Is Nigeria losing its natural vegetation and landscape? Assessing the landuse-landcover change trajectories and effects in Onitsha using remote sensing and GIS

Abstract: Onitsha is one of the largest commercial cities in Africa with its population growth rate increasing arithmetically for the past two decades. This situation has direct and indirect effects on the natural resources including vegetation and water. The study aimed at assessing land use-land cover (LULC) change and its effects on the vegetation and landscape from 1987 to 2015 using geoinformatics. Supervised and unsupervised classifications including maximum likelihood algorithm were performed using ENVI 4.7 and ArcGIS 10.1 versions. The LULC was classified into 7 classes: built-up areas (settlement), waterbody, thick vegetation, light vegetation, riparian vegetation, sand deposit (bare soil) and floodplain. The result revealed that all the three vegetation types decreased in areas throughout the study period while, settlement, sand deposit and floodplain areas have remarkable increase of about 100% in 2015 when compared with the total in 1987. Number of dominant plant species decreased continuously during the study. The overall classification accuracies in 1987, 2002 and 2015 was 90.7%, 92.9% and 95.5% respectively. The overall kappa coefficient of the image classification for 1987, 2002 and 2015 was 0.98, 0.93 and 0.96 respectively. In general, the average classification was above 90%, a proof that the classification was reliable and acceptable.

Keywords: geoinformatics, population growth, urbanization, supervised and unsupervised classifications, kappa coefficient

1 Introduction

Nigeria is among the top largest countries in Africa in relation to population and land area. The diversity of the vegetation landscape (Sahel savanna, Sudan savanna, Guinea savanna, Rainforest, montane forest, derived/woody forest, mangrove forest and fresh-water swamp forest) makes it a biodiversity rich country. With annual urban growth rate of 4%, and more than 50% of the population living below 5 USD per day [1], there is high dependent on the natural resources. The continuous growth in population has caused increase in the exploitation of vegetation, soil and water. Technological advancement and elevated human needs have deprived the environment the potential of sustaining its carrying capacity. Incessant need for more food, shelter, firewood, charcoal, timber, soil, quality water, industries and services, has brought severe degradation to the natural vegetation ecosystem [2] which in turn created substantial effects on the LULC.

Land cover can be referred to every biophysical feature on the earth’s surface including plants, water, topography, soils and rocks [3, 4] while, land use on the other hand, refers to how people use the landscape – whether for development, conservation, or multiple uses [5, 6].

LULC change is a continuous process, and the change rate could either be gradual or spontaneous [7]. Five types of causes for LULC changes were outlined by Lambin [8]. These were: (i) human-induced modification of vegetation cover and landscapes, (ii) human-induced global warming and/or greenhouse effect, (iii) ecological and geomorphological processes, (iv) inter-annual climate variability and (v) long-term natural changes in climate conditions.

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To facilitate sustainable management of the natural resources, vital tools and techniques are needed to detect, describe, and predict the LULC changes. And these tools have prompted accurate information on LULC change and have effectively supported many recent studies on change detection [9–12].

Assessment of the LULC trajectories enables an understanding of the relationships between man and the environment for sustainability. The impacts of LULC change on the environment could be long-term, and cut across the living organisms (animals, man, plants, microbial) and the non-living components (climate, soil and elements) [13]. An appraisal of the dynamics of LULC change with knowledge of its underlying causes is rapidly being considered an essential area of research on either local, regional or global scale. In the past, inadequate data was the key challenge confronting both researchers and planners in the field of LULC change but, advent of remote sensing and GIS has brought efficiency and reliability. As a major source of information on land cover, aerial photograph remains an essential source of LULC data [14] especially in the developing countries. Today, the availability of Landsat and many commercial remote sensing satellites has made LULC data accessible at all scales including multiple spatial, thematic and temporal resolutions. And GIS has further enhanced mapping, modelling and prediction of LULC changes. The integration of remote sensing and GIS tools brought a new paradigm in environmental studies. As good LULC change evaluation tools, remote sensing and GIS have been widely adopted in environmental resources management, and have severally been applied in LULC classifications [3, 15–17], as well as in change detection [18–20].

