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Geospatial Modeling and Prediction of Land Use/Cover Dynamics in Onitsha Metropolis, Nigeria: A Sub-pixel Approach

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Authors' contributions

This work was carried out in collaboration between all authors. Author SUO designed the study and prepared the first draft. Author PSUE performed the geospatial and geostatistical analyses and the final draft of the manuscript. Author NAI performed and managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Based on a sub-pixel approach, this study analysed the Land Use/Cover (LU/C) dynamics of Onitsha Metropolis in Anambra State, Nigeria. Landsat TM/ETM+ satellite imageries of 1986, 2001 and 2016 were characterized into different LU/Cs using Ridd's Vegetation, Impervious Surface, Soil and Water (VIS-W) model via Linear Spectral Mixture Analysis (LSMA). LU/C endmember fractions obtained were hardened to produce the final LU/C maps of the study area, per study years considered. Cellular Automata Markov (Ca-Markov) chain and the Land Change Modeler (LCM) were used to predict future LU/C for the year 2031 and the transition of each LU/C categories between 2016 and 2031, respectively. Also, the Chi-square test was used to test the significance of change in LU/C fractions between 2016 and 2031. ArcGIS 10.5, Idrisi Selva and Statistical Package for Social Science (SPSS 22) were used to perform the analyses. The result of the LU/C classification on one hand, revealed the dynamics of LU/C endmember fractions for the study years and on the other hand, revealed the actual area coverage of each LU/C category. It showed clearly that vegetation reduced drastically over the three epochs from 178.72sq.km in 1986 to 147.70 sq.km

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in 2001 and slightly to 140.87 sq.km in 2016; impervious surface increased from 26.10 sq.km in 1986 to 62.28 sq.km in 2016; soil cover decreased from 8.65 sq.km in 1986 to 3.10 sq.km in 2016; and water cover, experienced an increase from 11.44 sq.km in 1986 to 18.75 sq.km in 2016. The Ca-Markov and the LCM models further revealed that all LU/C fractions, apart from soil possessed very high probability of being retained in 2031, thus, are envisaged to be slightly modified in future. However, the result of the Chi-square test confirms no statistically significant difference in the LU/C fractions between 2016 and 2031 ($P=.964$, α = $.05$). Therefore, it was upheld in this study that the rapidity of urbanisation in Onitsha Metropolis has drastically reduced while the degree or intensity of urbaneness was on the increase, especially in recent years and the same trend is expected to continue except otherwise, other factors set-in. The continuum-based approach of this study however, presents an objective means of characterizing LU/C fractions and recommended in modelling the urban fabrics of any area, especially when other non-linear and chaotic urban phenomena, such as Urban Heat Island (UHI); urban land suitability/compatibility, flooding, physiological discomfort, etc. are of interest.

Keywords: Linear spectral mixture analysis; cellular automata Markov chain; land change modeler; endmember fraction.

1. INTRODUCTION

Urbanization remains a global force to be reckoned with - human-centered, human-driven and human-dominated. Otherwise known as urban drift, urbanization is a process of shift from rural to urban areas in which an increasing proportion of an entire population lives in cities as well as suburb of cities (Nnebue, Adinma, & Sidney-Nnebue [1]). According to the UN-Population Division [2], only about 18% of people lived in cities of the world in 1950, in 2000 the proportion increased to 40%. It is envisaged that in 2032 this value will rise to more than 56% in the developing world at an annual growth rate of 2.3%.

Apparently, with more than 40% of the human population living in cities of the world, in the face of degrading vegetal covers, urbanization has been confirmed by Voldoire and Royer [3] and Zhang, Odeh and Han [4] to be an important contributor to local and global warming due to its remarkable urban heat island effect (UHIE). As a consequence of the emergence of the urban landscape, Land use/cover (LU/C) changes such as loss of agricultural or primary forested lands and grasslands coupled with growing impervious surfaces such as roads, sidewalks, parking lots, rooftops etc. has been experienced.

There exist several models often adopted for LU/C studies, however, one of the most quantitative approach is the Ridd's Model, otherwise known as the V-I-S model. This model is based on the assumption that the urban fabric is complex and heterogeneous and that the urban land cover is a linear combination of three (3) biophysical components: Vegetation, Impervious Surface and Soil, hence the name, V-I-S Model (Ridd [5]). Proposed as a fundamental theory, the V-I-S model was developed to simplify the quantification of different surface components which are not often times orthometrically or spatially separated in satellite imageries (Hung [6], Zemba [7]).

A conventional approach to urban change studies using remotely sensed data has an assumption of homogeneity within a pixel for the LU/C classes under study, however as noted by Yang, Xian, & Klaver, [8]; Zhang, Odeh, & Han, [4]; Essa, [9]; etc., this has resulted in no quantifiable degree of use/cover and/or its changes and its impact on surface conditions. As shown by the Ridd [5] V-I-S model, remotely sensed data (Landsat, ASTER, etc.) can, away from the much-generalized urban concepts be characterized of pixels which are mixed and composed of several LU/C types. Thus, it is expected that for careful assessment of surface conditions in view of exploring a more conventional method of modelling and simulating LST in urban areas (or other non-linear phenomena that are peculiar to urban fabrics), there is need to use a sub-pixel approach.

The components of the VIS model as adopted in this study are represented as a range of values where features or pixels can be shown as a set of combination of the components within certain thresholds. Thus, it has been recognized that the spatial varying character of land cover as shown in the study of Ridd [5], can be better described by probability surfaces (Zhan, Molenaar and Gorte [10]). In other words, each pixel is allowed to have a "class member" probability rather than a single class label and the result of this operation has been idealized by Eastman [11] in his soft classification method. This is said to offer more meaningful information to planners in better understanding land use patterns and changes over time. Hence, from this basis could then be based on the degree of membership rather than just a member and again, such a perspective can be more objective in relating land cover to other surface phenomena. For instance, a residential or built-up area can consist of houses, green spaces, footpaths and small water bodies as different members for which different end-members can be obtained [10].

However, it is well-established that urban areas have complex morphologies vis-à-vis their LU/C spatial expression which is also not fixed but mixed and dynamic. As such, a more objective LU/C classification approach such as the VIS-W model submitted by Ridd [5], Zemba [7], Abubakar [12], Mróz & Sobieraj [13] Ahmed, Kamruzzaman, Zhu, & Rahman [14] have not been (widely) adopted in modelling LU/C, especially in Anambra State. With more than 60% of the population of Anambra State residing in urban areas, it is expected that there would be grave implications for LU/C pattern in the State (Ifeka & Akinbobola [15], Odunaga & Badru [16]). Hence, the main objective of this study was to assess LU/C in Onitsha Metropolis, Nigeria and adopted the VIS-Water approach to characterize, model and predict future LU/C of the study area in order to enhance sustainable urban development.

2. METHODOLOGY

2.1 Description of the Study Area

Onitsha which is the largest urban center in Anambra State; a major commercial town in the south-eastern region of Nigeria and a commercial hub in sub-Saharan Africa. It is relatively located on the eastern side of the lower Niger basin about 1km south of the confluence (in Kogi State). The city is absolutely located between Latitudes 6°06' 56.0"N and 6°14' 34.0"N and Longitude 6°45' 30.0"E and 6°52' 32.0"E of the Greenwich Meridian as shown in Fig. 1. The town is majorly an annex of Onitsha North and South Local Government Areas as well as parts of Obosi and Nkpor areas of Anambra State.

