Scientific Research Publishing

Advances in Remote Sensing, 2020, 9, 33-52
https://www.scirp.org/journal/ars
ISSN Online: 2169-2688
ISSN Print: 2169-267X

Degradation of Urban Green Spaces in Lagos, Nigeria: Evidence from Satellite and Demographic Data

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How to cite this paper: Twumasi, Y.A., Merem, E.C., Namwamba, J.B., Mwakimi, O.S., Ayala-Silva, T., Abdollahi, K., Okwemba, R., Lukongo, O.E.B., Akinrinwoye, C.O., Tate, J. and LaCour-Conant, K. (2020) Degradation of Urban Green Spaces in Lagos, Nigeria: Evidence from Satellite and Demographic Data. *Advances in Remote Sensing*, **9**, 33-52.
https://doi.org/10.4236/ars.202091003

Received: January 19, 2020
Accepted: March 28, 2020
Published: March 31, 2020

Abstract

The study aimed to assess the potential of using Remote Sensing (RS) data to evaluate the changes of urban green spaces in Lagos, Nigeria. Landsat Thematic Mapper and Landsat 8 (Operational Land Imager) data pair of May 4, 1986, December 12, 2002 and January 1, 2019 covering Lagos Government Authority (LGA) were used for this study. Supervised image classification technique using Maximum Likelihood Classifier (MLC) was used to create base map which was then used for ground truthing. Random Forest (RF) classification technique using RF classifier was utilized in this study to generate the final land use land cover map. RF is an ensemble learning method for classification that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification). Lagos census population data was also used in this study to model population projection. Extrapolation of the model was used to predict data for the years, 2020 and 2040. Results of the study revealed a reduction of urban green spaces due to agriculture and settlement. While the remote mapping revealed the gradual dispersion of ecosystem degradation indicators spread across the state, there exists clusters of areas vulnerable to environmental hazards across Lagos. To mitigate these risks, the paper offered recommendations ranging from the need for effective policy to green planning education for city managers, developers and risk assessment. These measures will go a long way in helping sustainability and management of land resources in Lagos.

Keywords

Remote Sensing, Urban Green Spaces, Population Projection, Lagos

1. Introduction

Urban green spaces such as parks and sports fields as well as woods and natural meadows, wetlands and other ecosystems provide several benefits. They serve as filters of pollutants and dust from the air, facilitate physical activity and relaxation, provide shade and lower temperatures in urban areas, and they reduce erosion of soil into the waterways [1]. Trees produce oxygen, and help filter out harmful air pollution, including airborne particulate matter [2]. Despite these benefits, urban green spaces in recent years have come under intense pressure due to increase in population growth. Increasing population could be attributed to the social and economic benefits associated with urban centers compared to rural areas [3]. Rapid urban growth, however, has major social and economic consequences including congestion and environmental degradation of green spaces. Published research by authors on environmental impacts of urban expansion shows pressure on undeveloped green spaces [3] [4] [5] [6]. Similarly, early work of Merem and Twumasi [7] on urban growth management in Central Mississippi region which is home to over half a million people revealed decline of the area's agricultural land resources due to urban development. Indeed, the impacts of land use change associated with the development and urbanization have well been documented [8] [9] [10]. Early work of Twumasi *et al.*, [11] and [12] and Manu *et al.*, [13] used satellite data to map urban green spaces in Accra, Ghana; Bamako, Mali and Niamey, Niger. Results of these studies showed that the decline in green spaces in these cities was associated with urban development and urbanization. In Lagos, Nigeria, anthropogenic activities that drive changes in land use and cover include urban development which is associated with urbanization and agricultural practices. Such activities have exerted much pressure through intense use of green spaces for residential and industrial purposes [14] [15] [16]. Several studies have employed remote sensing data to assess the integrity of green spaces and ecosystem in Lagos [17] [18] [19] [20] [21]. However, none of these studies integrate remote sensing data with demographic analysis. This calls for the need to find appropriate method to aid in identifying spatio-temporal changes in urban green spaces in Lagos. Perhaps, the most important element in these efforts is the need to integrate satellite data with demographic analysis to assess the status and trend of the urban green spaces. The primary objectives of this study were to couple remote sensing data with demographic data to evaluate the changes of urban green spaces in Lagos, Nigeria to enable planners and policymakers contribute to improved land administration and enhance their competence in decision-making (Figure 1).

2. Methodology

2.1. The Study Area

Lagos state is situated in the South Western Nigeria within latitudes 6 degrees 23'N and Longitudes 2 degrees and 3 degrees 42 E. As shown in Figure 2 and Figure 3, the state is bounded from the North and East by Ogun State, in the West by the Republic of Benin and the South by the Atlantic Ocean. The total land mass of the state stretches over 3345 kilometers. Like most African cities, Lagos, Nigeria, is experiencing a fast-sustained urban expansion (Figure 3). According to 2019 World Population Review and Statistical Data, Lagos population is increasing at a startling rate. The current 2019 population is estimated at 13,903,620. In 1950, the population of Lagos was 325,218. This has grown by 1,664,414 since 2015, which represents a 3.24% annual change. While the state appears physically smaller, it is ranked as the most highly populated state in the country with an estimated population of about 14 million inhabitants representing 10% of the total population of Nigeria [22].

2.2. Data Acquisition

This paper used satellite remote sensing and census-population data for the analysis.

2.3. Image Data Acquisition and Processing

Landsat Thematic Mapper and Landsat 8 (Operational Land Imager) images listed in Table 1 covering Lagos, Nigeria were acquired from the United States Geological Survey Earth Explorer free Online Data Services for land use land cover change classifications analysis [24]. The images were acquired with minimum cloud cover (<10%). The footprint of the Landsat data is shown in Figure 4.

Figure 1. A heavily crowded street in Lagos, Nigeria. Curtesy: Reddit [16].

