	20.3330874	**566.3621831**	3.126164264	2.380173404	6.211725506	0.0126010	598.426
	Forest	27.08849085	28.37353307	**376.0116037**	110.8448555	31.71745236	0.298699759	574.335
	Vegetation	132.6919746	116.7050766	261.5241651	**683.8261655**	5.918283757	0.062634112	1200.728
	Water	1.598409984	7.899491559	18.61441854	2.184087234	**709.7863815**	6.914535172	746.997
	Wetland	1.547164973	10.05409075	12.70887013	0.877772412	10.33329266	**0.0140818**	35.535
	Grand Total	345.280	1083.654	693.595	887.113	770.434	7.328	3787.404

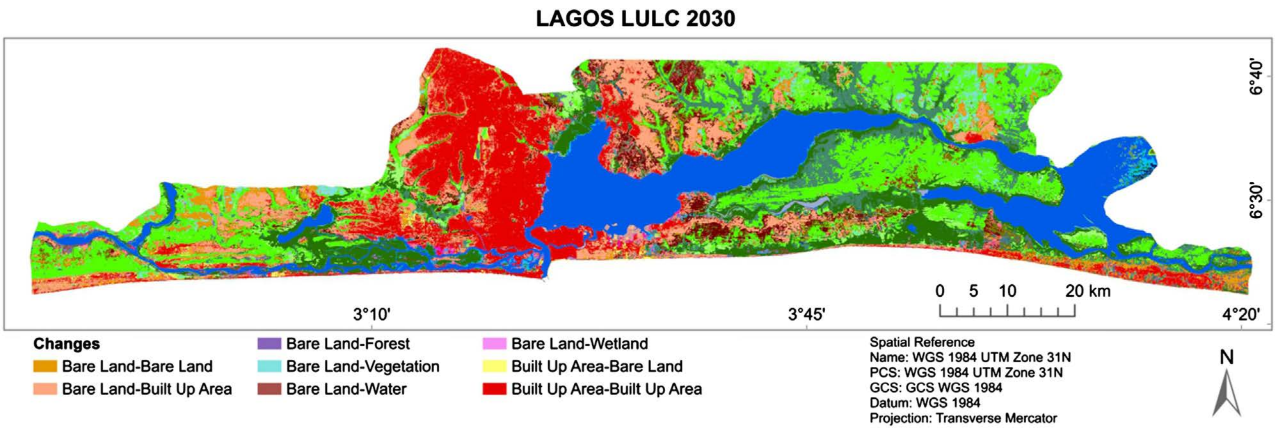

Figure 5. Predicted statistics of LULC in 2030.

Table 5. LULC changes matrix as detected from 2010 to 2020.

	LULC Classes	2020 Area in km²						
		Bare land	Built-up a	Forest	Vegetation	Water	Wetland	Grand Total
2010 Area km²	Bare land	**82.26970093**	172.4180936	35.74251493	54.57116682	0.278311679	0	345.280
	Built-up	74.22500632	**986.3755405**	11.42160716	11.0902816	0.541356459	0	1083.654
	Forest	12.73745874	19.38466806	**402.4310974**	253.1324276	4.895696138	1.013980542	693.595
	Vegetation	22.02057866	62.84774154	301.556304	**499.7600735**	0.666967442	0.261760537	887.113
	Water	3.350147808	30.22754802	57.86897743	5.04522985	**642.0407519**	31.90101655	770.434
	Wetland	0.04040174	0.032631051	0.923367413	0.829041386	0.372366164	**5.130270477**	7.328
	Grand Total	194.643	1271.286	809.944	824.428	648.795	38.307	3787.404