Using the National Population Commission's [17] growth rate of 2.83%, the 2006 population of Onitsha projected from the 1991 figure of 256,941 would have been 390,509 persons as against 261,604 recorded at the census, which amounted to 0.01% annual growth rate (UN-HABITAT) [18]. Unfortunately, according to Eni [19], the population of Onitsha is not well reflected in the Nigerian census figures of 2006 because the traders migrated to their bases, neighbouring villages and states during census events reducing the official figures. In the view of UN-HABITAT [18], the 390,509 persons estimated for 2006 is only the night time population as against the day time population which could be up to 1,500,000. Onitsha is well noted for its prominence in commercial activities. In fact, it is one of the largest markets in Africa and one of the fastest growing commercial cities in Nigeria (Eni) [20]. The existing land uses in Onitsha is to a very large extent determined by the location of recent commercial as well as industrial activities in the urban area (Izueke & Eme [21]).

2.2 Research Design

This study adopted both experimental and survey designs to achieve its objectives. The experimental design involved the acquisition, processing and analyses of remotely sensed satellite imageries and other related dataset in a GIS laboratory. On the other hand, the survey design employed in the study was for the purpose of ground truthing and/or validation of all analytical results and datasets obtained in the study. The analytical workflow of the study is shown in Fig. 2 and explained succinctly in the succeeding sub-sections.

2.3 Data Sources

Medium resolution Landsat TM/ETM+ and TIRS satellite imageries of the years 1986, 2001 and 2016 covering the study area (i.e. Path 188 and Row 56) from summer months were downloaded online from the United States Geological Survey (USGS) Earth Resources Observation System Database. The Existing base map of Onitsha was obtained from the Office of the Surveyor General of Anambra State. Global Positioning System (GPS) readings of the study area collected in 2016 were also used in this study.

This study made use of primary and secondary data. Primary data involved detailed reconnaissance survey and ground truth data acquisition via the use of Garmin 78SC handheld Global Positioning System (GPS) with which spatial (i.e. Longitude and Latitude) and aspatial (or attribute) data campaign were made possible.

As for the secondary data required for the study, medium resolution Landsat TM/ETM+ and TIRS satellite imageries of the 1986, 2001 and 2016 covering the study area (i.e. Path 188 and Row 56) were downloaded online from the United States Geological Survey (USGS) Earth Resource Observation System Database.

2.4 Image Pre-processing

The satellite imageries obtained (for the purpose of characterizing land use/land cover) were pre-processed where necessary (e.g. for atmospheric correction and image destriping) to ensure the use of accurate data for the analysis. This could be due to atmospheric effects on the satellite sensor (as at the time of image acquisition) or as caused by variable detector output in scanner imagery, beyond the researchers' control. The IDRISI software was used to pre-process all satellite data used in the study. The algorithms used are the Destripe, Pan-sharpen and ATMOSC where necessary. See Weng, Lu and Schubring [22].

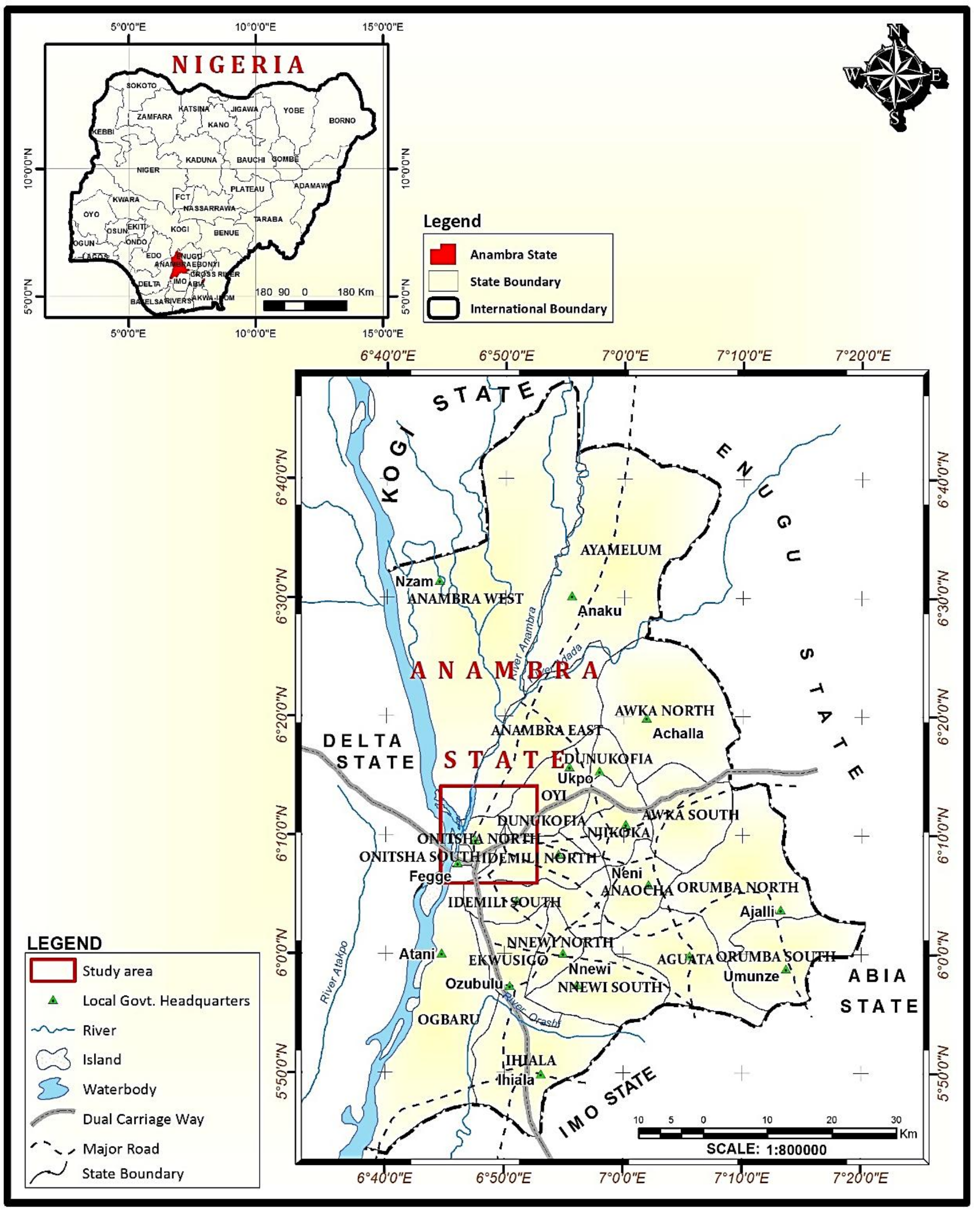

Fig. 1. Map of the study area

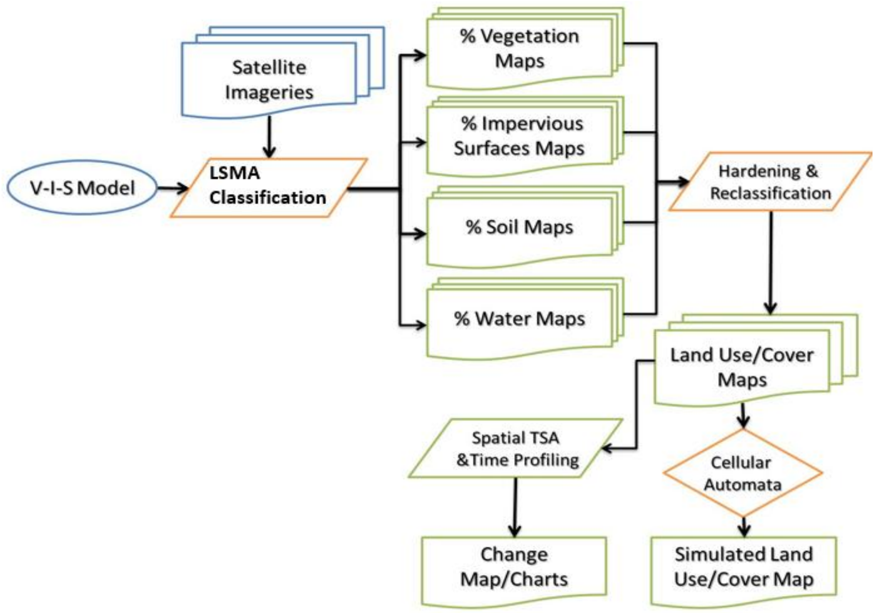

Fig. 2. Workflow of the study

Table 1. Description of the data used for LU/C analysis

Data types	Date of acquisition	Resolution (Meters)
Landsat 4 Thematic Mapper (TM)	21/12/1986	30
Landsat 7 Enhanced Thematic Mapper Plus (ETM+)	17/12/2001	30
Landsat 8 OLI/TIRS	15/03/2016	30

2.5 Land Use/Cover (LU/C) Classification

The soft and hard classification algorithms were used to characterize LU/C fractions in this study. The (broad) LU/C scheme adopted for the study in the view of Ridd [5] is shown in Table 2.