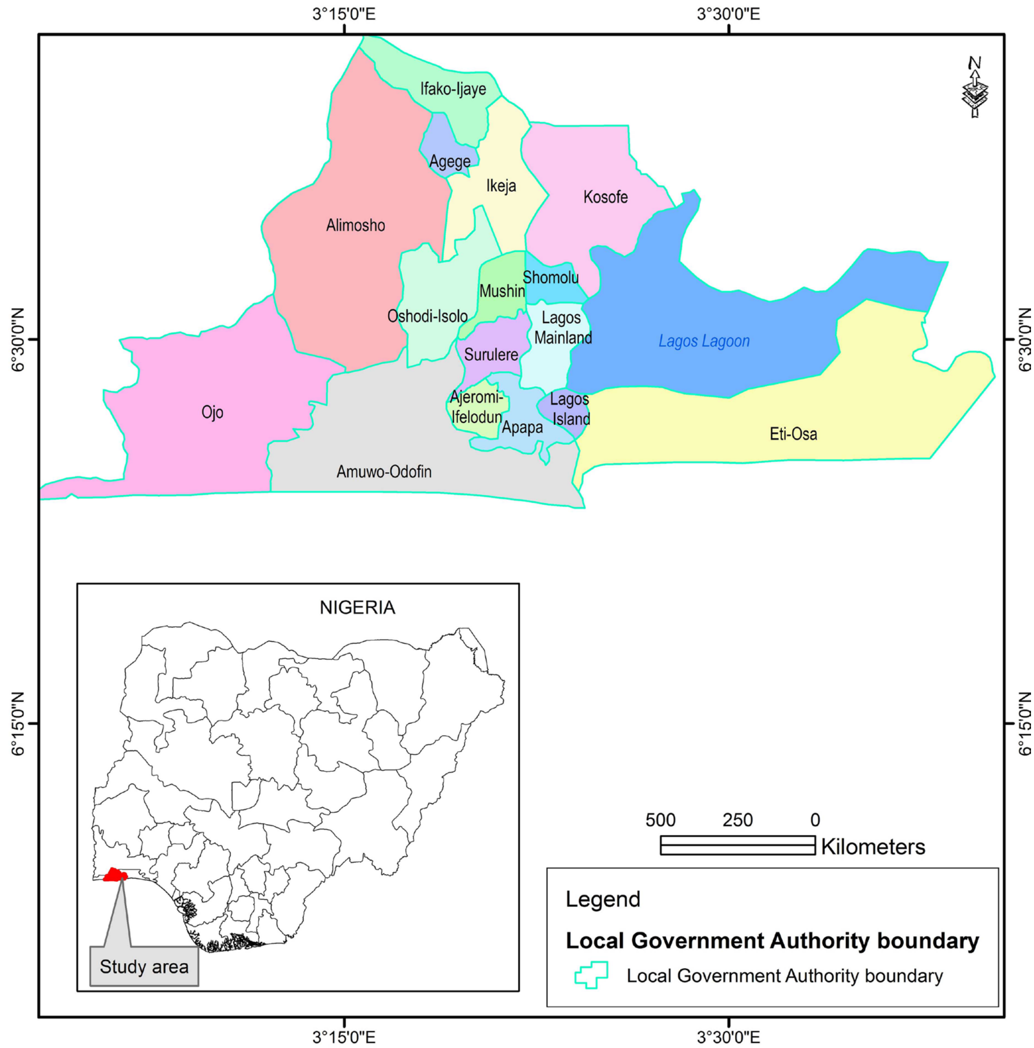

Figure. 2. Study area. The map shows Lagos Metropolitan Areas. Insert shows the position of Lagos in Nigeria.

Figure 3. Map of Metropolitan Lagos from Google [23].

Table 1. Landsat images used in the mapping land use land cover of LGA.

Reference year	Sensor	Resolution	WRS: P/R	Date of Acquisition
2019	Landsat 8	30m	191/055	2019/01/01
2002	Landsat TM	30m	191/055	2002/12/28
1986	Landsat TM	30m	191/055	1986/04/12

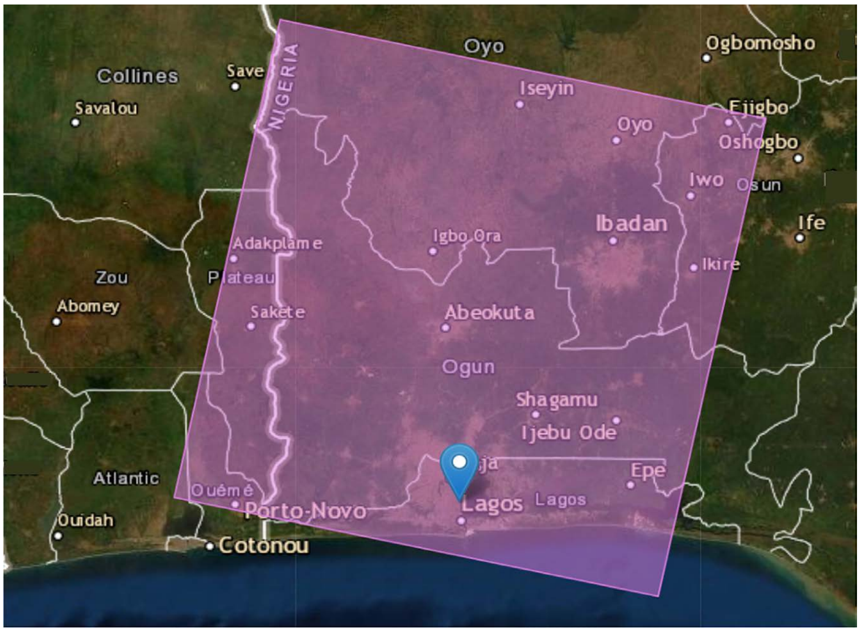

Figure 4. Footprint of Landsat imagery in the study area shown in dark purple color box [24].

2.4. Image Processing

To process the images, three tasks were performed. These include: Image preprocessing, rectification and image enhancement.

