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Modeling Urban Green Space Dynamics and Associated Proximate Drivers in Ibadan Metropolis, Ibadan, Nigeria

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Abstract

Urban Green Space (UGS) provides economic, ecological and social benefits to the populace across the globe. However, there is dearth of information on the dynamic of UGS caused by proximate drivers (PD) in Ibadan metropolis of Oyo State, Nigeria having flooded the direct drivers. Therefore, this study was designed to assess UGS changes and the PD that contribute to the changes in the last 34 years. Landsat images of 1984 (TM), 2001 (ETM+) and 2018 (OLI), coordinates of bench mark places of Ibadan metropolis were obtained. Geometric correction and principal component analysis were carried out on the satellite images. Land cover classification was achieved using maximum likelihood classifier method. Shapefile of Ibadan metropolis was super imposed on the classified images for land use/land cover assessment and Kappa statistics was used to carry out accuracy assessment on the image classification. The change detection analysis was carried out on the classified images using geometric geoalgorithm of ArcGIS. Urban green space change (dependent variable) and Proximate Distance (distance from; UGS edges, roads, built-up area and elevation) were extracted from the Landsat images using the distance command in IDRISI with Cramer's V test of association analysis. Four land use/land cover categories were identified; urban green space, built-up, water body and bare-soil. The UGS and water body decreased from 126,344 ha (85.36%) and 233.01ha (0.16%) to 100,481.20 ha (67.88%) and 136.17ha (0.09%) respectively from 1984 to 2018. On the other hand, built-up area and bare-soil increased from 9,250.72 ha (6.25%) and 12,193 ha (8.23%) to 32,227.16 ha (21.77%) and 15,176.20 ha (10.25%) respectively from 1984 to 2018. Distance from built-up (0.59) and UGS edges (0.56) are the dominant PD of UGS dynamics. About 25,863 ha of green space at rate of 760 ha per annum is given up to built-up area and bare-soil between 1984 and 2018. Urban green space decreased with increase in built-up area. The dominant proximate drivers influencing the changes were the distance from the built-up area and urban green space edges.

***Keywords**:* Urban green spaces, change detection, proximate drivers, land use change.

Introduction

Background of the Study

Urban Green Spaces are outdoor places in cities with significant amounts of vegetation (*Mwirigi et al., 2012).* The extent and distribution of urban green spaces vary among and within cities , which also dependents on the size and form of the city, socio-political factors, population growth, economics and biophysical factors (Fuller and Gaston 2009). It was reported by Olaleye, (2013) that the idea of green city was introduced in 19th century by Ebenezer Howard with the aim of overcoming the depressing ugliness, haphazard growth and unhealthy conditions of cities. A healthy green space system plays a crucial role in promoting sustainable development of city and society as it provides a variety of ecosystem services (ESS), enhance sustainability of urban forest, with resilience to environmental disasters as well as to minimize poverty (Andersson, 2006; Benedict and McMahon 2002; Sandström, 2009; .

The increase in urban construction and development has affected the urban green spaces in terms of its size . Therefore, urban green space dynamics can be defined as an increase or decrease in urban land cover . The green loss tend to influence the microclimate condition of the area and could have severe consequences on biological organisms (D'odorico *et al*., 2013; Li *et al*., 2016), and climate due to the biophysical changes that modify the water cycle, surface energy balance and alterations to the carbon balance . According to Siles, (2009), drivers of urban green space dynamics can be grouped into underlying and proximate drivers. Understanding the proximate factors that influence urban green space dynamics is very important for future urban planning. These proximate causes include human activities or immediate actions at local level: such as road expansion or increase in built-up area which tend to stem from proposed land use and directly influence urban vegetation cover dynamics (Siles, 2009).These factors can be assessed using Cramer's v test of association. Cramer's V is a correlation test that assesses the strength and association between dependent and independent variables without considering any form of data distribution. It is a useful tool in determining the independent variables that should be included in a model when predicting the dependent variable. As a result, UGS changes can be predicted if its drivers are known, thereby aid urban Environmental planning and support appropriate decision making initiatives as earth's vegetative cover is massively altered where it directly contributes to climate change through a variety of processes (Bakar *et al.*, 2016). In most of our cities in Nigeria, the direct drivers have however been over flooded (Raheem and Adeboyejo, 2016) while attention has not been given to the effect of proximate drivers in UGS changes especially in the study area. Hence, this study assessed the dynamics of urban green space and its proximate drivers in Ibadan metropolis with a view to provided baseline information for sustainable management of urban green space in the study area.