The ‘trajectories of change’ concept has gained wider usage in theory and application. Trajectories of change can be defined as spatio-temporal pattern of interactions between variables that modify the effects on man and nature on the environment [21]. According to Mertens [22], trajectories of change concept is complex and depends on several circumstances including biophysical factors, geographical contexts and human policies. However, the generic paths of change can be identified, for example, the typical sequences of LULC change prevalent across tropical regions [3]. Trajectories of change, in general, is highly associated with demographic phenomena and long-term induced processes on either agriculture and soil [23], landscape [24, 25], vegetation [26], ecosystem and energy [27], watersheds [28] or governance-economic policies [29]. Besides human beings, natural forces such as climate [30], and environmental hazards [31] are also at the central force of the trajectories of change concept. The trajectories of LULC change in this work referred to replacement of LULC classes by another for a given sampling unit over many years.

Onitsha is one of the largest commercial cities in Africa [32]. It is faced with the challenges of providing a growing population with food, water, shelter, sanitation and basic amenities [32, 33]. Urbanization has created rapid growth of housing/industrial estates, proliferation of ghettos, slums, and shanty areas to accommodate the increased population, and has necessitated anthropogenic activities which consequently altered the LULC [34]. Natural forests and grasslands are being converted to arable lands, commercial centers and residential areas. Thus, many plant species and their associated ecosystem services have been lost. During the last two decades in the study area, 0.2-0.4 hectares of land was lost annually to soil erosion due to high rate of deforestation while, more than 3% of the total vegetation cover was replaced by either settlement, sand deposits or floodplain [34]. The government, the agriculturists and the urban planners have increased the number of housing units and facilities development, established more commercial towns, and expanded arable lands to satisfy the growing population. Many studies have been focused on modelling and detecting the LULC change without identifying the primary effects on plant species [9–12]. This study therefore aimed at assessing the effects of LULC change on natural resources especially vegetation and water between 1987 to 2015. We hypothesized that (i) longer-term influence of human activities significantly intensified LULC change leading to rapid decline in the natural vegetation size and compositions. (ii) population growth increased settlements which subsequently expanded the floodplains at the expense of the plant species and waterbody.

2 Materials and methods

2.1 Study area

The study area (Onitsha) and its environs lie between latitude 6° 32’ N - 6° 58’ N and longitude 6° 02’ E - 6° 57’ E (Figure 1). Onitsha has a rapid population growth of 623,274 with a metropolitan size of 1,003,000 persons [36]. It is currently one of the fastest growing cities in the world. Onitsha as a commercial hub of Nigeria and Africa became the focus of this study. It is located within the humid tropical rainforest belt of Nigeria (Figure 1) with an annual rainfall ranging from 200 cm to 300 cm, and annual mean temperature ranging from 26°C – 29°C [37]. The geologi-
Is Nigeria losing its natural vegetation and landscape?

2.2 Data: collection, pre-processing, classification, accuracy assessment, and land use-land cover (LULC) change analysis

Data collection:

Ancillary and satellite data were used for this study (Figure 2). The ancillary data included:

- the topographic (base) maps and geographical layers of the study area, which were roads, rivers, ecological and geographical boundaries, and land-cover maps. These were obtained from the National Space Research and Development Agency, Abuja (NASRDA), and the United States Geological Survey (USGS).
- GPS collected ground truth data for the LULC classes and coordinates,
- data from oral interview with the local people,
- data from previous researches.
- dominant plant species, photographs and field notes recorded in 2015 during a field survey;
- Google Earth images used as reference data during the classification and validation phases of the analysis;
- population data from the national population commission (NPC).

The data from the ground truth served as the reference points, and were acquired from January to September 2015 for the 2015 image analysis. The ground truth data were used for image pre- and post-classification and overall accuracy assessment of the classification results. Satellite and topographic data were also collected (Table 1). The population data was derived from the National Population Census [40], while the settlement data were derived from the LULC classification.
Table 1: Data Characteristics and Source

<table>
<thead>
<tr>
<th>Data type</th>
<th>Year</th>
<th>Path &amp; Row</th>
<th>Resolution</th>
<th>Source(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat Image (MSS)</td>
<td>1987</td>
<td>p189, r056</td>
<td>30 m</td>
<td>NASA(^a)</td>
</tr>
<tr>
<td>Landsat Image (TM)</td>
<td>2002</td>
<td>p189, r056</td>
<td>30 m</td>
<td>USGS(^b), NASRDA(^c).</td>
</tr>
<tr>
<td>Landsat Image (TM)</td>
<td>2015</td>
<td>p189, r056</td>
<td>30 m</td>
<td>USGS.</td>
</tr>
<tr>
<td>Topographic/Base map(s)</td>
<td>1987, 1997, 2007</td>
<td>1:50,000</td>
<td></td>
<td>FSN(^d).</td>
</tr>
</tbody>
</table>

\(^a\) = National Aeronautics and Space Administration;  
\(^b\) = United States Geological Survey;  
\(^c\) = National Space Research and Development Agency (Nigeria);  
\(^d\) = Federal Surveys of Nigeria.