2.4.1. Image Pre-Processing

In image Image pre-processing, both visual and digital image processing were done, and prior to image processing, images were imported into ERDAS Imagine Image Processing Software for further processing. Since the images were in single bands, layer stack technique was performed to group the bands together. The stacked images were further exported to ArcGIS 10.6 software. Lagos Government Authority (LGA) shapefile was used to extract from the full scenes to subset the area of interest which is the Lagos Government Authority (LGA).

2.4.2. Image Rectifications

Image rectifications were performed in order to correct the data for distortion which may have been developed from the image acquisition process using the Impact toolbox developed by the European Union Joint Research Centre. To ensure accurate identification of temporal changes and geometric compatibility with other sources of information, the images were geocoded to the coordinate and mapping system of the national topographic maps. All the images were projected to the Universal Traverse Mercator (UTM) coordinates zone 31 North. The spheroid and datum was also referenced to WSG84.

2.4.3. Image Enhancement

Image enhancement was done in order to reinforce the visual interpretability of images, a colour composite (Landsat TM bands 4, 5, and 3) was prepared and its contrast was stretched using a standard deviation to further enhance visual interpretability of linear features like Rivers, and land use features like agricultural land, forests etc. Aside using Erdas Imagine Image Processing software to perform the layer stack of the images, all image processing was carried out using ArcGIS software and Impact toolbox.

2.5. Preliminary Image Classification and Ground Truthing

Supervised image classification using Maximum Likelihood Classifier (MLC) was used to create base map which was then used for ground truthing. The maximum likelihood classifier was selected since, unlike other classifiers it considers the spectral variation within each category and the overlap cover the different classes. Accordingly, the land use and land cover was classified into eight classes, namely forest, bushland, and agriculture with scattered settlements, grassland, bare soil, wetland, water and Settlements (Urban Area) (**Table 2**).

2.6. Final Image Classification

Random Forest (RF) classification using RF classifier was utilized in this study to generate the final land use land cover map. RF is an esemble learning method for

Table 2. Detailed description of land use land cover Lagos Government Authority.

Land Use Land cover (LAND COVER) Categories	Description
Forest	An area of land with at least 0.5 ha, with a minimum tree crown cover of 10% or with existing tree species planted or natural having the potential of attaining more than 10% crown cover, and with trees which have the potential or have reached a minimum height of 3 m at maturity in situ. It includes montane, lowland, mangrove and plantation forests, woodlands and thickets.
Bushland	Bushland is fundamentally defined as being predominantly comprised of plants that are multi-stemmed from a single root base. It includes dense and open bushland
Grassland	For the most part, grassland occurs in combination with either a limited wooded or bushed component, or with scattered subsistence cultivation
Agriculture with Scattered Settlements	Land actively used to grow agricultural crops including agro forestry systems, wooded crops, herbaceous crops and grain crops
Bare Soil	The land which includes bare land and coastal sands
Settlements/Built up Area	Built up areas especially urban areas
Water	Includes inland water and ocean
Wetland	Land which is water logged seasonally. May be wooded such as marshland, perennially flooded plains and swampy areas

classification that operates by construction of a multitude of decision trees at training time and outputting the class which is the mode of the classes (classification). The advantages of RF is that it is not sensitive to over-fitting; good at dealing with outliers in training data, and it is able to calculate useful information about errors, variable importance, and data outliers [25]. This information can be used to evaluate the performance of the model and make changes to the training data if necessary.

2.7. Preparation of Land Cover and Land Use Maps

Classified images were recorded to the respective classes. Classified images were then filtered using a majority-neighbourhood filter in order to eliminate patches smaller than a specified value and replace them with the value that is most common among the neighboring pixels.

2.8. Change Detection and Assessment of the Rate of Change

In this study Post classification, comparison was used to quantify the extent land use, land cover changes over a 30 year period (1986, 2002 and 2019). The advantage of post classification comparison is that it bypasses the difficulties associated with the analysis of the images that are acquired at different times of the year, or by different sensors and results in high change detection accuracy [26]. Estimation for the rate of change for different land use land cover was computed based on the following formulae.

$$\%\ \text{Cover change} = \frac{Area_{i\ \text{year}\ x} - Area_{i\ \text{year}\ x+1}}{\sum_{i=1}^{n} Area_{i\ \text{year}\ x}} \times 100 \tag{1}$$

$$\text{Annual rate of change} = \frac{Area_{i\ \text{year}\ x} - Area_{i\ \text{year}\ x+1}}{t_{\text{years}}} \tag{2}$$

where: $Area_{i\ \text{year}\ x}$ = area of cover i at the first date,

$Area_{i\ \text{year}\ x+1}$ = area of cover i at the second date,

$\sum_{i=1}^{n} Area_{i\ \text{year}\ x}$ = total cover area at the first and

t_{years} = period in years between the first and second scene acquisition date.

2.9. Census-Population Data Acquisition and Processing

Population data for this study was obtained from World Statistical Data website [22]. The Lagos population data was modeled using Microsoft Excel's statistical data analysis tool. **Table 3** represents the data used for modeling. Also, linear time series slopes were analyzed to model population projection. Extrapolation of the model was used to predict data for the years, 2020 and 2040.