Methodology

The Study Area

Ibadan is the third largest metropolitan area, by population, in Nigeria after Lagos and Kano, with a population of 2.84 million located in Oyo State, Nigeria (UNWUP, 2010). It lies on the geographical coordinates of latitudes 7˚26'33"N and 7˚38'22"N and longitudes 3˚14'56"E and 3˚16'58"E (Agbor *et al.*, 2012). The soils of Ibadan region were formed from the underlying rocks especially granite gneisse, quartz-schist, biotitegneisse and schist. They were formed under moist semi-deciduous forest cover and belong to the major soil group called ferruginous soils . Ibadan is situated in the tropical rainforest zone of Nigeria, thus, has tropical climate with two distinct seasons with raining season spanning through April to October and the dry season spanning through November to March. The mean annual rainfall is above 1,505 mm while the relative humidity is between 60% and 80% (Raheem and Adeboyejo, 2016)

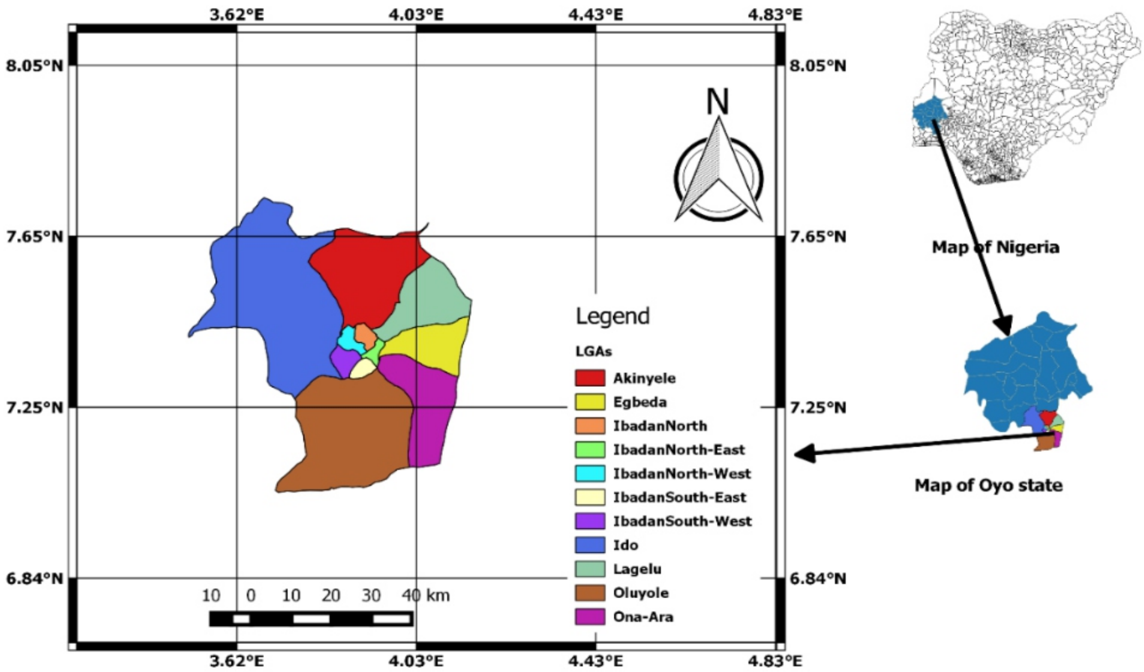

Figure 1:The local governments that form part of Ibadan metropolis, Nigeria.

Data Collection

This study involved two sets of data collection, which are primary and secondary data collection. The primary data includes; coordinates of some bench mark places within Ibadan metropolis, shapefile of the study area while the secondary data includes; Landsat satellite images of 1984, 2001 and 2018 were obtained (Table 1). The study area is located in the Landsat path 191 and row 55. The pixel sizes of the images are 30 m x 30 m (Chander and Markham, 2003). All the images were obtained in the same season (dry season).