First, all the acquired Landsat satellite imageries were separated into identifiable end-member classes using their respective mean digital numbers and spectral signatures for each band, which is also based on the VIS-W model approach. To achieve this, pure endmember signatures for different image bands were used to develop endmember fractions per LU/C category using the Linear Spectral Mixture Analysis (LSMA) as described by Eastman [11] and Zemba [7]. See Table 3.

Table 2. Details of land use classification scheme adopted for the study

S/no.	Land use/cover type	Description
1.	Impervious Area (I)	Also known as built-up area and comprises of all infrastructure – residential, commercial, mixed use and industrial areas, villages, settlements, road network, pavements, and man-made structures.
2.	Water Body (W)	Comprises of river, permanent open water, lakes, ponds, canals, permanent/seasonal wetlands, low-lying area, marshy land and swamps
3.	Vegetation (V)	Trees, natural vegetation, mixed forest, gardens, parks and playgrounds, grassland, vegetated lands, agricultural lands and crop fields
4.	Soil (S)	Fallow land, earth and sand land in-filling, erosion sites, construction sites, developed land, excavation sites, open space, bare soils and the remaining land cover types.

Table 3. Digital numbers (DNs) used for signature (EndSig) development

Satellite sensor/ Year	Land use/ Cover	Digital number (watts/(meter squared*ster*µm)						
		Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7
Landsat 4 [1986]	Vegetation	79.817	33.362	31.447	58.030	NA*	NA*	24.244
	Impervious surface	89.873	41.557	47.889	45.322	NA*	NA*	55.807
	Soil	100.477	54.112	72.722	78.082	NA*	NA*	128.266
	Water	87.703	40.432	40.880	27.540	NA*	NA*	11.243
Landsat 7 [2001]	Vegetation	92.408	72.420	69.811	58.180	NA*	NA*	53.321
	Impervious surface	96.401	76.715	82.594	42.323	NA*	NA*	68.810
	Soil	109.960	104.343	131.232	73.325	NA*	NA*	176.253
	Water	101.340	87.967	92.992	33.027	NA*	NA*	21.127
Landsat 8 [2016]	Vegetation	11593.703	10864.408	10546.059	10106.067	17062.592	NA*	NA*
	Impervious surface	12602.554	12075.557	11729.208	12001.651	13942.503	NA*	NA*
	Soil	12941.899	12701.077	13812.929	15546.862	19467.973	NA*	NA*
	Water	12162.903	11643.064	11814.005	11692.575	10642.420	NA*	NA*

**Not applicable*

From Table 3, the four (4) image endmembers that were generated per year are recognizable LU/C materials that have homogeneous spectral properties all over the images. As mentioned earlier, the LSMA assumes that the spectrum measured by a sensor is a linear combination of the spectra of all components within such a pixel which can be explained using the mathematical model given in equation 1.

$$R_i = \sum_{k=1}^{n} f_k R_{ik} + E_i \tag{1}$$

Where:

i= number of spectral bands

k = number of end-members

R_i = the spectral reflectance of band i of a pixel that contains one or more end-members

F_k = the proportion of end-member k within the pixel

R_{ik} = the known spectral reflectance of end-member k within the pixel in band i

E_i = the error for band i or remainder between measured and modelled DN (band residual)

To solve f_k, the following conditions were satisfied:

i. Selected end-members were independent of each other,
ii. The number of end-members were not larger than the spectral bands used, and
iii. Selected spectral bands were not highly correlated.

Hence, the degree of membership of each image pixel to a particular endmember fraction, for instance water, could be expressed in absolute terms and not generalized completely. However, final endmember fractions where further subjected to a supervised, hard classification method, using the maximum likelihood algorithm. Finally, due to the peculiarity of the study, particularly for its sub-pixel approach, the classification methods (i.e. soft and hard) were visually cross-validate and found to be in tandem with groundtruth data obtained from GPS survey campaign.

2.6 Land Use/Cover Prediction

The hardened VIS-W LU/C maps obtained for the most recent times, i.e. t_1 and t_2 were used to generate the Markov probability statistic which served as input in the Cellular Automata (Ca-Markov) operation that was used to predict future LU/C for a future time, t_3. In general, in the Markovian process, the future state of a system in time t_2 can be predicted based on the immediate preceding state, time t_1. Hence, according to Eastman [16], if $X[k]$ is a Markov chain with the states $\{x_1, x_2, x_3, \cdots\}$, then the probability of transition from the state i to the state j in one-time instant can be expressed as:

$$p_{i,j} = Pr\left(X\left[k+1\right] = j \middle| X\left[k\right] = i\right) \quad (2)$$

If Markov chain therefore has a finite number of states, i.e. *n,* transition probability matrix can still be defined as follows:

$$\begin{bmatrix} P_{1,1} & P_{1,2} & \cdots & P_{1,n} \\ P_{2,1} & P_{2,2} & \cdots & P_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n,1} & P_{n,2} & \cdots & P_{n,n} \end{bmatrix} \quad (1)$$

First, the Markov Chain model was used to produce related probability change matrices and then, CA tool was used to consider the composition of associations of pixels based on concept of proximity (i.e. regions closer to existing areas of the same class will have a higher propensity to change to a different class) and then was used to project the future state of such cells. It focuses mainly on the local interactions of cells (or image pixels) with their distinct temporal and spatial coupling features and the powerful computing capability of space. The CA model can however be expressed as follows:

$$S(t, t + 1) = f (S(t), N) \quad (4)$$

Where

S = set of limited and discrete cellular states

N = the cellular field

t and t +1 = difference in times and

f = transformation rule of cellular states in local space.

Thus, the hardened LU/C maps of 2001 and 2016 were used to first determine the different cell transition rules before applying a CA contiguity filter of 5 x 5 and the number of iterations required to predict LU/C for 2031, that is 15. A period of 15 years was used based on an equal interval scenario and in-view of adopting a more current LU/C consumption trend, for the prediction.

2.7 Statistical Analysis

The study made use of the non-parametric Chi-square. This goodness-of-fit test compared the observed and expected frequencies in each LU/C category to test that all categories contain the same proportion of values. In other words, the test was used to ascertain the statistical significance of the change in areas (in square kilometres) occupied by vegetation, impervious surfaces, soil and water between 2016 and the predicted LU/C categories for 2031 in Onitsha using a level of significance of *.05.* The statistical Package for Social Science (SPSS 22) was used to test the the null hypothesis (H_o) which states viz:

H_o = There is no significant difference in the area coverages of LU/Cs in Onitsha between 2016 and 2031.