3. Results and Discussion

Table 3 and **Figure 5** show the results of the classification for 1986, 2002 and 2019 Landsat images. From **Table 4**, land area under water declined from the

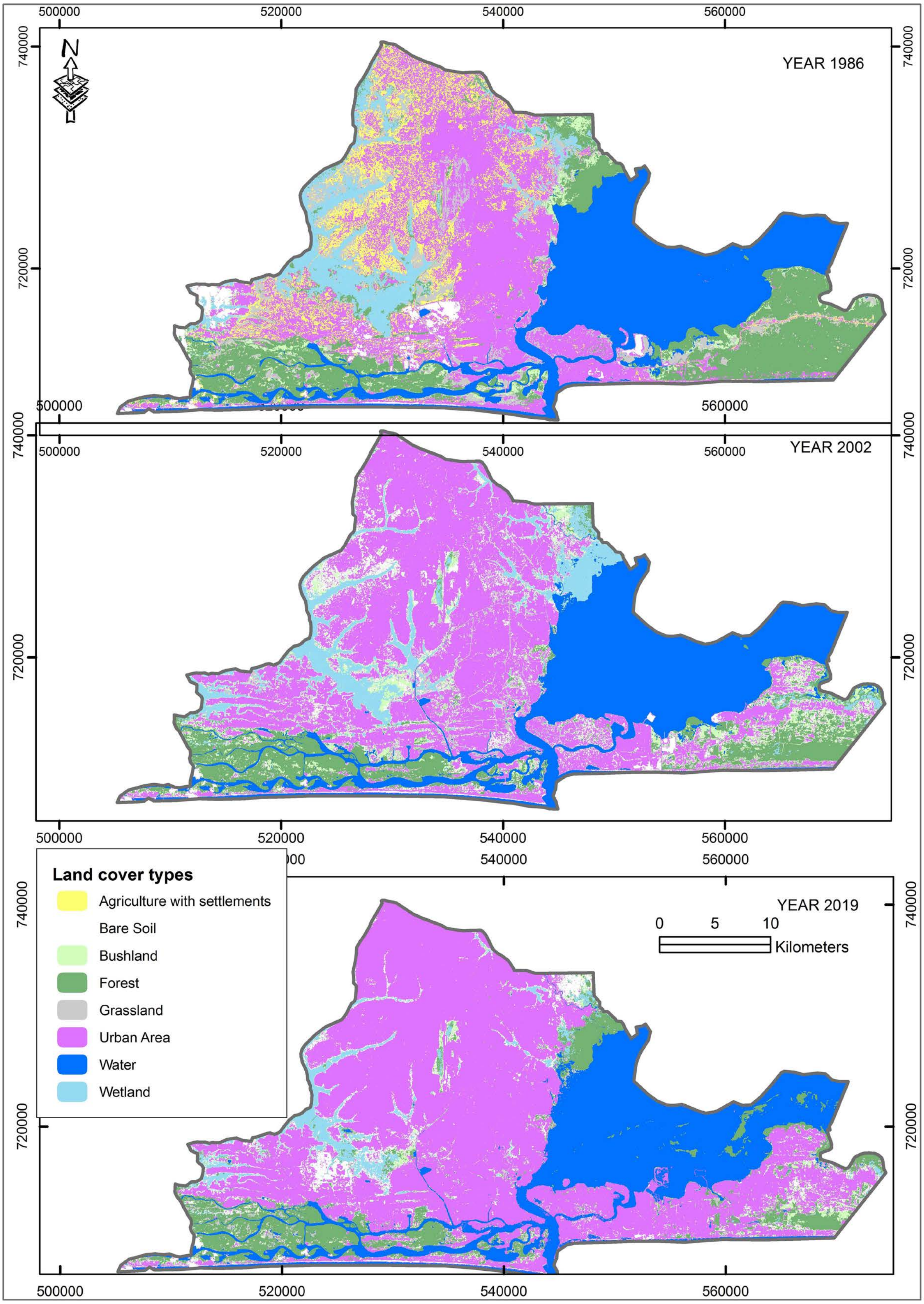

Figure 5. Land cover maps of LGA 1986-2019.

Table 3. 1950-2019 Lagos population data for modeling, based on 1950,1960, 1970, 1980, 1990, 2000, 2010 and 2019 data.

Population versus Year Analysis	
Year	Population
1950	325,000
1960	762,000
1970	1,414,000
1980	2,572,000
1990	4,764,000
2000	7,281,000
2010	10,441,000
2019	13,904,000

Table 4. % Change of land cover area between 1986 and 2019 in the LGA.

	Land Use/Cover Types	COVERAGE			Land Cover Change	
		1986	2002	2019	% Change	
		Ha	Ha	Ha	1986-2002	2002-2019
1	Agriculture with settlements	12,208	7959	5549	−34.81	−30.28
2	Bare Soil	2324	649	220	−72.07	−66.10
3	Bushland	2716	6505	3161	139.50	−51.40
4	Forest	21,246	12,231	11,509	−42.43	−5.90
5	Grassland	9359	5150	1870	−44.97	−63.68
6	Urban Area	33,469	47,575	64,245	42.14	35.03
7	Water	29,005	29,466	27,662	1.58	−6.12
8	Wetland	7916	8708	4026	10.01	−53.76

initial estimate of 29,466 hectares (ha) in 2002 to 27,662 in 2019. This represents an overall decrease of 6.12 percent. Urban area experienced significant expansion for the whole area from 1986 to 2019, while the size of area covered by vegetation, which include coastal mangrove (wetland), forest, bushland and grassland areas experienced a significant decline from 1986 to 2019 (Figure 5 and Table 4). Overall, the shrinking of the water resources (Water bodies and Wetlands) in the LGA (Tables 4-6) signifies worrying situation in LGA hence, needs serious intervention to rescue the situation.

Over the past two decades, the landscape of LGA has witnessed changes in its land use/cover (Figure 5, Table 4). The changes have been exhibited throughout the landscape.

Demographic Analysis

Results of census-population data analysis are shown in Table 7 and Table 8. Table 7 was generated by linear regression of 1950, 1960, 1970, 1980, 1990, 2000,

Table 5. Land cover change by cross tabulation for year 1986 and 2002.

	Year: 1986									
Year 2002	Agriculture with settlements	Bare Soil	Bushland	Forest	Grassland	Urban Area	Water	Wetland	TOTAL	**Gross gain [Total-unchanged]**
Agriculture with settlements	1494	126	97	1318	1468	2433	82	830	**7848**	6354
Bare Soil	11	72	48	121	80	260	124	0	**716**	644
Bushland	364	97	839	2389	1028	484	76	1184	**6461**	5622
Forest	45	124	878	10,144	646	234	87	41	**12,199**	2055
Grassland	427	91	71	1116	961	2118	121	245	**5,149**	4187
Urban Area	9542	1518	111	2933	4043	27,811	484	1208	**47,651**	19,840
Water	4	7	230	720	340	108	28,015	0	**29,424**	1409
Wetland	193	258	434	2521	802	134	32	4453	**8826**	4373
TOTAL	**12,080**	**2294**	**2708**	**21,260**	**9368**	**33,582**	**29,021**	**7961**		
Gross loss	10,586	2222	1869	11,117	8407	5771	1006	3508		

Table 6. Land cover change by cross tabulation for year 2002 and 2019.