Table 1: Satellite Images

Satellite Sensor	Spatial resolution	Acquisition Years	Path	Row	Source
Landsat 5, 7	30m x 30m	1984, 2001,	190	55	GLCF
Landsat 8 (OLI)	30m x 30m	2018	190	55	USGS
Asterdem	30m interval	2018	190	55	GLOVIS

Source: Field Survey, 2018

Data Analysis

Image Classification

After pre-image analysis of geometry and principal component analysis, modified version of the Anderson scheme of land use/cover classification was adopted for the image classification. The study utilised maximum likelihood classification algorithm as integral part of the classification processes. Accuracy assessment was carried out to determine the accuracy of the assessment. Comparing the map and reference classification at each sample unit allows the construction of an error matrix. Kappa statistics was used as a measure of agreement between model predictions and reality (Congalton, 1991) or to determine if the values contained in an error matrix represent a result significantly better than random (Jensen *et al.*, 2000). Kappa coefficient was computed (equation 1)

$$k = \frac{N\sum_{i=I}^{r} x_{ii} - \sum_{i=I}^{r} x_{ii}(x_{i+}\, x_{+i})}{N^2 - \sum_{I=1}^{R}(x_{i+}\, x_{+i})} \quad \text{........ (eq.1)}$$

Where: N = total number of sites in the matrix R = number of rows in the matrix x_i= *number in row* i *and column* i, x_{+1}= *total for row* i, x_{1+}= *total for column* i, x_{ii}= *total number in row* i *column* i.

Change detection analysis

The change detection required comparison of independently classified image for the different time interval. This showed a complete matrix of land use land cover change detection. It determined the percentage and the rate of changes that occurred within the selected years. Therefore, the area in hectares and percentage of each of the selected year was determined. The percentage change and the rate of changes that occurred were computed by dividing observed change by absolute sum of change as shown in the equations 2 to 5.

$$\%\,\Delta = \frac{OC}{ASC} \times 100 \quad \text{............... (eq.2)}$$

$$\%\,\Delta \text{in year} = \frac{Y_2 - Y_1}{Y_1} \times 100 \quad \text{....... (eq.3)}$$

$$\text{Average Rate of}\,\Delta = \frac{Y_2 - Y_1}{T_2 - T_1} \quad \text{....... (eq.4)}$$

$$\%\,\text{average Rate of change} = \frac{AverageRateofchange\left(\frac{ha}{yr}\right)}{Differenceinyear} \times 100$$

(eq.5)

Where: OC is the Observed Change, ASC is absolute sum of change i.e fixed year (starting year), Y_2-Y_1 *is the observed change,* Y_2 *is the ending year,* Y_1 *is the starting year,* T_2-T_1 *is the periodic interval between the initial period and the final period.*

Proximate drivers of UGS Dynamics.

The effects of the proximate drivers were assessed using Cramer's V test of association by creating suitability (distance) maps of the selected variables in a GIS and co-registered geometrically with the urban green spaces change map derived from the analysis of remote sensing images. The factors or land cover constraints was standardized to a continuous scale of suitability from 0 (the least suitable) to 255 (the most suitable). The 0-255 range provided byte data type (Eastman *et al.,* 2012) with an assumption that the pixel closer to an existing land cover type has higher suitability with that land cover type. Hence, the suitability decreases with distance. Therefore a simple linear distance decay function was appropriated for this basic assumption. Urban green space was used as dependent variable while proximate drives were used as the independent variable and the model was developed in IDRISI. The Cramer's V value was calculated with *Eq. 19 (Cramer, 1946)* and adopted by *Bergsma, (2013).*

$$v = \sqrt{\frac{x^2}{N(m-1)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(eq.19)}$$

Where: x^2*: Chi-square, N: Population and m: The numbers of the columns or lines on the table*