2.8 Transition Mapping of LU/C Categories

Transition mapping was carried out in an attempt to show the areas where different categories of LU/C will likely be converted into other categories or persist between 2016 and 2031. The transition zones include the following namely;

i. Persistent Vegetation
ii. Impervious surface to vegetation
iii. Soil to Vegetation
iv. Water to Vegetation
v. Vegetation to Impervious surface
vi. Persistent Impervious surface
vii. Soil to Impervious surface
viii. Water to Impervious surface
ix. Vegetation to Soil
x. Impervious surface to Soil
xi. Persistent Soil
xii. Water to Soil
xiii. Vegetation to Water
xiv. Impervious surface to Water
xv. Soil to Water
xvi. Persistent Water

The Land Change Modeller (LCM) tool in IDRISI software was applied for this purpose to characterize the hardened LU/C maps for all the years: their respective spatial coverages, net change, gain and loss statistics.

3. RESULTS AND DISCUSSION

3.1 Linear Spectral Mixture Analysis

The Linear Spectral Mixture Analysis (LSMA) was the initial step for LU/C assessment of the study area. An analysis of four broad land cover categories was performed from which end-member fractions, Vegetation (V), Impervious surface (I), Soil (S) and Water (W) were extracted (via soft and hard classification), from which change detection and prediction analyses were performed accordingly.

The result of the LSMA for Vegetation and Impervious surface covers are presented in Fig. 3, for 1986, 2001 and 2016. At a sub-pixel level, the sub-maps show a gradual degradation of areas characterized by high membership of vegetation (shown as purple) but at the same time reveals a higher degree of membership of vegetation increasing in some other areas in 2016 that were low in previous years. This can be attributed to rural-urban migration as farming activities in the countryside reduced from 1986 to 2016. Built-up or impervious surfaces also displayed spatial increases from 1986 and 2001, but a slight spatial increase was observed from the impervious surface image of the area in 2016.

Fig. 4 shows the result obtained from the LSMA of Soil and Water end-member fractions for the different study epochs in Onitsha. The sub-maps for soil maintained a gradual decrease in areas characterized by a high degree of membership to soil, particularly, sandbars for the periods. This must have been due to the excavation of such sands or the increase in surface flow of the Niger River over time. Ascertaining this fact is beyond the scope of this study. However, other areas with medium intensity of soil were only more in 2001 but by 2016 these areas reduced again.

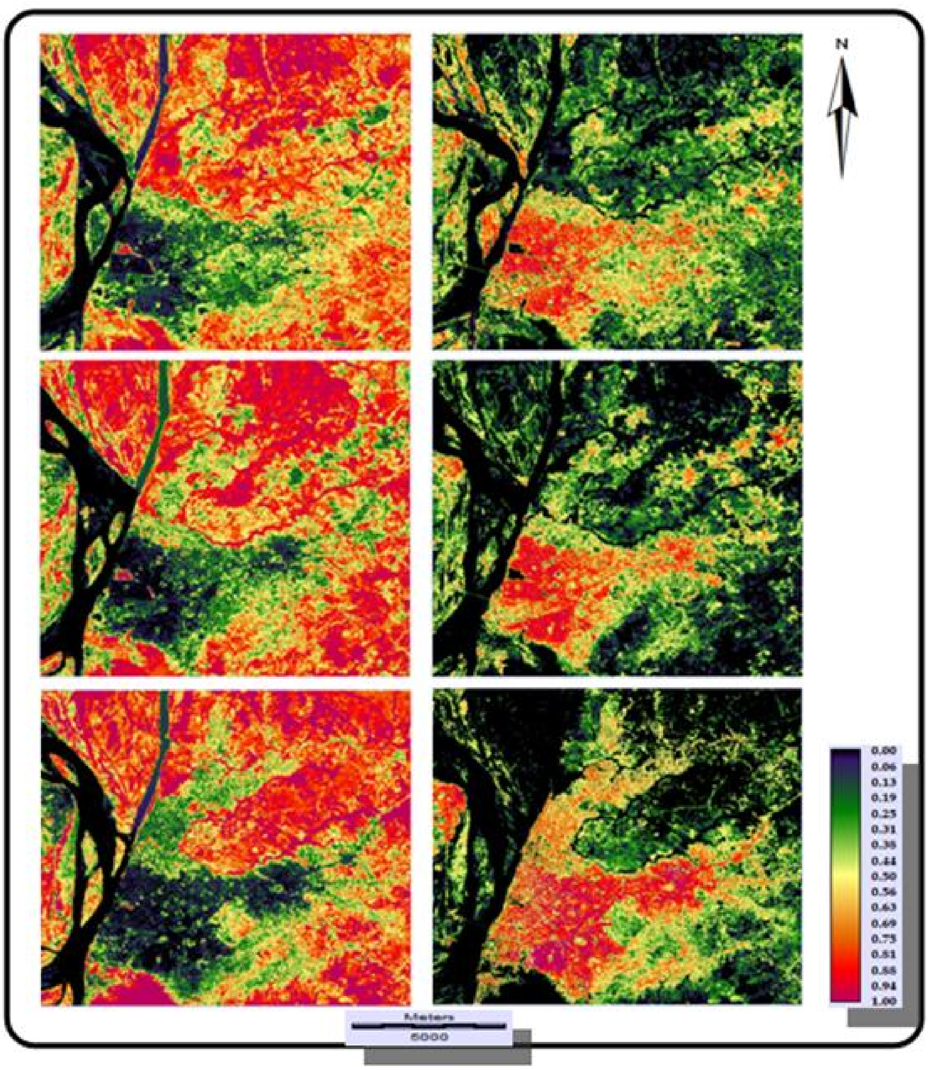

Fig. 3. LSMA result of unmixed land use/cover maps of Onitsha: Top LHS, Middle LHS and Bottom LHS – Vegetation endmember fractions of 1986, 2001 & 2016, respectively; Top RHS, Middle RHS and Bottom RHS – Impervious surface endmember fractions of 1986, 2001 & 2016