	Year: 2002									
Year 2019	Agriculture with settlements	Bare Soil	Bushland	Forest	Grassland	Urban Area	Water	Wetland	**TOTAL 2019**	**Gross gain [Total-unchanged]**
Agriculture with settlements	1060	6	1077	640	273	876	30	1524	**5485**	4425
Bare Soil	0	262	0	0	0	0	0	0	**262**	0
Bushland	217	2	884	913	288	238	39	575	**3155**	2272
Forest	158	11	869	7597	150	121	1010	1587	**11,503**	3905
Grassland	41	0	397	566	559	39	184	89	**1875**	1316
Urban Area	6352	386	2970	2265	3816	46,298	967	1164	**64,217**	17,919
Water	13	46	67	186	58	61	27,180	54	**27,664**	484
Wetland	13	0	182	52	11	13	7	3833	**4111**	278
TOTAL 2002	**7853**	**713**	**6445**	**12,219**	**5155**	**47,646**	**29,416**	**8826**		
Gross loss	6794	451	5561	4622	4596	1348	2237	4993		

Table 7. Regression statistics table.

Regression Statistics	
Multiple R	0.956719
R Square	0.91531
Adjusted R Square	0.901195
Standard Error	1,560,157
Observations	8

Table 8. Regression model table, based on 1950, 1960, 1970, 1980, 1990, 2000, 2010 and 2019 data.

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower* 95%	*Upper* 95%	*Lower* 95.0%	*Upper* 95.0%
Intercept	−3.8E+08	48,184,663	−7.94467	0.000211	−5E+08	−2.6E+08	−5E+08	−2.6E+08
Year	195,475.3	24,274.33	8.052757	0.000196	136,078.1	254,872.4	136,078.1	254,872.4

2010 and 2019 data. The model explains about 90% of the data's variation and is statistically significant, $p < 0.05$ (**Table 8**).

The trend of population using the linear model was compared to the actual population for the year range 1950-2019 and illustrated by **Figure 6**. As shown in **Figure 6**, the linear model's population projections from 2009 and beyond were lower than the corresponding actual populations. The model is presented in **Figure 7** in an extrapolated form, illustrating clearly the increasing difference between the projected and actual populations. The red dots illustrate the actual data while the blue line represents the linear model projection the population. Also presented in **Figure 7**, are the model equation and its coefficient of correlation. Although it explains about 91% of the variation in the population data, its projection of 2019 population is approximately 12,000,000, which is about 2 million below the actual figure. When the data was fitted to a polynomial second order model by Microsoft Excel data analysis tool kit, the predictions approximated to the actual data (**Figure 8**). The coefficient of correlation for this model is approximately 100%. Hence, the model explains about 100% of the variation in the population data. Based on its strength, this model was adopted projection the population of the city beyond the year 2019.

Extrapolation of the second order polynomial (quadratic) model was used to predict data for the years beyond 2020.

The population projections based on the second order polynomial model are presented in **Table 9**.

To model the change in population per year for the years, 1950, 1960, 1970, 1980, 1990, 2000, 2010 and 2019, the population changes between each consecutive pair of data were computed and the difference divided by the corresponding span of time for the change. The computation was carried out as follows. The population growth/year for a 10-year interval Tn and $Tn+10$ was determined using the following formula.

$$P/\text{year for interval}\left(T_{n+10}-T_n\right)=\left(P_{Tn+10}-P_{Tn}\right)/10 \tag{3}$$

The following graph illustrates the rate of population change (number of people/year) per year versus time in years.

As illustrated in **Figure 9**, the rate of population growth is positive and can be represented by the linear model,

$$y = 5991.6x - 10000000 \tag{4}$$

where y and x represent the population change/year and time in years respectively. The computed data is presented in **Table 10**. In **Table 10**, the year n refers to the time interval, year n-10 to year n. For example, 1960, refers to the interval, 1950-1960.

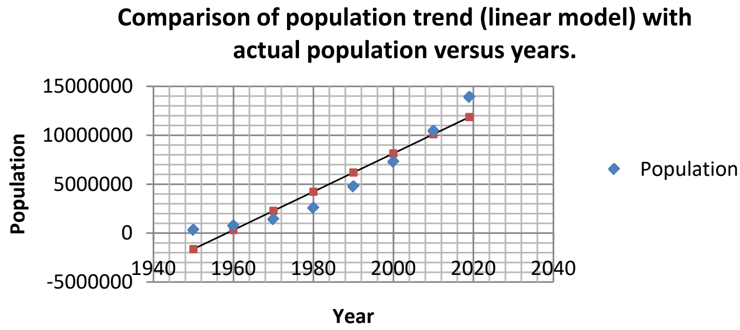

Figure 6. Comparison between actual population and predicted population using linear model, based on 1950, 1960, 1970, 1980, 1990, 2000, 2010 and 2019 data.

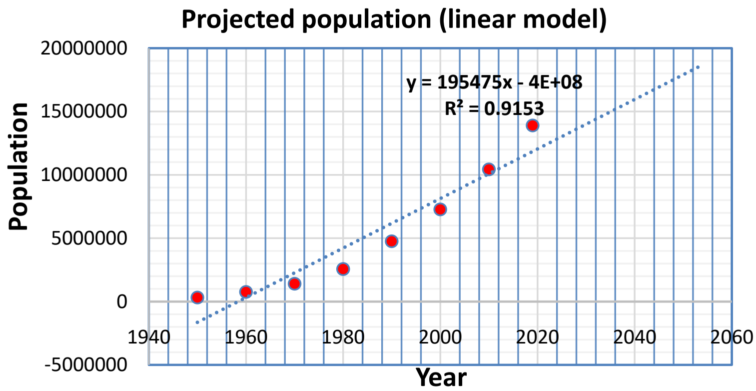

Figure 7. Projected population beyond 2020, using linear model for Lagos City Population versus year based on 1950, 1960, 1970, 1980, 1990, 2000, 2010 and 2019 data.