Results and Discussion

Four land use/land cover categories were identified; urban green space, built-up area, water body and bare-soil. The urban green spaces covered about 126,344 ha of land in Ibadan metropolis accounting for about 85.36% of the total area of the metropolis in 1984 (Table 1). This was followed by built-up area with 9,250.72 ha accounting for 6.25% and bare soil covered 12,193.00 ha accounting for 8.24% of the total land area while water body occupied the least area (233.01 ha) 0.16%. Between 1984 and 2001, built-up area increased from 9,250.77 ha (6.25%) to 16,843.60 ha (11.38%). However for the same period, green spaces land cover type reduced from 126,344 ha (85.36%) to 122,838 ha (82.99%), in the same vein, water body also decreased from 233.01 ha (0.16%) to 221.85 ha (0.15%) and bare soil land from 12,193ha (8.23%) to 8,117.28 ha (5.48%). Between 2001 and 2018, built-up area recorded 10.39% increase (16,843.60 ha to 32,227.16 ha), bare land increased from 5.48% to 10.25% (8,117.28 ha to 15,176.20 ha) while green spaces decreased by -15.11% (122,838 ha to 100,481.20 ha) and water body also decreased by - 0.06% (221.85 ha to 136.17 ha) of the total area of Ibadan metropolis.

The steady gain in the built-up area from 9,250.72 ha in 1984 to 32,227.16 ha in 2018 at the rate of 675.78 ha/yr. was as a result of increase in immigration and population growth. The total area covered by bare soil also increased from 12,193 ha to 15,176.20 ha between 1984 and 2018 at the rate of 87.74 ha/yr. this can be attributed to increased demand for land for the construction of more facilities and amenities as identified from field survey, this result is in agreement with Adetoro and Salami, (2018) who stated that built – up areas increases as immigration and population growth increases. The water bodies were of the maximum in 1984, which reduced drastically in 2018 at the rate of -2.84 ha/yr. This was because many people have encroached into water bodies, thereby making those in the area vulnerable and at risk to flooding. In the same vein, there was a drastic decrease in the size of the green space areas in the study area from 126,344 ha to 100,481 ha between 1984 and 2018 at the rate of -760.67 ha/yr. This can be attributed to the increase in urbanization (built-up area) as identified from the analysis of proximate factors of UGS change in this study. Hence the result is also similar to the works of (Babalola and Akinsanola, 2016; Adetoro and Salami, 2018; Mengistu and Woldetsedik, 2018) though with variation in percentages which was due to the difference in the size of the total area considered in each study.

The result of classification accuracy showed that the producer's and user's accuracy were greater than 50%. The total accuracy result for year 1984, 2001 and 2018 described 0.76%, 0.86% and 0.89% classification accuracy respectively. Similarly, the kappa statistic assessment showed that the level of accuracy in the classification was 88.75%, 88.75% and 87.75% in 1984, 2001 and 2018 respectively. Hence, land cover classes classification was accurate at total accuracy level and kappa statistic value greater than 0.6 and 80% respectively therefore can be used for further analysis.