Table 2: Land Use-Land cover (LULC) classification

<table>
<thead>
<tr>
<th>LULC class</th>
<th>Categories</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-up area</td>
<td>Residential, Commercial, Industrial, Recreational, and educational</td>
<td>Public, private, government, and commercial estates, Shopping malls, markets, stores, warehouses, trade-fair centers. Production sites, manufacturing factories for textiles, plastics and leather products, Government facilities and settlement.</td>
</tr>
<tr>
<td>Sand deposit</td>
<td>Open land and non-vegetated land.</td>
<td>Bare surfaces, sand deposits, rock outcrops, accumulation of sediments from river erosional and denudational processes. Man, also influenced this LULC class.</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Thick forest, Light/crop fields.</td>
<td>Evergreen forest and mixed forests with higher density of trees, fallow lands, crop fields/arable lands or agricultural lands.</td>
</tr>
<tr>
<td>Riparian Vegetation</td>
<td>Trees, shrubs, grasses.</td>
<td>Type of vegetation found in water logged/riverside areas. Alluvial scrublands. Others include hydrophytes such as algae, water lilies, duck weeds.</td>
</tr>
<tr>
<td>Water bodies</td>
<td>Wetlands, ponds, rivers, streams, dams.</td>
<td>Areas cover by open water such as river, ponds, Lagoons, dam, reservoirs and water-logged area.</td>
</tr>
<tr>
<td>Floodplain</td>
<td>River floodplain.</td>
<td>Floodplain formed due to lowland terrain. The river and streams eroded silts and deposits.</td>
</tr>
</tbody>
</table>

Data processing and classification

Supervised and unsupervised classifications was employed. This was carried out on the satellite images covering the study periods. The classifications supported LULC classes visual appropriateness. Firstly, the unsupervised classification was performed on the images and the features generated were clustered into defined classes of interest. This was followed by a supervised classification which included field visit and identification of LULC classes. The classification scheme was developed to include: built-up area (settlement), sand deposit (bare soil surfaces), water (waterbodies), floodplain and vegetation types (thick vegetation, light vegetation /arable land, riparian vegetation) (Table 2). The classification scheme gave a broad classification where the LULC classes were identified by a single digit. The band 4, 3 and 2 images were imported into the ENVI (version 4.7) software to form color composite of the study, using the vector frame in ArcGIS 10.1 software environment. The region of interest was created from the map of the study area and saved as shape file. The clustered features were used to reclassify the images by introducing a maximum likelihood classifier which classifies the pixels in relation to the maximum probability of similarity with a specific class. To rectify
noise effect and smoothen the classes, the final classified images were then filtered using a neighborhood majority function which replaces the center pixel in the 3 × 3 matrix with the most common data file value. Furthermore, there was cases of major misclassification of features such as shadow, in this case, recoding was applied. The degree of accuracy of each classified image was evaluated by a set of 280 random (reference) points based on the number of classes (40 points per class). These reference points were overlaid on the images and each point was designated to one of the land-use classes.

The topographic maps were scanned and imported into ArcGIS environment. They were rectified (UTM WGS84) to the salient land-use layer with a nearest-neighbor resampling (RMSE <0.5 pixels, or <15 m). The projections from the Landsat images were imported to consolidate the georeferencing/rectification of the topographical maps. To correct atmospheric, environmental and sensor related effects, radiometric corrections and histogram equalization were carried out in the ENVI 4.7 and ArcGIS 10.1 for all the images [41].

In addition, a confusion matrix was developed for every map. Each row showed land-use classes in the classified map while, each column represented the reference land-use classes. By using the matrix, the overall accuracy (%) and kappa co-efficient (K) were generated for each classified map [42, 43]. The Kappa co-efficient is calculated by the formula Eq. (1):

\[ K = \frac{P(A) - P(E)}{1 - P(E)} \] (1)

where, \( P(A) = \) the number of times the k raters agree, and \( P(E) = \) the number of times the k raters are expected to agree only by chance [44, 45].