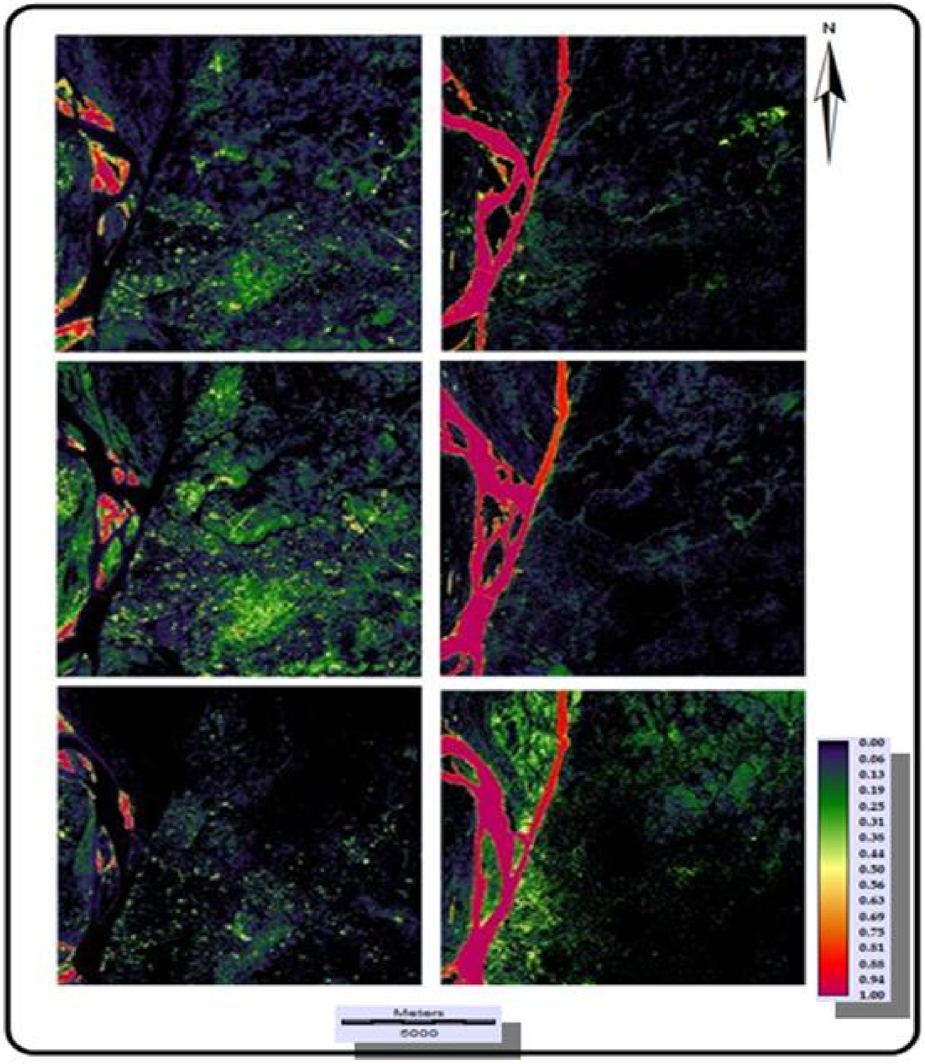

Fig. 4. LSMA result of unmixed land use/cover maps of Onitsha: Top LHS, Middle LHS and Bottom LHS – Soil endmember fractions of 1986, 2001 & 2016, respectively; Top RHS, Middle RHS and Bottom RHS – Water endmember fractions of 1986, 2001 & 2016, respectively

As earlier mentioned, such areas were converted into more impervious settings due to the rapidity of land consumption and (further) conversion at the city centre. On the other hand, water end-member fractions with higher degrees or intensities were observed to be constant at the course of River Niger within the region. However, it was equally observed that pixels with medium to lower indices (0.50 – 0.25) increased in spatial extent around areas close to the river course. This is a clear indication that areas in close proximity to the river tend to be more susceptible to increase water or wetland invasion, especially in view of the topography of the Metropolis.

3.2 Land Use/Cover Classification

In order to categorize the LU/C fractions obtained from the LSMA (soft classification), the hardening operation was performed. As shown in Fig. 5 and the bar graph in Fig. 6, vegetation reduced over the years from 178.73 sq.km (79.43%) in 1986 to 147.70 sq.km (65.64%) in 2001 and slightly to 140.87 sq.km (62.61%) in 2016. Impervious surface category on the contrary, increased from 26.18sq.km (11.64%) in 1986 – before the creation of Anambra State, to about 51.63 sq.km (22.95%) in 2001, ten (10) years after the creation of the state, and finally increased to about 62.28 sq.km (27.68%) in 2016.

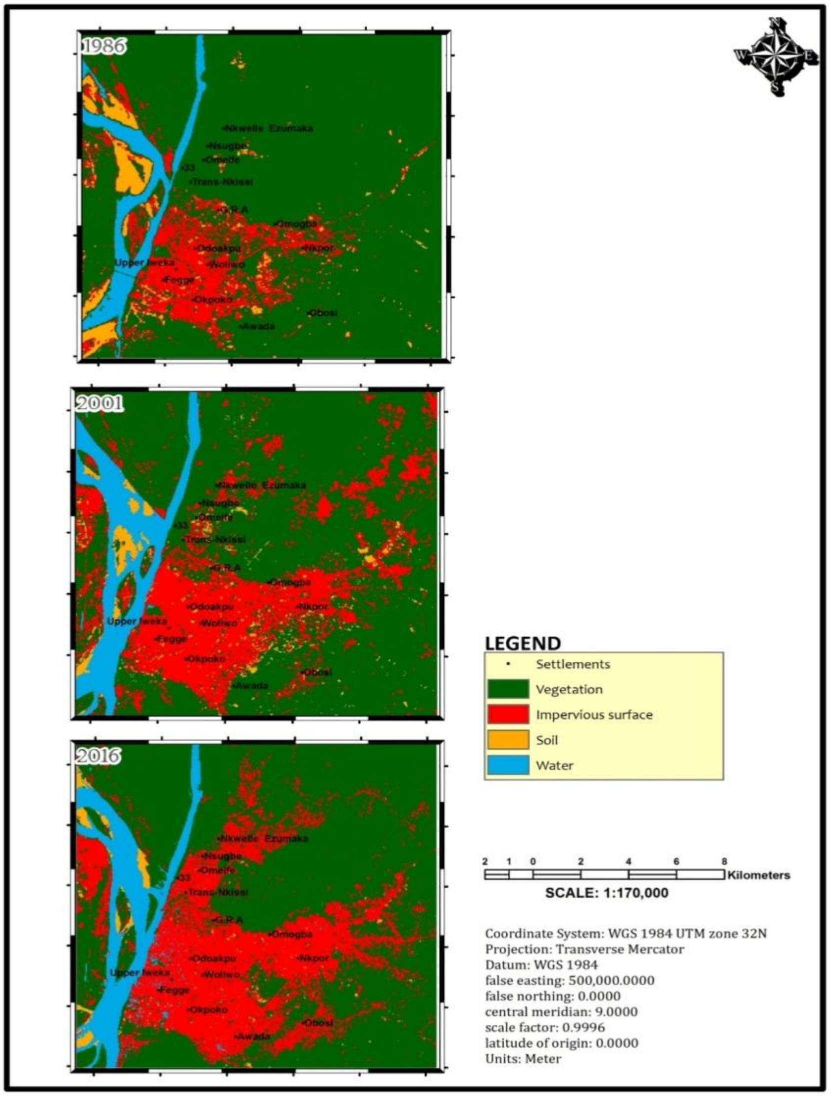

Fig. 5. Land use land cover categories of Onitsha (Top: 1986; Middle: 2001; & Bottom: 2016)

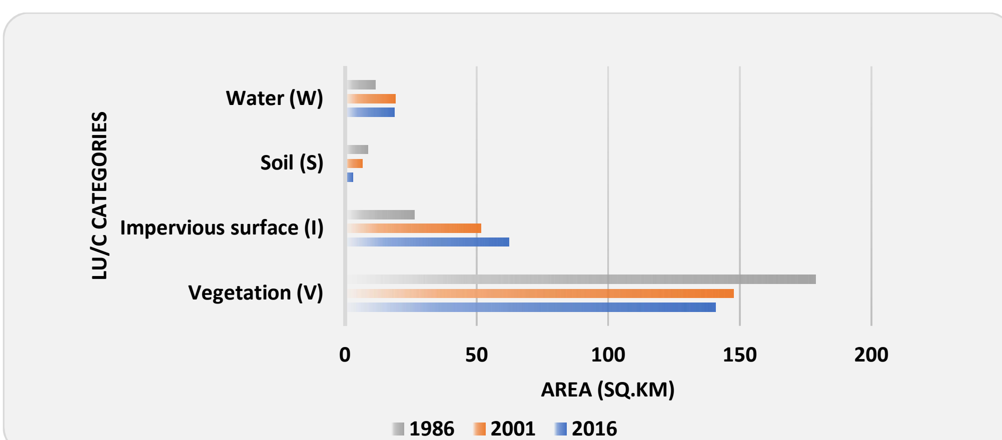

Fig. 6. LU/C categories of Onitsha (1986, 2001 & 2016)

Also, soil cover amounted to about 8.65 sq.km (3.84%) in 1986 but reduced to about 6.54 sq.km (2.91%) in 2001 and to about 3.10 sq.km (1.37%) in 2016. As hitherto mentioned, this gradual reduction in soil cover can be attributed to the rapidity of urban land consumption and conversion rate in Onitsha main town, the extraction of sandy materials close to the river course for construction work and the overall rise in water level of the River Niger. Meanwhile, water cover showed an increase from about 11.44 sq.km (5.08%) in 1986 to about 19.13 sq.km and 18.75 sq.km (around 8%) in 2001 and 2016, respectively.

This further justifies the view that the volume of surface water has increased as well as the invasion of water and wetland areas into the urban morphology as mentioned earlier.