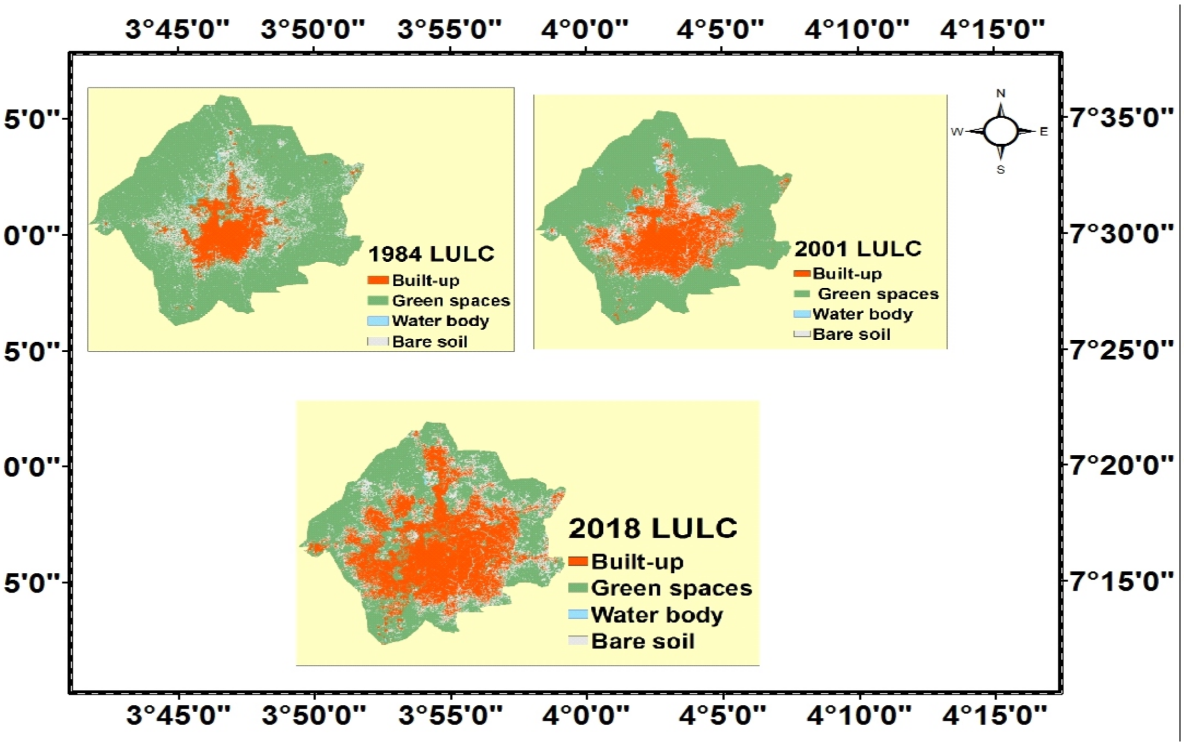

Figure 2: land cover types change

Table 1: Land use/ land cover distribution and error matrix of image classification

Land use/land cover distribution							Error Matrix		
Classification	1985		2001		2018		1985	2001	2018
	Area (ha)	Area (%[1])	Area (ha)	Area (%)	Area (ha)	Area (%)	1984 $Pa, Ua.$	2001 $Pa, Ua.$	2018 $Pa, Ua.$
Green Spaces	126,344.00	85.36	122,838	82.99	100,481.20	67.88	64, 68	66, 73	60, 72
Built-Up	9,250.72	6.25	16,843.60	11.38	32,227.16	21.77	61, 65	58, 63	60, 69
Water Body	233.01	0.16	221.85	0.15	136.17	0.09	89,93	90,92	90,94
Bare Soil	12,193.00	8.23	8,117.28	5.48	15,176.20	10.25	76, 82	77, 80	87, 90
Total	148,020.70	100	148,020.70	100.00	148,020.70	100			
Kappa Statistics (k)							0.76	0.86	0.89

Pa is Producers Accuracy and Ua is Use's accuracy

[1] *Percentage*

Proximate drivers associated with Urban Green Spaces (UGS) Dynamics.

The distance maps represented in Figures 3 and 4 were generated using simple Euclidean distance function which measured the distance between each cell from the featured image and was used in running the Cramer's V test of association. The unit of measurement is in meter. Running the Cramer's V module in IDRISI software environment generated Cramer's values in Table 2. The values represent the degree of association between the independent variables (possible proximate factors of UGS changes) and dependent variable (UGS change map). The distance from built-up and distance from forest edge had a good association with UGS changer with (Cramer's V. value of 0.59 and 0.56 respectively) while distance from roads and elevation showed a poor association with (Cramer's V. value of 0.09 and 0.13 respectively).