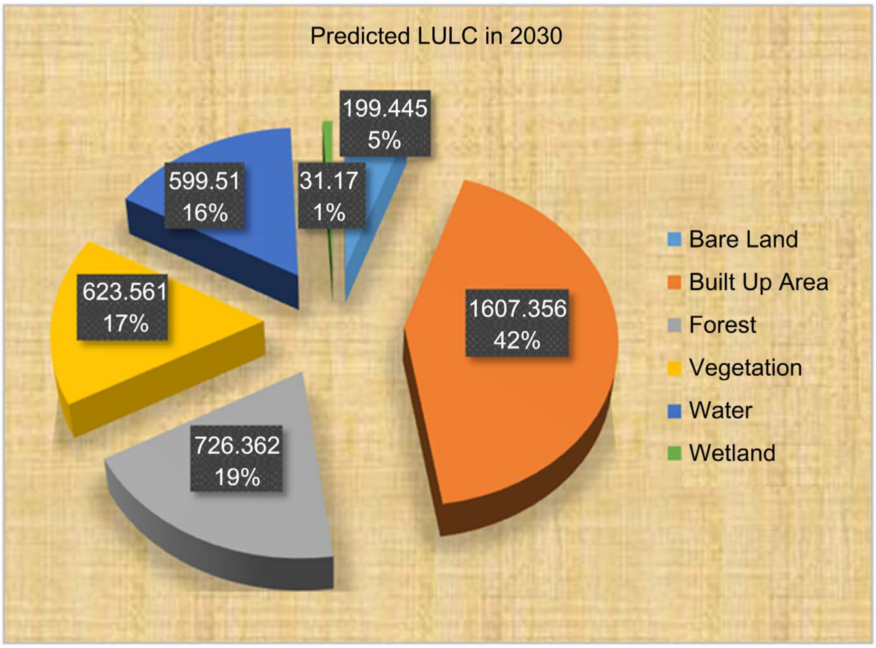

Figure 6. Lagos prediction LULC in 2030.

Table 6. LULC changes matrix as detected from 2000 to 2020.

	LULC Classes	2020 Area in km²						
		Bare land	Built-up	Forest	Vegetation	Water	Wetland	Grand Total
2000 Area km²	Bare land	**85.98835031**	431.3036642	74.53830382	38.19272814	1.359571015	0	631.383
	Built-up	31.95738873	**553.8791243**	7.649076793	3.42235595	1.517988983	0	598.426
	Forest	18.56834136	53.21949368	**327.9991565**	165.2609825	8.14478168	1.141879504	574.335
	Vegetation	54.13099738	195.2997201	336.2804647	**613.2148339**	1.784779766	0.017503704	1200.728
	Water	2.093732408	22.65520651	47.44018954	3.42591563	**634.234759**	37.14752087	746.997
	Wetland	1.904484004	14.92901394	16.03667698	0.911404484	1.753569332	**0.000124026**	35.535
	Grand Total	194.643	1271.286	809.944	824.428	648.795	38.307	3787.404

Table 7. Summary of LULC changes in each period.

LULC Class	Net change in 2000-2010	Net change in 2010-2020	Net change in 2000-2020
	Area in km²	Area in km²	Area in km²
Bare land	−286.103	−150.636	−436.739
Built-up	485.228	187.632	672.860
Forest	119.261	116.349	235.609
Vegetation	−313.615	−62.685	−376.300
Water	23.436	−121.638	−98.202
Wetland	−28.207	30.979	2.772

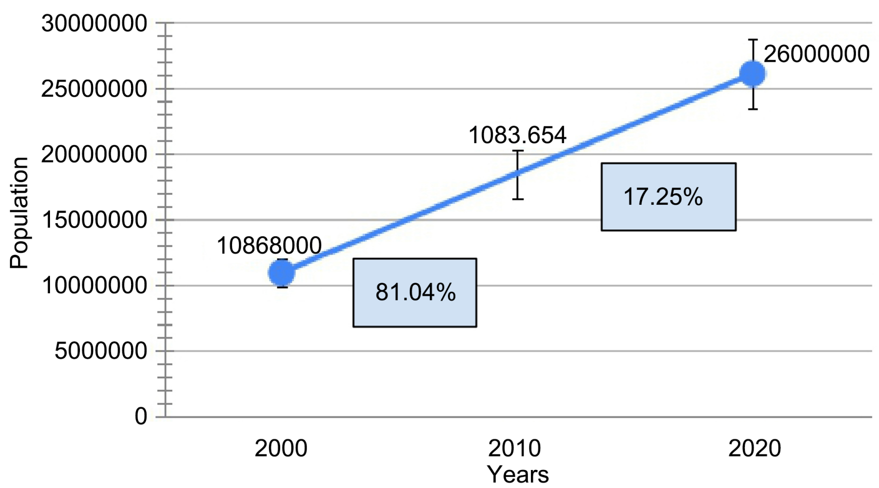

Figure 7. Lagos population growth.

16.46%, 5.27%, 0.82%, and 15.83%, respectively, and increasing trends in built-up developed by 42.44%. There will be a dramatic build-up increase from 33.57% in 2020 to 42.44% in 2030, and those significant changes will be derived from the ongoing population growth as predicted by the UN [33] [34]. It has an annual growth rate of 2.91% [35] [36]. Lagos City is expected to increase from 26 million people in 2020 to 33.6 million in 2030, which will impact existing LULU. According to the 2030 predicted model, 42.44% of the whole area will be built-up. Figure 8 indicates the trends of Lagos city population growth from 2000 to 2010, 2010 to 2020, and 2020 to 20230, with a percent increase of 69.61%, 41.04%, and 36.79%, respectively. In addition, the overall percentage of increase from 2000 to 2030 is estimated to be 227.25%. In conclusion, Lagos city experienced tremendous urban expansion over 30 years.