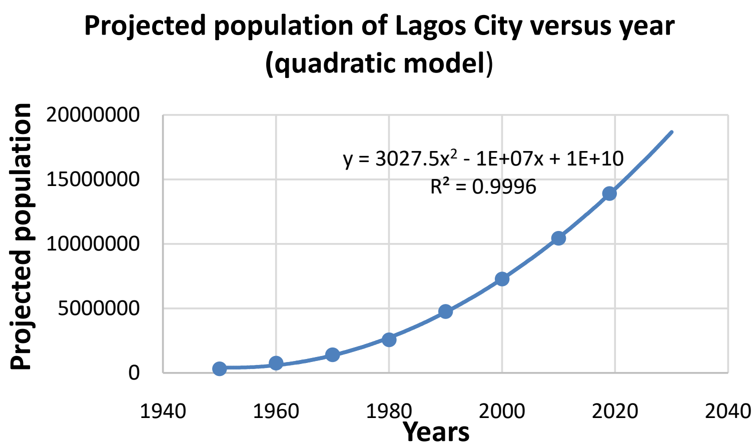

Figure 8. Projected population using a polynomial second order model for Lagos City Population versus year based on 1950, 1960, 1970, 1980, 1990, 2000, 2010 and 2019 data.

Table 9. Lagos City population projections based on the second order polynomial model.

Year	Projection
2025	17,000,000
2030	19,000,000
2035	22,000,000

Table 10. Population change/year based on 1950, 1960, 1970, 1980, 1990, 2000, 2010 and 2019 data.

Year	Rate of population change (change/year)
1960	43,700
1970	65,200
1980	115,800
1990	219,200
2000	251,700
2010	316,000
2019	384,778

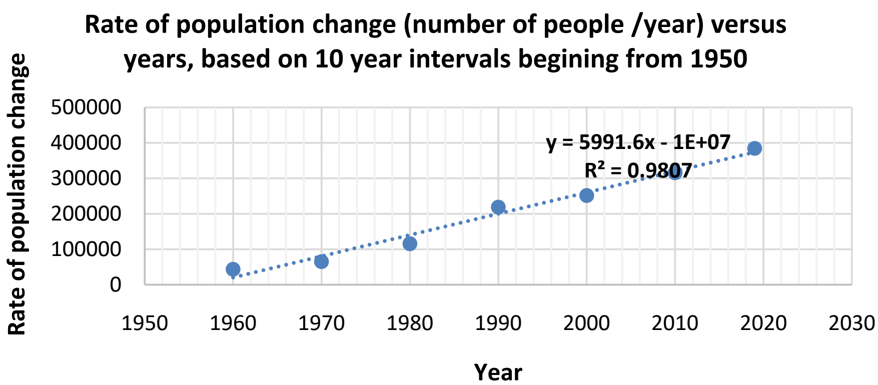

Figure 9. The rate of population change (number of people/year), based on 1950, 1960, 1970, 1980, 1990, 2000, 2010 and 2019 data, measured at 10 year intervals.

The lowest population growth/year occurred during the time span 1950-1960. It was determined using Equation (4) as follows.

$$\dot{P}_{(1950\text{-}1960)} = (762000 - 325000/10) = 43700 \text{ per year},$$

where $\dot{P}_{(1950\text{-}1960)}$ is the corresponding rate of population change. The period with the highest population growth was found to be 1980-1990. The corresponding rate of population change was computed as follows.

$$\dot{P}_{(2010\text{-}2019)} = (13904000 - 10441000/9) = 384778$$

The percentage change in population between a span of time is the ratio of the population change over a time interval in years, to preceding population, multiplied by 100%. It was determined as follows.

$$\text{Percentage change in population} = \left(\left(P_t - P_{t-10} \right) / P_{t-10} \right) * 100\% \tag{5}$$

where P_t and P_{t-10} represent the populations for the years t and $t-10$ (10 years earlier than t), respectively. The percentage changes in population for consecutive 10-year intervals, 1950-1960 and were computed using Equation (5) as follows.

$$(762000 - 325000/325000) * 100\% = 134.46\%$$

The percentage change in population per consecutive 10 years for Lagos population was computed for the data for 1950-2019 and illustrated in **Table 11**.

Using curve fitting with Microsoft Excel, four possible models, exponential, polynomial (quadratic and cubic) and linear models were built to predict the percentage change in population per 10 years intervals. Each of the models is illustrated in the following graphs (**Figure 10**, exponential, **Figure 11**, quadratic, **Figure 12**, cubic and **Figure 13**, linear).

The polynomial second order (quadratic) model for predicting the change in % change in population/10 years versus years is given as, $y = 0.0107x^2 - 44.019x + 45360$. The coefficient of correlation R^2 is 90%. Hence, the model explains 90% of the variability in the population data.

The cubic model is given as, $y = -0.0009x^3 + 5.6547x^2 - 11272x + 7000000$, with $R^2 = 0.9235$.

The exponential model is represented by the following equation.

$y = 3\text{E} + 20\text{e}^{-0.022x} = 0$, with $R^2 = 0.9264$. It explains almost 93% of the variation in the population data.

The linear model for % change in population is given by the following equation, $y = -1.5076x + 3073.7$

Table 11. % Change in population for 10-year intervals.