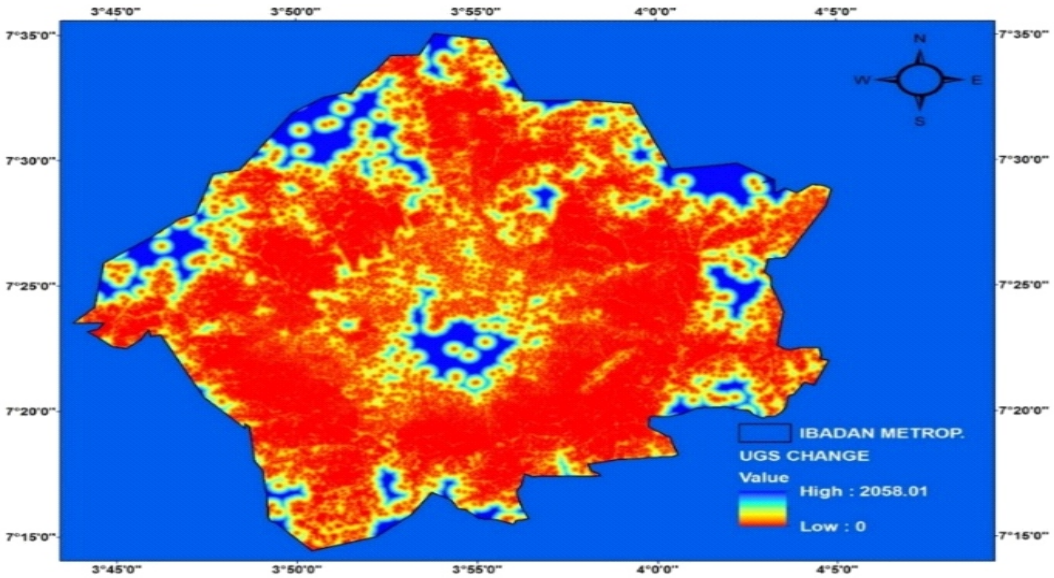

Figure 3: UGS Change Map (Dependent variable)

Source: field survey, 2018

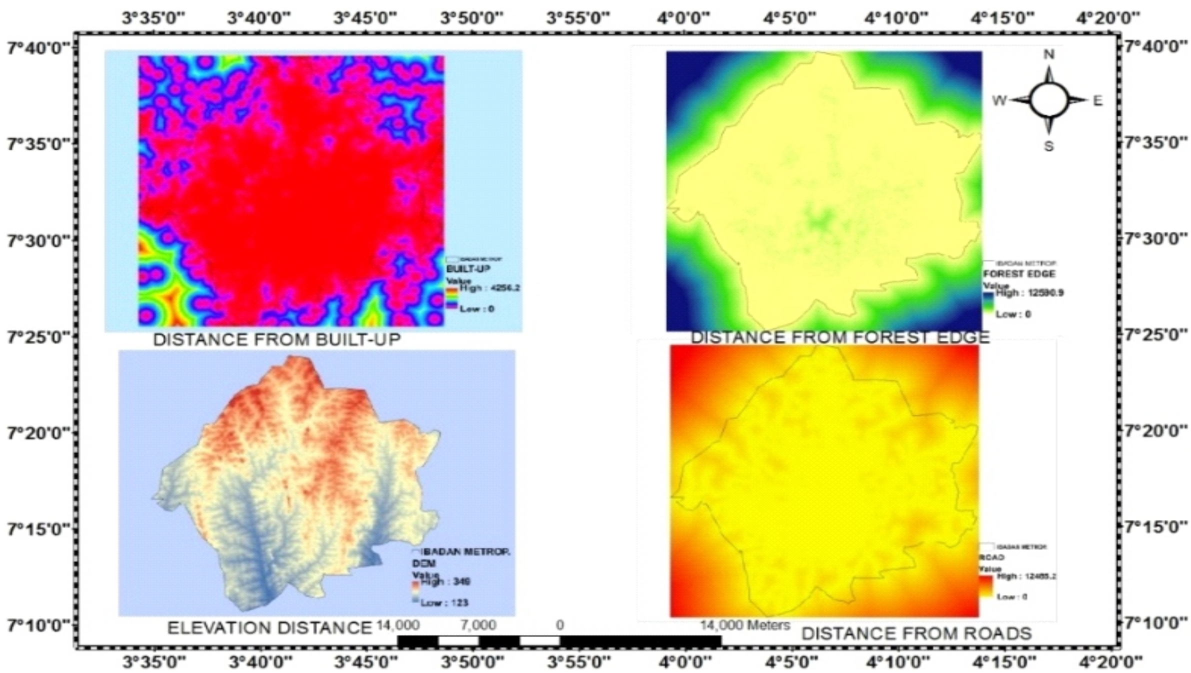

Figure 4: Distance Images (Independent variables)

Source: field survey, 2018

Table 2: Statistical test of association between dependent and explanatory variables

Dependent Y	Variables Explanatory X	Cramers' V value
UGS areas change image with (change and 'no-change') categories.	Distance from built-up area	0.59
	Distance from forest edge	0.56
	Distance from road	0.09
	Elevation	0.13

Source: field survey, 2018

This test is useful as a measure of strength of relationship and it has been applied successfully in other studies related to spatial predictions (Almeida *et al*., 2003). If the results of Cramers's V test are close to 1, the model assigns a higher probability of driver of UGS change to the explanatory variable. If the results are close to 0, the model assigns a lower probability of UGS change.