4. Discussion

4.1. The Impact of Urbanization on Environmental Aspects

LULC changes have significant environmental consequences at local and global levels. These changes have extreme consequences at the regional and global level, such as damage to biodiversity, distress of hydrological cycles, rise in soil displacement, and sediment deposition [35]. In addition to environmental aspects such as water quality, air pollution, and the temperature of land, urbanization significantly impacts slums (Table 8).

Generally, African urbanization is occasionally defined as "parasitic urbanism," "urbanization of poverty," or "premature urbanism" [41]. Mainly, African urbanization often differs from Western cities [42]. Moreover, this resulted in the high slum creation and made slums the primary residential land use type [41].

4.2. The Leading Indicator of Built-Up Expansion

The data provided illustrates a strong correlation between population growth and the increase of built-up areas in Lagos. The substantial population increases experienced by Lagos City over two consecutive decades, as depicted in Figure 7 and Figure 8, have had significant implications on LULC patterns within the region.

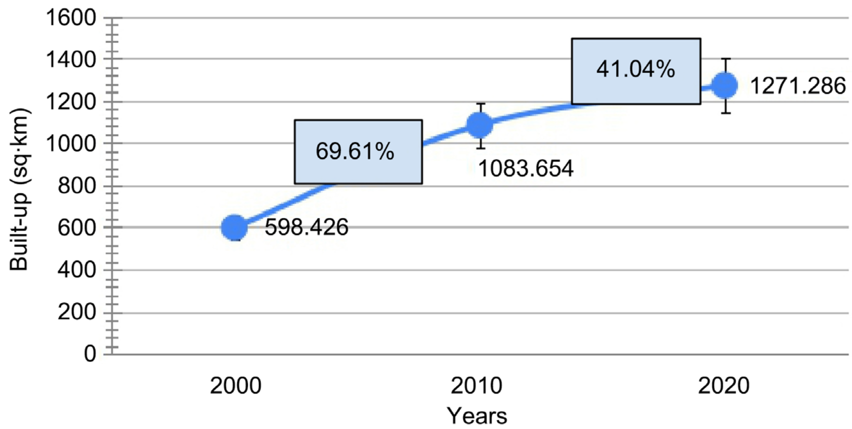

Figure 8. Lagos built-up expansion.

Table 8. Comparing the impact of urbanization between Lagos and Shanghai city based on different factors.

SN	Factors	Lagos	Shanghai
1	Slum	➢ Globally, Lagos is one of the most populated cities, with over 14 million residents. World Bank reports showed that over 70% of Lagos residents live in unplanned settlements called slums without access to basic facilities such as clean water and hygiene [36]. ➢ Poor planning, high population growth, urbanization, and inequality are reasons behind this problem of unplanned settlements still available at a high percentage of 70.	➢ Based on a systematic survey conducted, it was confirmed that Shanghai is a developed city and has no slums. This process of examining whether Shanghai has slums or not was based on on-site visits, interviews with urban officials in the water and sanitation sector, meetings with some Chinese scholars, and seminar discussions with staff and students at Chinese universities [37]. ➢ Good land use planning.
2	Water quality	➢ **Lagos mainly faces water quality-related problems due to improper** disposal of raw dirt and residue carried through runoff, resulting in serious health concerns. Accessibility to clean water is significantly low. Many Lagos inhabitants mainly depend on boreholes, wells, streams, and rainwater. However, Lagos is a metropolitan bounded by much water with over 2000 mm of annual precipitation, but it is unsafe to drink. Consequently, this high demand for clean water results from urban expansion [38]. ➢ Water pollution, inadequate sanitation, and urban sprawl/expansion are the leading causes.	➢ Due to the rapid development of Shanghai in the past many decades, numerous water channels have become seriously contaminated. Moreover, just 3% of the water in the city was adequately clean to drink. In addition, researchers showed that rapid urban growth correlated with the rapid lowering of water quality in Shanghai [39]. ➢ Moreover, despite its significantly higher level than Lagos, Shanghai encounters water pollution issues due to urbanization.
3	Air pollution	➢ The different reports indicated that Nigeria is the 10th most contaminated country in Africa, with a 44.8% rate of air pollution due to urbanization. Moreover, air pollution in Lagos is mainly caused by the different aspects of urban expansion, like road transport, which is the most significant source of PM2.5 of air pollution at 30%, and mismanagement of waste [38]. ➢ Urbanization, poorly planned road transport, and waste mismanagement are drivers of the problem.	➢ Shanghai has experienced the problem of air pollution due to urban expansion. Car and industrial unit releases count for at least 50% of Shanghai's contaminated air. 10.5% originates from destruction and rebuilding sites. In addition, pollution in Shanghai also comprises the wastewater settled and waste gas released in the atmosphere [39]. ➢ Urbanization and inadequate zoning practices play significant roles in issues similar to those experienced in Lagos. However, the problem is exacerbated by industries, excessive car usage, and air transport, which are more prominent factors than Lagos. Such factors are abundant in Shanghai, and lessons can be learned from Lagos' approach to addressing these challenges.