The conversion of vegetal cover into impervious surfaces as observed in the study area has been reported to be the major cause of increased temperatures in urban centers. This increase in temperature have been linked to the general discomfort of residents, spread of infectious diseases as well as disease carriers such as mosquitoes and ticks which may experience improved reproduction and survival rates as temperature increases (Patz, Lendrum, Holloway and Foley) [23].

The loss of vegetation and a subsequent increase in impervious surface have been reported in other LU/C studies in Nigeria, although the extent and magnitude may differ. Such studies include that of Ifeka and Akinbobola [15] carried out at some selected stations in Anambra State, Ezeomodo and Igbokwe [24] conducted in Onitsha, Ejaro and Abdullahi [25] which focused on Suleja, Niger State and a study carried out by Musa, Owa and Vivian [26] in Jos South Local Government area.

As shown in Fig. 6, the increase in water is clearly visible, the decline in vegetation and soil covers clearly displayed and an increase in impervious surfaces also clearly shown.

3.2.1 The dynamics of the LU/C categories

The dynamics of the LU/C categories were analysed for change detection for each period under investigation and the findings are presented in Table 4.

Fig. 7 is a graphical representation of the change detection analysis performed for the different LU/C categories in the study area per study epoch. The result, as obtained from the LCM reveals the gains, losses and net change of individual LU/C categories in square kilometres.

This is particularly in tandem with the findings of Ifeka and Akinbobola [15] whose results of change detection in LU/C of some selected stations in Anambra State showed that built-up land increased by 16% between 1986 and 2000 but only about 4% between 2000 and 2013.

In contrast to built-up cover, the magnitude of change of soil cover was more pronounced in the period, 2001 – 2016 accounting for about -3.44 sq.km with an annual reduction rate of about -0.23 sq.km (14 ha) per year. This was as low as -2.10 sq.km (-0.14 sq.km per year) between 2001 – 1986. Indicating that soil exposure increased more in recent times and may still continue due to the gradual sprawl of the town towards the neighbouring fringes. Lastly, water cover only experienced a high magnitude of change (7.69 sq. km) between 1986 and 2001, while this value was reduced by -0.03 sq. km in 2001 – 2016 periods, signifying a slight reduction in the water cover of the town, Onitsha. In other words, the river channel and other water bodies in the hinterland have not encountered any serious modification since 2001.

Table 4. Summary of multi-temporal land use/cover change detection of Onitsha metropolis

Land use/ cover categories	**2016**	**2001**	**Change [2016-2001]**		**2001**	**1986**	**Change [2001-1986]**		**Change [2016-1986]**	
	Area (Sq.km)	**Area (Sq.km)**	**Mag.**	**Freq.**	**Area (Sq.km)**	**Area (Sq.km)**	**Mag.**	**Freq.**	**Mag.**	**Freq.**
Vegetation (V)	140.8707	147.7008	-6.8301	-0.46	147.7008	178.735	-31.0338	-2.07	-37.8639	-1.26
Impervious surface (I)	62.2773	51.6267	10.6506	0.71	51.6267	26.1819	25.4448	1.70	36.0954	1.20
Soil (S)	3.1023	6.5421	-3.4398	-0.23	6.5421	8.6454	-2.1033	-0.14	-5.5431	-0.18
Water (W)	18.7497	19.1304	-0.3807	-0.03	19.1304	11.4381	7.6923	0.51	7.3116	0.24
Total	**225**	**225**			**225**	**225**				

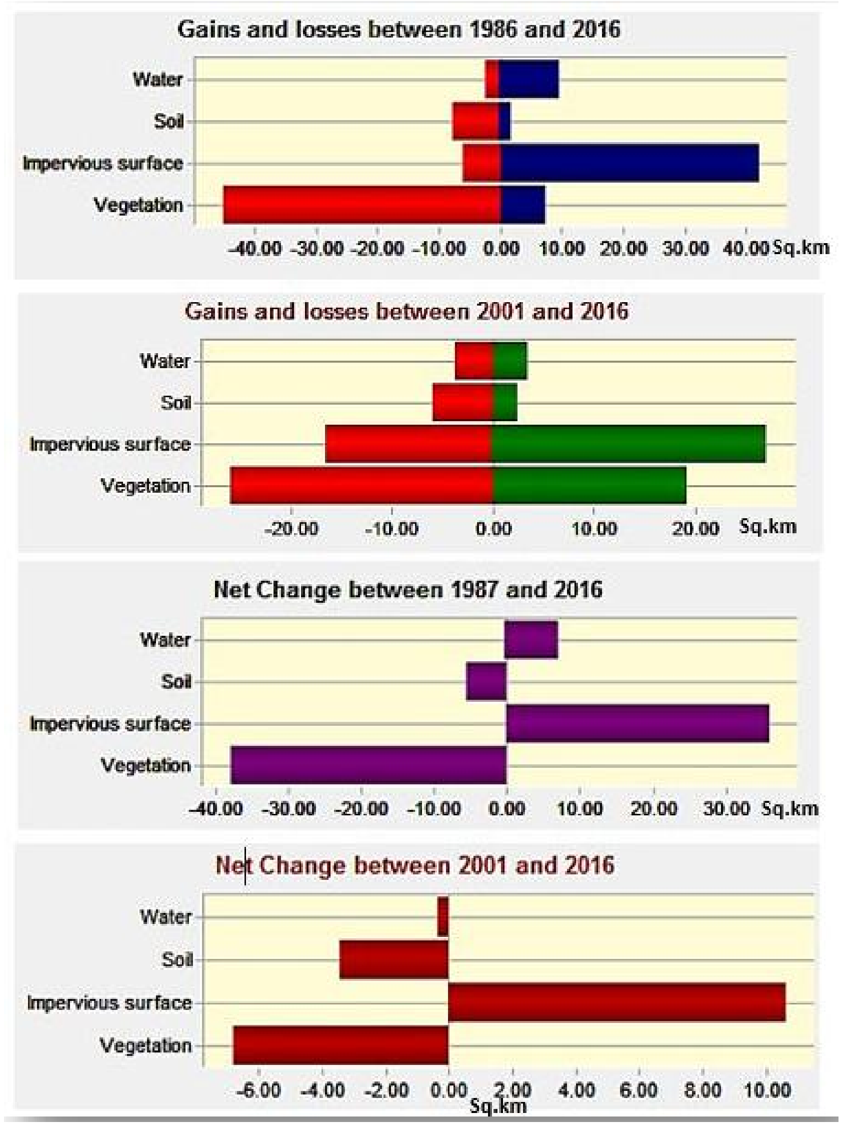

Fig. 7. LU/C dynamics of Onitsha metropolis between 1986 - 2001, 2001 - 2016 and 1986 – 2016

3.2.2 Prediction of future LU/C categories for the year 2031

The observed dynamics in LU/C were used to predict future LU/C of Onitsha for the year 2031 via the application of the Ca-Markov simulation tool. The result of the Markov Chain probability matrix of Onitsha from 2016 to 2031 is shown in Table 5.

The result of the Markov chain analysis as presented in Table 5 shows a very high probability of vegetal cover, impervious surfaces and extent of water bodies to be retained in 2031. In contrast, soil fractions, displayed a probability of being converted or changed to impervious surfaces. This is an indication that in 2031, only a slight modification in LU/C will occur since all other LU/C categories apart from soil are envisaged to be more or less unchanged, except for the occurrence of any extraneous event which are obviously beyond the scope of this study. Subsequently, the LU/C transition map shows areas to be modified in 2031, with vegetated areas to be converted to impervious surfaces being although little with most of the vegetation – impervious surfaces conversion are envisaged to take place in and around built-up areas. The predicted LU/C map of Onitsha is shown in Fig. 8, while the magnitude of change for the various LU/C categories in the study area from 2016 to 2031. Similarly, the predicted magnitude of change for the various LU/C categories in the study area from 2016 to 2031 is presented in Table 6.