We also assessed the user’s and producer’s accuracies. The user’s accuracy measured the fraction of each class which is correctly classified in the map as a given class while, producer’s accuracy evaluates the percentage of land-use class which is correctly classified as the actual landscape present on the ground.

The population growth rate, the land consumption coefficient, and their projections were also calculated. These helped to understand the ratio of built-up areas to population vis-a-vis the relationships and effects on the LULC. The population growth rate and projection were calculated using the formula Eq. (2):

\[ \text{Population growth rate (G)} = \frac{[P(t_2) - P(t_1)]}{[P(t_1)(t_2 - t_1)]} \] (2)

where, \( P(t_1) = \) the size of the growing population at the initial time \( (t_1) \); \( P(t_2) = \) The size of the growing population at present time \( (t_2) \); \( (t_1) = \) Initial year; \( (t_2) = \) Present year.

And for this study the arithmetic numerical projection equation was used to project the population. The general equation is given as Eq. (3):

\[ P(\text{projected}) = P(t_1) + P(t_2 - t_1) \] (3)

where, \( P(\text{projected}) = \) The size of the projected population at present time; \( (t_1) = \) Initial year; \( (t_2) = \) Present year; \( P(t_1) = \) The size of the growing population at initial time \( (t_1) \).

The land consumption coefficient (LCC) was also calculated (Eq. (4)):

\[ \text{LCC}(t_n) = \frac{\text{LU}(\text{projected})(t_n)}{\text{P}(\text{projected})(t_n)} \] (4)

where; \( \text{LCC}(t_n) = \) Land Consumption Coefficient at the given year; \( \text{LU} (\text{projected})(t_n) = \) Land use \( (\text{km}^2) \) of Onitsha at the given year; \( P(\text{projected})(t_n) = \) Population of Onitsha at the given year.

In 2015, the number of dominant plant species in each LULC class was counted and recorded in the field while, update for the previous years was gathered from the ministry of forestry, local communities, and past literature. A principal component analysis (PCA) followed by a Monte Carlo Permutation test with 999 permutations in the Canoco software [46] was used to evaluate the relationships between the dominant plant species and the LULC classes. Plant species data were log-transformed \( (y' = \log10(y + 1)) \). Ordination diagram was produced by employing the CanoDraw program software which prompted the presentation and visualization of the PCA result.

### 3 Results

#### 3.1 Overall LULC changes

The LULC area and changes for Onitsha municipal was created for 1987, 2002, and 2015, (Table 3; Figure 3). In 1987, light vegetation \( (35.9 \text{ km}^2) \) recorded the highest area which represented 32.9% of the total LULC. Built-up area, \( 35.2 \text{ km}^2 \) (32.3%) had the highest LULC area in 2002. Our result revealed a remarkable increase in built-up area by more than 100% in 2015 when compared with that of 1987. Sand deposit recorded an increase difference of \( 1.1 \text{ km}^2 \), \( 3.0 \text{ km}^2 \), and \( 4.2 \text{ km}^2 \) between 1987 and 2002, 2002 and 2015, 1987 and 2015 respectively. The areas covered by floodplain also showed a high increase of \( 6.5 \text{ km}^2 \) in 2015. Generally, thick and light vegetations, and waterbodies revealed continuous decrease throughout the study period due to inflated anthropogenic activities as postulated in the first hypothesis.
Table 3: LULC area, change differences, classification accuracy, and Kappa statistics

<table>
<thead>
<tr>
<th>LULC Classes</th>
<th>Area (km²)</th>
<th>%</th>
<th>Area difference (km²)</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-up Area</td>
<td>20.7</td>
<td>35.2</td>
<td>42.8</td>
<td>19.0</td>
</tr>
<tr>
<td>Water Body</td>
<td>10.1</td>
<td>8.4</td>
<td>8.0</td>
<td>9.3</td>
</tr>
<tr>
<td>Thick Vegetation</td>
<td>21.6</td>
<td>16.2</td>
<td>12.1</td>
<td>19.8</td>
</tr>
<tr>
<td>Light Vegetation</td>
<td>35.9</td>
<td>29.5</td>
<td>16.5</td>
<td>32.9</td>
</tr>
<tr>
<td>Sand Deposit</td>
<td>3.4</td>
<td>4.6</td>
<td>7.7</td>
<td>3.1</td>
</tr>
<tr>
<td>Flood Plain</td>
<td>8.9</td>
<td>9.7</td>
<td>15.4</td>
<td>8.2</td>
</tr>
<tr>
<td>Riparian Vegetation</td>
<td>8.4</td>
<td>5.3</td>
<td>6.6</td>
<td>7.7</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>109</strong></td>
<td><strong>109</strong></td>
<td><strong>109</strong></td>
<td><strong>100</strong></td>
</tr>
</tbody>
</table>