Continued

4	Urban heat land	➢ More than 78% of Nigerians live in cities, which impacts climatic variations. Lagos Metropolis is situated in a region of significance for rapid urbanization, which has produced an extraordinary Urban Heat Island (UHI) effect [40]. ➢ Shanghai's urban heat island (UHI) effect is primarily attributed to urbanization and the dense population like Lagos. Therefore, Lagos can benefit from Shanghai's experience in implementing environmentally friendly policies by learning from them.	➢ As an important economic center in China, Shanghai has experienced much growth in the past few decades. Farmland and vegetation are replaced by an urban-resistant surface, leading to a severe Surface Urban Heat Island (SUHI) effect, especially in the urban center. Furthermore, due to proper urban planning and appropriate green policies since 2010, the SUHI trend has slowed [35]. ➢ Urban Heat Island has been effectively addressed through environmentally friendly policies since 2010, thanks to the implementation of appropriate urban planning measures.

As the population of Lagos has grown remarkably, the demand for residential, commercial, and industrial spaces has increased. This population surge has necessitated converting previously undeveloped or vegetated areas into built-up areas to accommodate housing, infrastructure, and economic activities. Consequently, the expansion of built-up areas has resulted in a reduction of vegetation cover. The relationship between population growth and the increase of built-up areas becomes even more apparent when examining specific years.

As the population has grown remarkably, the demand for residential, commercial, and industrial spaces has increased. This population surge has necessitated converting previously undeveloped or vegetated areas into built-up areas to accommodate housing, infrastructure, and economic activities. Consequently, the expansion of built-up areas has resulted in a reduction of vegetation cover. The relationship between population growth and the increase of built-up areas becomes even more apparent when examining specific years. For example, from 2000 to 2010, the population of Lagos experienced a remarkable increase of 69.61%. As a result, the built-up areas expanded to cover approximately 81.04% of the total land area in 2000. Similarly, between 2010 and 2020, there was a significant rise in population by 41.04%, leading to a 17.25% expansion of the built-up areas. As the population grows, there is a greater demand for housing, infrastructure, and economic activities.

4.3. Limitations

- ✓ The foremost limitation is the quality of images that are available on Google Earth Pro, where some satellite images were blurred or cloud-covered in some study areas, and they were used as references while performing accuracy assessment.
- ✓ Some images have a low level of haze due to atmospheric conditions, which may affect the image classification accuracy.

- ✓ Temporal resolution: the images are corrected at different times, and changes in the landscape between short periods were not detected because the interval set for this change may be long.

5. Conclusion and Recommendation

In conclusion, the findings of this study show a significant change in the LULC of Lagos City from 2000 to 2020. The analysis revealed the substantial reduction in vegetation, bare land and wetlands, and the development in the built-up area. This shift in LULC is attributed to swift urbanization, population expansion, and economic growth. Utilizing GIS and remote sensing methods has proved to be valuable in monitoring and mapping these changes, particularly in mitigating the potential risks associated with such changes, such as flooding. Policymakers and urban planners must consider the environmental and ecosystem impacts of LULC changes and establish sustainable development plans. Based on the results of this research, several recommendations may be suggested to mitigate the negative effects of urbanization and promote sustainable development in Lagos. First, politicians and urban planners must emphasize the conservation of vegetation cover, which has decreased significantly throughout the study's period. This can be accomplished by creating protected areas, replanting projects, and enforcing environmental restrictions to avoid further destruction of natural habitats. Second, efforts should be made to promote more sustainable urban development patterns, such as compact and mixed-use urban forms, which reduce the need for major land use alteration. This could include encouraging high-density development near existing urban centers and providing efficient public transportation systems to reduce reliance on private cars. Third, the study highlights the need for more accurate and updated spatial data on urban growth and land use/cover change to inform evidence-based policy and decision-making. Therefore, there should be continued investment in using remote sensing and GIS technologies to monitor LULC changes in Lagos and other urban areas in Nigeria. Finally, the study's findings have significant suggestions for policymakers and urban planners in Lagos and other cities in Nigeria. It is feasible to mitigate the negative influence of urbanization on the environment and create a more livable and resilient future by taking a more comprehensive and sustainable approach to urban development.

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Author Contributions

Katabarwa Murenzi Gilbert and Yishao Shi planned the study and selected the data; Katabarwa Murenzi Gilbert processed and analyzed the data; results interpreted and discussed by Yishao Shi and Katabarwa Murenzi Gilbert; and Yishao Shi reviewed the paper.

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Data Availability Statement

Apart from the spatial data available on the USGS website, additional data and materials can be provided via email upon request by the authors.

Conflicts of Interest

The authors declare no conflict of interest.

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