Table 6 further shows (as predicted) that in 2031, Onitsha Metropolis will be characterized by vegetal cover of about 137.250 sq.km and to have lost about 3.62 sq.km (362 ha) at the rate of 0.241 sq.km (24.1 ha) per year. Impervious surface categories are envisaged to spatially increase with a magnitude of about 4.77 sq.km (47ha) in 2031, at a rate of 0.318 sq.km (31.8 ha) per year. Soil cover and water bodies appear to experience a very slight reduction of about -0.402 sq.km (-40.2 ha) and –0.750 sqkm (-75 ha), respectively. This is further translated that water and soil covers are envisaged to be reduced at an average annual rate of 5ha and 2.7ha per year, respectively.

The result of the LCM gives also a graphical representation of the gains and losses, net change and contribution to net change for each LU/C category between 2016 and 2031. See Figs. 9 and 10.

Table 5. Markov Chain LU/C probability matrix for Onitsha, 2031

Given:	Probability of changing to			
	Vegetation	Impervious surface	Soil	Water
Vegetation	**0.8238**	0.1659	0.0027	0.0075
Impervious surface	0.2958	**0.6781**	0.0060	0.0200
Soil	0.3343	**0.3804**	0.0980	0.1874
Water	0.0910	0.0141	0.0912	**0.8037**

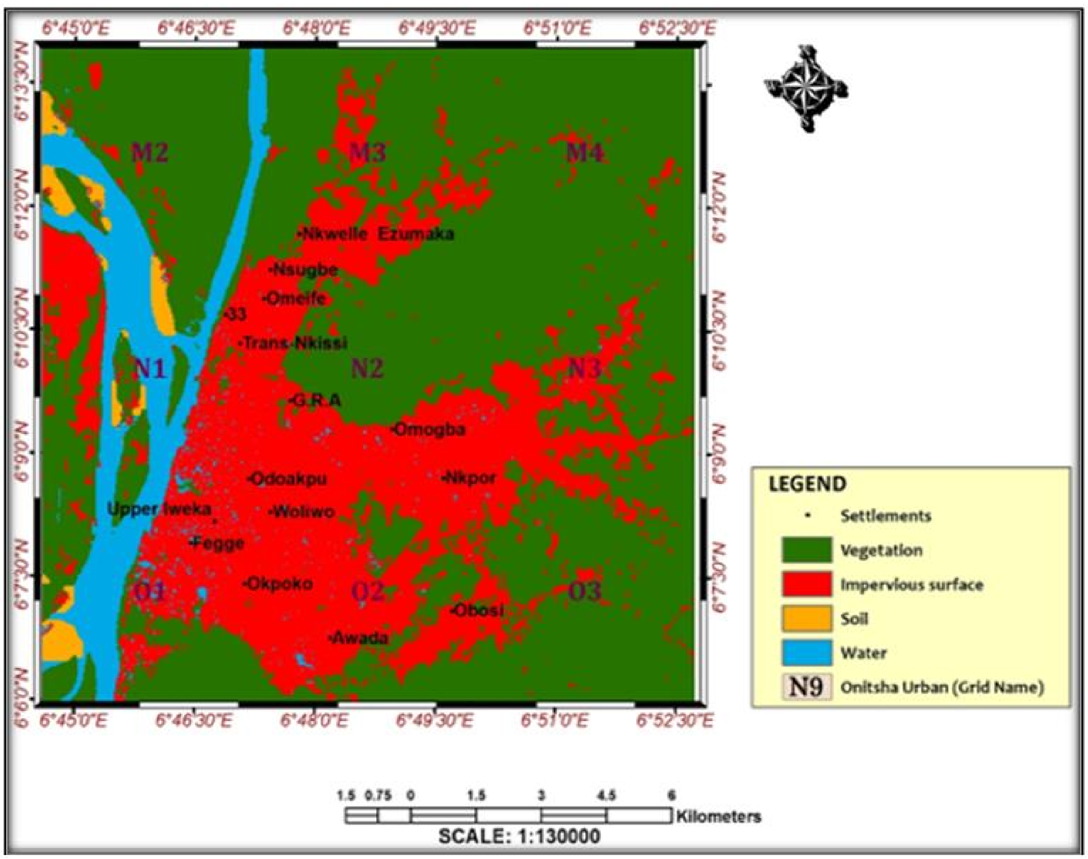

Fig. 8. Predicted LU/C map of Onitsha metropolis (2031)

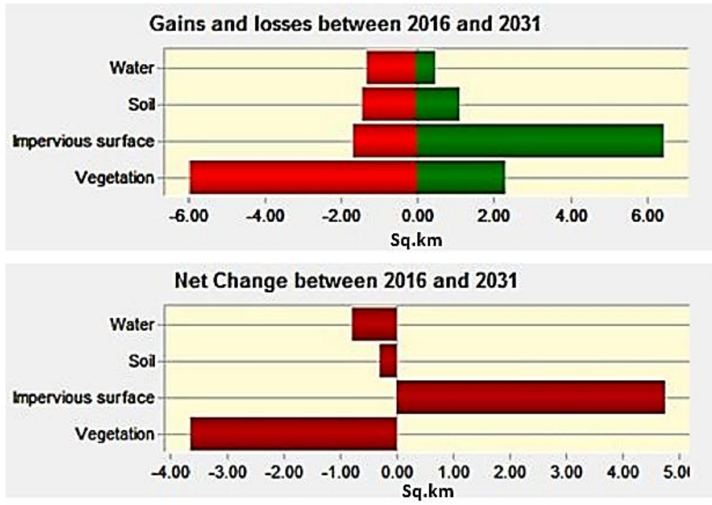

Fig. 9. Gains and losses and net change graphs of LU/C classes of Onitsha between 2016 and 2031

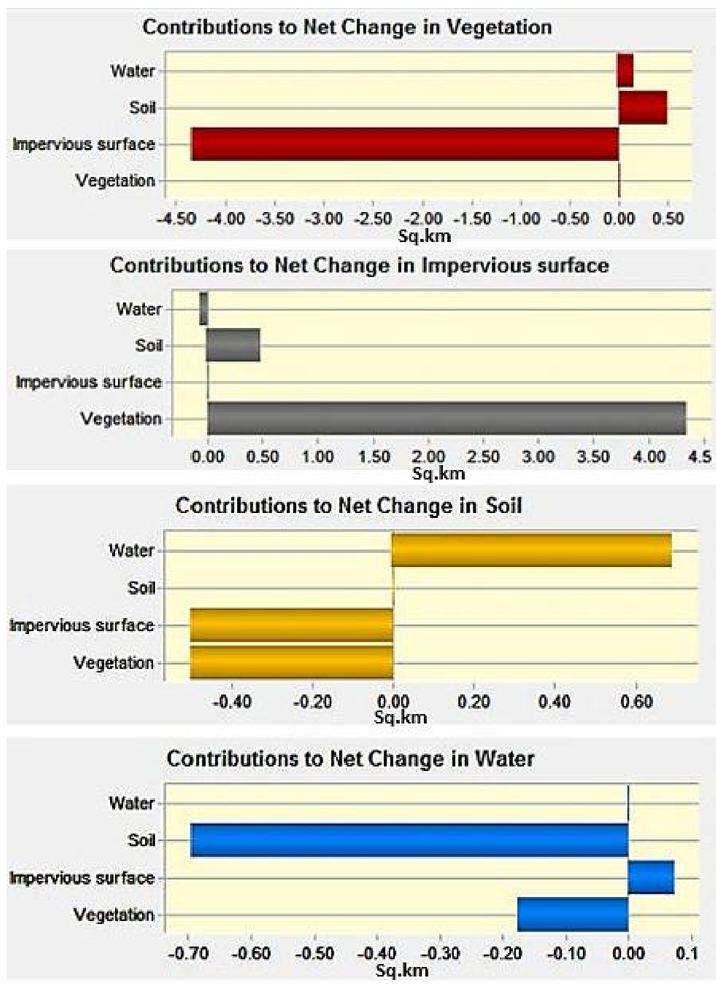

Fig. 10. Contribution to net change in each LU/C class between 2016 and 2031

Table 6. LU/C categories of Onitsha between 2016 and 2031

S/no.	LU/C categories	2031	2016	Change [2031-2016]	
		Area (Sq.km)	Area (Sq.km)	Magnitude	Annual frequency
1	Vegetation (V)	137.250	140.871	-3.621	-0.241
2	Impervious surface (I)	67.050	62.277	4.773	0.318
3	Soil (S)	2.700	3.102	-0.402	-0.027
4	Water (W)	18.000	18.750	-0.750	-0.050
	Total	**225**	**225**		

3.2.3 Transition and predicted LU/C map of the study area

As hitherto mentioned, the transition of each LU/C into different LU/Cs and their areas of persistence were modelled and presented in Fig. 11 while the statistics are shown in Table 7.