Overall Classification Accuracy (%)  
90.7 92.4 95.5

Kappa Statistics (K)  
0.89 0.93 0.96

The cross-tabulation matrix (Table 4) revealed that substantial LULC changes occurred between 1987 and 2015. The result indicated that light vegetation had about 75% decrease during the 28 years of study. On the other hand, the thick vegetation recorded more than 80% decrease from 1987 to 2015. However, floodplain increased from 8.9 km² in 1987 to 15.4 km² in 2015 with most of the increase gained from the vegetation areas (thick, light and riparian). The 3 types of vegetation (thick, light and riparian) monitored had constant decline trend in size due to increase in human population and housing (Figure 4a) as stated in the second hypothesis. An upsurge in population was projected (Figure 4b) which might consequently lead to elevated land consumption (Figure 4c).

![Figure 3: land Use-Land cover change maps (a) 1987 (b) 2002 (c) 2015](image)

![Figure 4: Summary of statistical analysis of the study area (a) population and built-up area (b) Projected LULC and population from 2005-2020 (c) Relationship between Land Consumption Coefficient rate and years](image)
Table 4: Cross-tabulation matrix of LULC classes between 1987-2015 (km$^2$)

<table>
<thead>
<tr>
<th>Class</th>
<th>1987 Area</th>
<th>Built-up Area</th>
<th>Water Body</th>
<th>Thick Vegetation</th>
<th>Light Vegetation</th>
<th>Riparian Vegetation</th>
<th>Sand Deposit</th>
<th>Flood Plain</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015 Built-up Area</td>
<td>11.2</td>
<td>1.6</td>
<td>4.4</td>
<td>21.2</td>
<td>2.5</td>
<td>0.8</td>
<td>1.2</td>
<td>42.7</td>
<td></td>
</tr>
<tr>
<td>Water Body</td>
<td>0.2</td>
<td>4.0</td>
<td>2.0</td>
<td>0.5</td>
<td>0.9</td>
<td>0.3</td>
<td>0.1</td>
<td>8.0</td>
<td></td>
</tr>
<tr>
<td>Thick Vegetation</td>
<td>2.5</td>
<td>1.3</td>
<td>4.7</td>
<td>1.4</td>
<td>1.0</td>
<td>0.2</td>
<td>1.0</td>
<td>12.1</td>
<td></td>
</tr>
<tr>
<td>Light Vegetation</td>
<td>3.1</td>
<td>0.4</td>
<td>2.0</td>
<td>9.0</td>
<td>0.5</td>
<td>0.6</td>
<td>0.9</td>
<td>16.5</td>
<td></td>
</tr>
<tr>
<td>Riparian Vegetation</td>
<td>1.9</td>
<td>0.4</td>
<td>1.6</td>
<td>0.5</td>
<td>1.0</td>
<td>0.2</td>
<td>1.0</td>
<td>6.6</td>
<td></td>
</tr>
<tr>
<td>Sand Deposit</td>
<td>1.0</td>
<td>0.7</td>
<td>1.3</td>
<td>1.5</td>
<td>0.3</td>
<td>0.2</td>
<td>2.7</td>
<td>7.7</td>
<td></td>
</tr>
<tr>
<td>Flood Plain</td>
<td>0.8</td>
<td>1.7</td>
<td>5.6</td>
<td>2.0</td>
<td>2.2</td>
<td>1.1</td>
<td>2.0</td>
<td>15.4</td>
<td></td>
</tr>
<tr>
<td>TOTAL</td>
<td>20.7</td>
<td>10.1</td>
<td>21.6</td>
<td>35.9</td>
<td>8.4</td>
<td>3.4</td>
<td>8.9</td>
<td>109</td>
<td></td>
</tr>
</tbody>
</table>

3.2 Classification accuracy

The overall classification accuracies for 1987, 2002 and 2015 was 90.7%, 92.4% and 95.5% respectively. In addition, the image classification for 1987, 2002 and 2015 produced an overall kappa coefficient of 0.89, 0.93 and 0.96 respectively (Table 3). The year 2015 showed the best classification accuracy when compared with either 1987 or 2002. Producer’s and user’s image classification accuracies and their Kappa coefficients were also generated (Table 5).