Year	% Change in population/10 years interval
1950-1960	134.4615
1960-1970	85.5643
1970-1980	81.89533
1980-1990	85.22551
1990-2000	52.83375
2000-2010	43.40063
2010-2019	33.16732

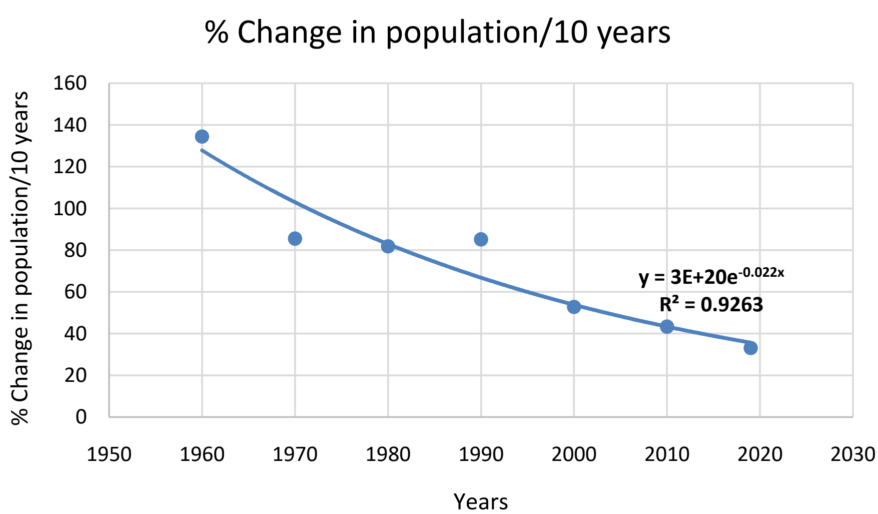

Figure 10. Percentage change in population/10 years versus years (exponential model).

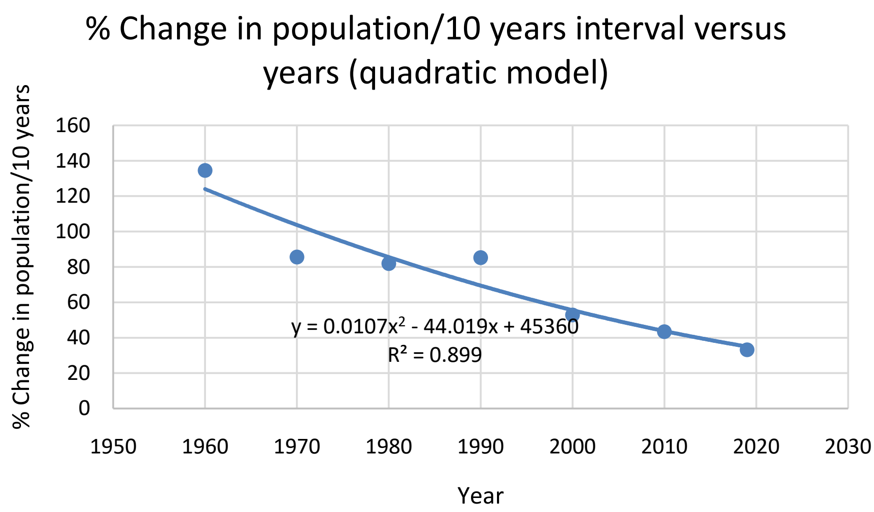

Figure 11. Percentage change in population/10 years versus years (quadratic model).

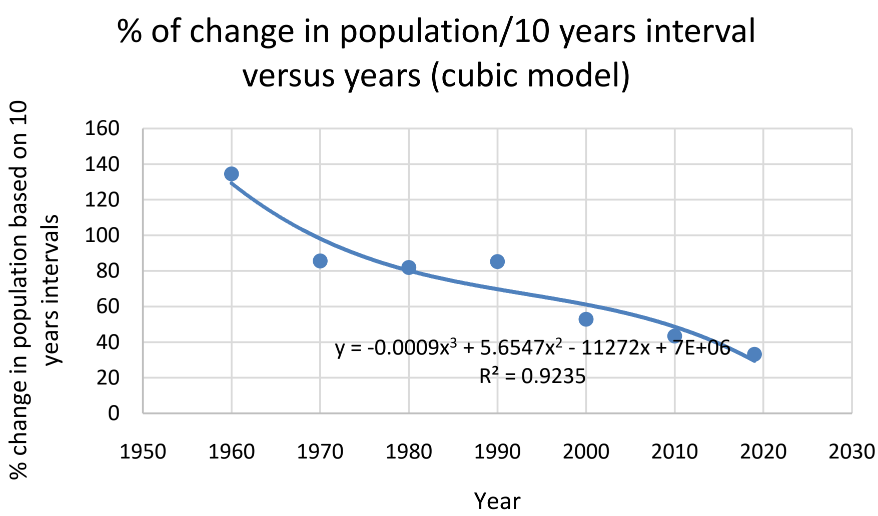

Figure 12. Percentage change in population/10 years versus years (cubic model).

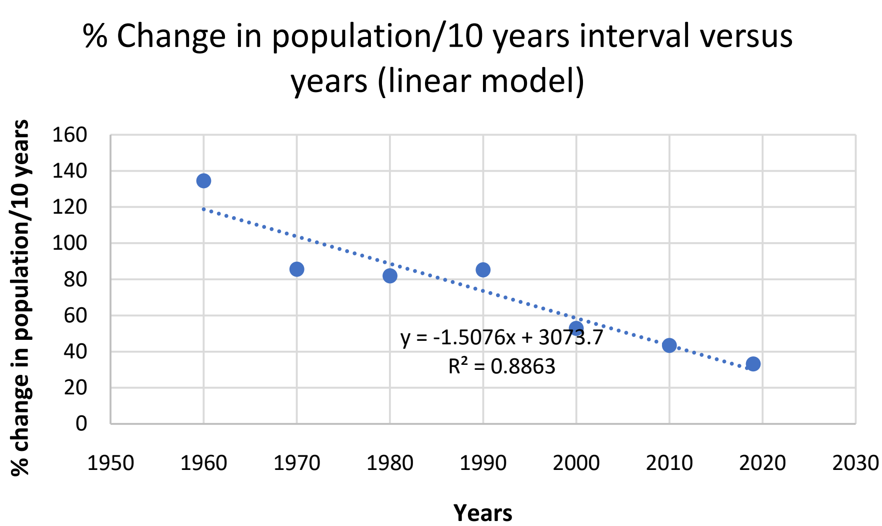

Figure 13. Percentage change in population/10 years versus years (linear model).