The result in Table 2 showed that the probability of urban green space change was positively correlated with proximity to all of the variables. Although, distance from built-up and distance from forest edge showed a higher positive association with UGS change while distance from road and landscape position showed a very low positive association. Going by this result, one can conclude that the changes in UGS between 1984 and 2018 were actively influenced by anthropogenic activity such as settlement expansion (built-up) and distance from forest edge this is also in agreement with the findings of Kaimowitz and Angelsen, (1998) who stated that forest loss increases with proximity to settlement (built-up) and forest edge. In the same vein, the work of Raheem and Adeboyejo (2016) revealed that of all the factors contributing to the decrease of urban green spaces in the Ibadan metropolis, erection of structure has the highest proportion thus further corroborating the result. This was also corroborated by Mengistu and Woldetsedik, (2018) who reported that population pressure, settlement, and fuel wood consumption contributed to reduction in forest cover. They further reported that substantial population increase over the last two decades is responsible for land use and land cover change in Southwest Ethiopia. Kong and Nakagoshi (2005) also reported that UGS reduction was influenced by urban sprawl, which also increase the population and consequently increased the built up area**.** In Ibadan, although proximity to road network is expected to increase forest loss, this was not so in the study area, as distance from the roads exhibited low correlation with UGS change, this can be attributed to the fact that forest patches are not suited close to roads and also the existing roads experienced little or no expansion that could contribute to a significant loss of UGS as observed from the field survey. Where there were road expansion, UGS was not much affected as physical structures like buildings. The degree of association between Landscape position and UGS change was relatively low this is because the study area has little topographic variation. Hence, increase in urbanization will lead to more built-up areas resulting to loss of vegetation cover thereby denying the urban populace the ecological, social and economic benefits it provides.

Conclusion

In this study, qualitative and quantitative analyses were used to determine the land cover dynamics and investigate possible proximate drivers of land cover (UGS) change as tools for decision making in sustainable urban forest management over selected urbanized areas in Ibadan Metropolis of Oyo State, Nigeria. Four land cover categories were identified in the study area include: green spaces, built-up, water body, and bare soil. The classification was considered accurate based on total classification accuracy and kappa statistic of 0.89 and 89% respectively. Urban Green Spaces and water body areas decreased while built- up and bare soil areas increased between 1984 and 2018. Thus, increase in built-up lead to the decrease in green spaces and water body areas. In the same vein, the possible proximate drivers of land cover dynamics determined using Cramer's V test of association identified distance from built-up and urban green space edges as dominant proximate drivers of land cover change amongst other explanatory variables. Conclusively, the study revealed the efficiency of remote sensing and GIS techniques in data capturing to produce reliable information for sustainable management of urban green spaces.

Recommendations

The results also showed that although remote sensing images were ideal for analyzing spatial data the main difficulty was in selecting images with similar conditions of cloud cover, humidity and geometric acquisition. This fact enhances the necessity of more studies to find corrections for these effects. Distance from built-up and urban green spaces edges were the main drivers of urban green space dynamics, hence, government should create a wide range of policies to manage urban growth and protect urban green spaces (UGS) as green space is the gateway to sustainability of any city (Pincetl, 2003). Since the highest proportion of the metropolis is concrete government and individuals should intensify efforts by making sure all available spaces such as rail lines, power lines and steep slopes as well as river courses and hilly spaces considered not fit for development are greened in order to compensate for the vast hectares of built ups in the city centre. The government should sensitise the populace on the importance of maintaining green space around their habitat and people should be mandated to keep greenings in containers both inside and outside all existing structures whether residential or commercial. Construction of skyscrapers houses should be encouraged so as to conserve space for greening.

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