3.3 Vegetation and plant species

The number of dominant plant species decreased with increase in population for most of the LULC classes (Figure 5a). Time also influenced the plant species decrease. For example, the number of the dominant species (per km$^2$) recorded under light vegetation in 1987 and 1997 was 983 and 701 while, thick vegetation had 681 and 423 respectively (Figure 5b). Between 1987 and 2015, 84.3% of dominant plant species were lost under the light vegetation while, 71.9% was lost under the thick vegetation.

The results of the PCA revealed that the first ordination axis and all ordination axes significantly differ ($p < 0.001$) in the plant species distribution under the different LULC classes (Figure 6). The percentage of explained variability by the first axis and all ordination axes was 50.6 and 39.7 respectively. The result further showed that the key plant species were related with four LULC groups. The first group was residential housing; second group was grazing area; third group was farmland, and the last group included fluvial-water erosion, floodplain-soil erosion and infrastructural development. The first, second and the third groups had the highest number of the plant species lost to the LULC change.

4 Discussion

4.1 Overall landuse-landcover (LULC) changes

The three types of vegetation (thick, light and riparian) classified showed constant decline trend in areas. Several reasons might be responsible for this decline. First reason was probably because of rapid increase in human population. High number of people in the area would have led
Figure 6: PCA showing major plant species lost under each LULC class in the study area. Abbreviations for the LULC were ResdHous: Residential Housing, FlooEros: Flood plain-Soil erosion, GrazArea: Grazing area, Farmland: Farmland, FluvEros: Fluvial-Water Erosion, InfrsDev: Infrastructural Development; Abbreviations for the plant species were BryoPinn: Bryophyllum pinnatum, ClauSuff: Clausena suffruticosa, SennAlat: Senna alata, SoleAmpl: Solena amplexicaulis, CrotPall: Crotalaria pallida, MikaCord: Mikania cordata, AndrGaya: Andropogon gayanus, BracDecu: Brachiaria decumbens, CynoDact: Cynodon dactylon, PaniMaxi: Panicum maximum, TripsIaxu: Tripsacum laxum, CajoCajn: Cajanus cajan, CentPuBe: Centrosema pubescens, StyGuiS: Stylosanthes guianensis, VernBame: Vernonia bamendae, VernNigr: Vernonia nigritiana, PennPedi: Pennisetum pedicellatum, CombAcul: Combretum aculeatum to increase deforestation due to the need for settlements, food and basic infrastructural development [41, 47, 48]. Second reason could be because of increase logging for timber and firewood by the local people [49].

The relationship between rapid population growth and LULC change indicated that substantial LULC change occurred and might continue if increasing population continues. Other possible causes of decrease in thick, light and riparian vegetation could be increased urbanization and establishment of estates and housing units [50]. In agreement with our result, land area for vegetation in Ramnagar was reported to have decreased from 10.29 km² in 1990 to 7.29 km² in 2010 due to increase in settlement [51].

Built-up areas (settlement) recorded remarkable increase across the years observed with more than 100% increase in 2015. One of the primary reasons for increase in settlement could be that Onitsha (the study area) has become a commercial hub center in Nigeria and Africa [52, 53]. There have been high emigrants into the city from within and outside Nigeria due to the recent industrial and commercial development in the area. The population growth caused higher demand for settlements and basic amenities. Higher demand for goods and services required more industrial settings which subsequently increased the built-up areas at the expense of the light vegetation (arable land), and other vegetative landcover types [54]. Between 2000 and 2010, the government increased budget allocation fund for industrial development, and this favored urbanization against natural vegetation. Our finding was consistent with previous studies on the role of population growth in LULC change [47, 51, 55–58]. It has been documented in Nigeria that in 1976, 100,000 residential structures accommodated 2-3 million people in each of the major states with an average of 29 persons per structure [56]. However, with the latest population increase, major urban centers like Onitsha with more than a million persons would need larger settlement areas. In Indian state of Uttarakhand, similar report was documented by Rawat [59], revealing increase in built-up areas to due population growth.