To predict the year when the population of Lagos city would stabilize y was equated to 0 and an attempt to solve for x in each model made.

Hence, for the exponential model, $y = 3\text{E} + 20\text{e}^{-0.022x} = 0$

The equation is solved by subtracting 3000 from the left-hand and right-hand sides simultaneously, $20\text{e}^{-0.022x} = -3000$.

Dividing the left-hand side and right-hand side by 20 and getting the natural logarithms of both sides yields the following.

$$-0.022x = \ln(-3000/20)$$

Dividing both sides by −0.022.

Hence, $x = \ln(150)/-0.022$, which has no solution.

Both the quadratic and cubic models offer no feasible solutions for predicting the year for population stabilization since they either have complex or real solutions falling outside future time (years). Hence, they cannot be used to predict the year of population stabilization for the given data. The best model was the linear model (**Figure 13**). The year for stabilization of population is computed from the linear model for % change in population as follows. The linear model is equated to 0 and then solved as follows:

$$y = -1.5076x + 3073.7 = 0$$

$$-1.5076x = -3073.7$$

$$x = (-3073.7/-1.5076)$$

$$x = 2038.8034$$

Hence, the population is expected to stabilize during the time span 2029-2039. The population corresponding to the year 2039 was estimated by extrapolating the polynomial model illustrated in **Figure 8** to the year 2039, using the format trendline option of Microsoft Excel. The resulting graph is illustrated in **Figure 14**. According to **Figure 14**, in 2039 the population of Lagos city will be 23,000,000, the stabilization population.

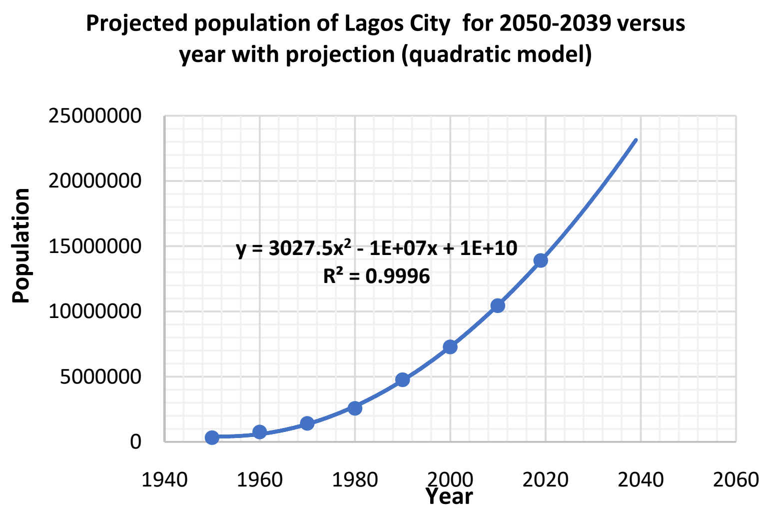

Figure 14. Projected population for the period 1950-2039, using a polynomial second order model for Lagos City Population versus year based on 1950, 1960, 1970, 1980, 1990, 2000, 2010 and 2019 data.

The rate of change of population/year based on 10 years intervals rose linearly with respect to time (years) as illustrated in **Figure 10**. The lowest population growth/year was shown to have occurred during the time span 1950-1960. Interestingly, the highest % change in population occurred also during this time span (see **Table 11**). This is the only time span found to have a % change in population above 100%.

The percentage increase in the city's population was found to be decreasing linearly with respect to time, in years (**Figure 10**). However, the city's population still rose since the percentage increase was still greater than 0%. The population is expected to stabilize when the percentage change drops to 0%. According to Abiodun (1974), between 1952 and 1963, the population of Agege and Ikorodu, sections of Lagos metropolitan area increased by 300% and 1000% respectively. The high percentage growth can be explained by a three-fold introduction of babies into Lagos by families immigrating into the city, for every baby born to residents (Abrams *et al*., 1980). This explains the high % increase in population during 1950-1960.

A factor that may influence the stabilization of a city's population is its urban carrying capacity. This refers to the maximum population able to survive in an urban environment, considering all other factors impacting the city's services and resources for sustainable development [27] [28]. A city's population is influenced by several factors. Among them are, space for construction of residential structure, design of city, shape of structures, capacity of structures, structural strength of structures, land cove/land use, land slope, hydrology of the city, climate, weather. Others are, politics quality of life, etc. These factors determine the sustainability and carrying capacity of a city. Some of the listed factors are fixed while others are dynamic. Although the model for population growth suggests continual increase with respect to time (years), the population of Lagos like other cities has a limit. The limit is reached when % change stops (equal to zero). According to this study, stabilization is expected when the population reaches 23,000,000. However, the number could be higher if factors affecting its carrying capacity favor the city to hold more residents sustainably.

4. Policy Recommendations and Conclusion

The rapid urbanization rate in the area not only created unprecedented consequences by diminishing the quality of the environment but it raised serious implications for land management in the region. Provision of green planning education for city managers, developers, and the public in the state is required. This would go a long way in raising awareness about the dangers of initiating future developments in areas deemed adjacent to sensitive natural habitats known for their ecological services for communities while familiarizing them of the risks of encroaching on ecologically fragile areas. There is also the need for use of information technologies in land administration. Although Nigeria has its own space administration with the goal of providing needed data in land management, the land administration has several challenges in use of information technologies such as multiples problems arising from lack of spatial information tools and infrastructure, inadequate training and lack of coordination between agencies [15] [17]. Use of information technogies will go a long way in helping sustainability and management of land resources.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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