As shown in Table 7 and Fig. 11, it is envisaged in this study that all the LU/C fractions (i.e. vegetation, impervious surface, soil and water) in Onitsha will persist or remain unchanged. 135.00 sq.km of vegetal cover, 60.53 sq.km of impervious surfaces, 1.58 sq.km of soil and 17.55sq.km of water covers have been identified. The conversion of vegetation to impervious surface is the highest transition category (5.85 sq.km at 0.39 sq.km/year). This is an indication of vegetal degradation, devegetation and deforestation – a product of continuous urbanization in the Onitsha Metropolis.

Furthermore, the result of the Pearson Chi-square test, computed to identify whether or not the difference in LU/Cs (i.e. vegetation, impervious surface, soil and water fractions) in Onitsha between 2016 and 2031 is statistically significant is shown in Table 8. The result revealed no statistically significant difference in the LU/C fractions between 2016 and 2031 ($P = .964$, $\alpha = .05$). This further justifies the findings of this study and therefore, can be deduced that the rapidity of urbanisation in Onitsha Metropolis has drastically reduced in recent times and that the same trend is expected to continue, except otherwise other factors set-in.

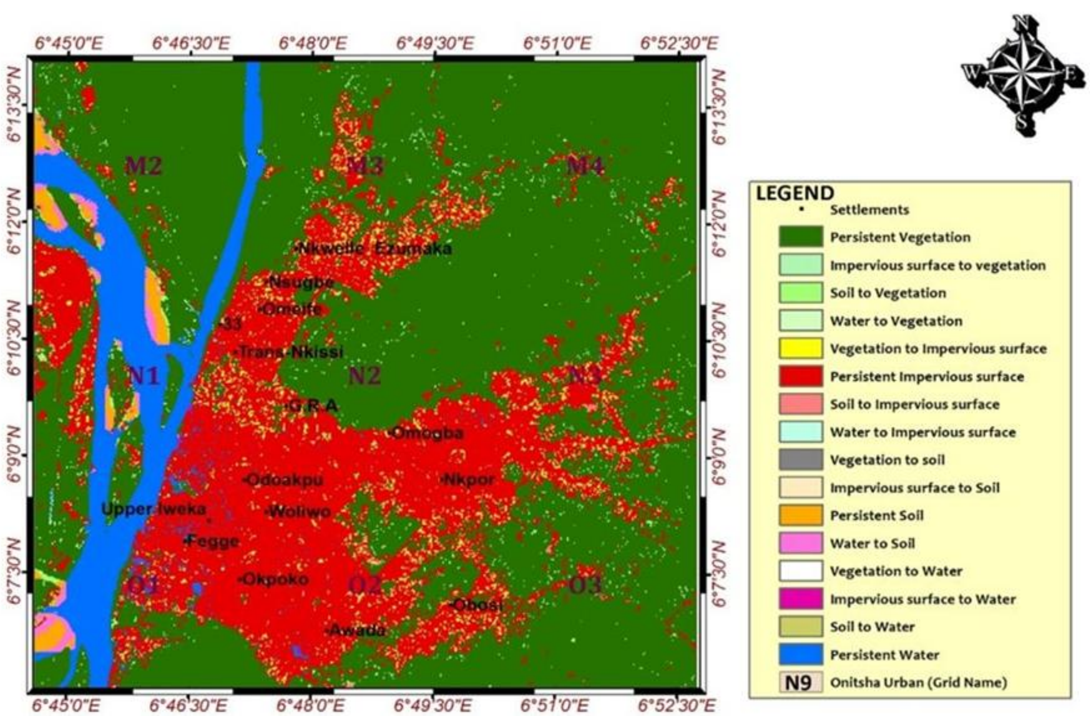

Fig. 11. LU/C transition map of Onitsha Metropolis between 2016 and 2031

Table 7. LU/C area transition statistics of Onitsha

S/no.	Land use transition categories	2016 – 2031	
		Area (Sq.km)	Annual rate (Sq.km)
1	**Persistent Vegetation**	**135.000**	0
2	Impervious surface to vegetation	1.575	0.105
3	Soil to Vegetation	0.450	0.03
4	Water to Vegetation	0.225	0.015
5	Vegetation to Impervious surface	5.850	0.39
6	**Persistent Impervious surface**	**60.525**	0
7	Soil to Impervious surface	0.450	0.03
8	Water to Impervious surface	0.000	0
9	Vegetation to soil	0.000	0
10	Impervious surface to Soil	0.000	0
11	**Persistent Soil**	**1.575**	0
12	Water to Soil	1.125	0.075
13	Vegetation to Water	0.000	0
14	Impervious surface to Water	0.000	0
15	Soil to Water	0.450	0.03
16	**Persistent Water**	**17.550**	0
	Total	**225**	

Table 8. Chi-square result

Study area		Value	Df	Asymp. Sig. (2-sided)
Onitsha	Pearson chi-square	.278	3	.964
	Likelihood ratio	.278	3	.964
	N of valid cases	450		

4. CONCLUSION

This study utilised the sub-pixel approach in characterizing LU/C fractions in urban areas and puts it forward as an objective, continuum-based approach in tracking the dynamics of urbanization. The results of this study indicated that vegetal cover reduced over the three epochs from 178.72 sq.km in 1986 to 147.70 sq.km in 2001 and slightly to 140.87 sq.km in 2016. Between 1986 to 2016 vegetal cover reduced by about -37.86 sq.km with a greater magnitude (-36.03 sq.km) noted to have occurred between 1986 to 2001; impervious surface increased by 36.10 sq.km with a greater magnitude observed between 1986 and 2001; soil fraction reduced by -5.54 sq.km with a greater magnitude of -3.44 sq.km observed between 2001 and 2016; and the area occupied by water increased by 7.31 sq.km which occured almost completely between 1986 and 2001. However, the result of the Markov chain analysis revealed a high probability of vegetal cover, impervious surfaces and extent of water bodies to be retained in 2031, with soil having a probability of being converted into impervious surfaces by the year 2031. Although the study envisages no statistically significant change in LU/C categories in Onitsha in 2031 it still maintains that the intensity (rather than the rapidity) of urbanization, coupled with the attendant environmental problems. For instance, the studies of Chaudhuri and Mishra [27], Maduako, Yun and Patrick [28], have shown how increases in built-up fractions can increase local land surface temperatures (LSTs) which can as well alter regional climates and invariably, human health as pointed out by Patz et al. [23]. The results presented in this study can go a long way to aid environmental managers in Onitsha to develop a phased intervention project or policy in the Metropolis to combat the negative impacts of urbanization on the environment. Thus, there is need for reliable and sustainable planning upon the existing to ensure mutual co-existence between man and his ecosystem service provider, the environment.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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