A slight decline in water bodies revealed in our study might be attributed to anthropogenic activities of land reclamation for housing, and road constructions. More exploitation of the water resources by the growing population could have also caused the drying up of some streams and river tributaries [49]. In addition, increase evaporation rate due to increase of temperature, high seepage, and percolation [60] could be contributing factors to the decline in water areas. Accelerated rate of surface run-off because of the absence of the plants roots to with-hold water might also be a further explanation for the decrease in water areas [61].

Uncontrolled deforestation caused severe soil erosion and enhanced surface run-off which consequently led to accumulation of sediments and silts. The outcome of this process increased the areas for floodplain, sand deposit and bare soil surfaces [49, 60, 62, 63]. Indiscriminate dumping of municipal solid wastes into the water bodies was observed in our study. This could probably be another reason for decreased water area, increase floodplain and sand deposit since the wastes obstruct water flow [64]. Furthermore, the reclamation of the rivers and streams promoted an overflow especially during the wet seasons. This factor also created more land for flood plain and sand deposits while, the riparian vegetation became reduced. Though not within the scope of this study: there has also been reports on the poor soil fertility in the area [65] because of significant increase in the land consumption rate over the years (Fig. 4c).
Table 5: Producer's and User's images classification accuracies and Kappa coefficient

<table>
<thead>
<tr>
<th>LULC Classes</th>
<th>Classification accuracies (%) and kappa coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-up Area</td>
<td>94.3 96.7 98.8 91.8 95.5 99.1 0.89 0.93 0.96 0.87 0.91 0.95</td>
</tr>
<tr>
<td>Water Body</td>
<td>92.1 91.9 97.4 90.6 93.0 98.0</td>
</tr>
<tr>
<td>Thick Vegetation</td>
<td>99.2 99.7 100.0 100.0 99.5 100.0</td>
</tr>
<tr>
<td>Light Vegetation</td>
<td>89.6 94.2 94.6 87.1 90.8 90.8</td>
</tr>
<tr>
<td>Sand Deposit</td>
<td>85.7 83.6 90.5 89.4 88.2 90.0</td>
</tr>
<tr>
<td>Flood Plain</td>
<td>83.9 89.9 90.8 74.7 86.5 91.2</td>
</tr>
<tr>
<td>Riparian Vegetation</td>
<td>90.3 94.1 96.7 92.0 91.9 96.4</td>
</tr>
<tr>
<td>Overall Classification</td>
<td>90.7 92.4 95.5 89.4 92.2 95.1</td>
</tr>
<tr>
<td>Accuracy (%)</td>
<td></td>
</tr>
<tr>
<td>Kappa Statistics (K)</td>
<td></td>
</tr>
</tbody>
</table>

Remarkable decline in the plant species was found in the study area during the study time. Several authors have recently reported high rates of plants species decline due to settlements and agricultural activities [66–69], which was intensified by population growth and rapid urbanization [70, 71].

4.2 Classification accuracy

Thick vegetation recorded almost 100% classification accuracy while, floodplain and sand deposit showed the lowest percentages accuracies among all the classified LULC classes. This might be explained by the distinct features of the thick vegetation which obviously separated it from other LULC classes. The thick vegetation in dominated by evergreen forest and high-density trees. The sand deposits and the floodplain were often confused with each other and with wetlands in some cases. This therefore reduced the reliability of their accuracies when compared with other LULC types classified. The classification was reliable and acceptable for further analysis based on the overall classification accuracies of more than 90% recorded.

5 Conclusions

In applying remote sensing and GIS, the objective of this study was achieved with the conclusion that LULC was substantially altered in the area, and this consequently affected the landscape during the 28 years of research. The vegetation classes were the most negatively affected LULC type whereas, the built-up areas increased in all the years investigated. Population growth and increasing socio-economic needs and activities were the key factors responsible for the change in LULC. The number of dominant plant species decreased with increase in population and settlements. Residential housing, grazing area and farmland had the highest number of the plant species lost to the LULC change. Although, climate had minimal effect on the landscape features but, human activities were the most agent of the changes detected. As human population, continuous to increase, the vegetation and water might continue to lose their areas to settlement, floodplain and sand deposit. Remote sensing and GIS have shown great advantage in the evaluation of the trajectories and effects of LULC change in Onitsha municipal. The study recommended the emancipation of the local people by the government and stakeholders as the most sustainable solution. These indigenous people should be encouraged to intensively plant trees as well as protect the old and new plants. Also, building of houses should be regulated by including proper environmental impact assessment (EIA) before approval and constructions.

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