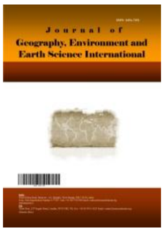

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Influence of Urban Growth on Landuse/Cover in Umuahia, Abia State Nigeria

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Understanding land use/landcover change (LULC) dynamics is very important in sustainable land resource management. This is especially so for developing countries of the world where majority of the people depend heavily upon natural resources for survival. In this study, moderate spatial resolution Landsat images were freely downloaded from the United States Geological Survey (USGS) archives for 4 decadal dates of 1991, 2001, 2001 and 2021 for Umuahia town, which became capital of Abia state of Nigeria in 1991. The images were analyzed in ERDAS Imagine 14 and ArcGIS 10.2 software environments to generate LULC statistics for the 4 dates. Post classification comparison algorithm was used to generate LULC change trends from 1991 to 2021. Key informants interviews and direct field observations were used to identify the main drivers of LULC change in the area. The results show that, the town has undergone significant LULC changes since its designation as Abia state capital in 1991. The extent changes for the various LULCs over the 30 year period (1991 to 2021) have been Built-up (+233%), Bareland (-34%), Woodland (45%), Uncultivated Farmland (-62%), Burnt Woodland (630%) and Agricultural land (-25%). Water Body did not undergo change over the period. It was concluded that though urban growth has promoted some degradation trends in the town, it has promoted increases in urban woodland areas which

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could go a long way in promoting climate change mitigation, as well as human health and comfort in the town. It was recommended that there is the need to promote deliberate reforestation efforts boost development in urban woodlands.

Keywords: Umuahia; land use; land cover; urbanization; satellite images; GIS.

1. INTRODUCTION

Analysis of LULC changes over spatio-temporal scale and the driving factors for such changes is very important for human beings to take informed decisions on sustainable land utilisation, carryout effective environmental monitoring and enable national governments to be in a position to generate needed information for international environmental reporting [1-5]. Human activities, especially urban growth, have significantly altered the natural landscape resulting into remarkable change patterns in the LUC over time [6-11]. UN estimates [12] have shown that only 30% of the population of the World was urban as at 1950. By the beginning of 21st century however, this figure jumped to about 54%, which is projected to increase to about 66% by 2050. Cities now shelter over 2.9 billion people which is about half of the population of the world [13]. Majority of those residing in urban areas are in developing countries. Urbanization at the global level remains a major development issue but is of particular concern in developing countries where urbanization is more often uncontrolled [12-14,11].

LULC change assessment is considered as an extremely important activity in properly understanding the relationship nature-human activities relationships. The enormous changes affecting the landscape at various scales (country, regions, counties, states, river basins, protected reserves e.t.c.) and advancements in mapping technologies (remote sensing, GIS and GPS) have encouraged researchers to collect and analyse more information on nature, causes and impacts of LULC changes. In particular, a number of computer-based change detection algorithms have now been developed and tested for use in assessing LULC changes in many areas, with the selection of an algorithm depending upon the scale of analysis required [8, 15-23]. Of the many algorithms available for LUC change analysis, post classification comparison involving comparisons of multitemporal LUC data to detect changes remains the most widely utilised under various scales of assessment [24-31].

LULC change can result from both natural and human causes, but it is largely regarded as the result of different human activities which cause disturbance of many aspects of the environment including biodiversity, water and radiation budgets, energy balance, trace gas emissions and other processes that cumulatively affect climate and biosphere [32]. As such, information about the change is increasingly needed in order to promote effective management of the environment, especially as human beings now battle to address climate change impacts globally. Planners, resource managers, scientists and decision makers from state, regional, local government and district levels use this information for a variety of purposes. Most of the studies on LUC change were carried out at broader regional spatial scales such as multi-county economic zones, mega cities, river basins and protected watershed zones. Fewer number of studies have comparatively been conducted on micro-scales such as small and medium towns [33-48,23].

This study makes a contribution in this context by examining LULC changes resulting from urban growth in Umuahia, a medium-sized town in Abia state of Nigeria. Multispectral satellite data for the period 1991 to 2021 was utilised for the study. The town was designated as capital of the state in 1991, a development that made it to witness remarkable expansion through construction of residential buildings, institutional, commercial and associated infrastructure.

1.1 Study Area

Umuahia, administravely divided into two local government areas (namely Umuahia North and Umuahia South) lies between latitudes 5°26′06.00″N and 05°36′04.00″N, and between longitudes 07°21′50.00″E and 7°34′03.00″E (Fig. 1), covering a land area of about 70km^2. The study area is located within the coastal plains of Nigeria, dotted with outcrops of sandstones and shales belonging to the Bende-Ameki of Eocene to Oligocene age. The outcrops consist mainly of medium-coarse-grained white sandstones [49].

The area has a varied and complicated topography of narrow ridges and valleys. The area belongs to Koppen Af climate class type and has a humid tropical rainforest vegetation type [50]. Average daily insolation is in general low (4.8h), though the area experiences mean annual maximum temperature of 31°C with low daily variations [51]. Rainfall is received over 8 months period in a year (March to October), with long term mean annual average of about 2, 280mm [52]. There are two peak periods during which highest rains are received every year, in June and September [53].

Umuahia is underlain by sedimentary rocks which have given rise to development of hydromorphic and organic soils along the coast and river floodplains. The soils of the area are generally sandy, with the topsoil being sandy loam to sandy clay loam in texture, with the clay content increasing with depth due to eluviation processes. The soils have high bulk density, with the topsoil values ranging between 1.34 and 1.55 Mg m^{-3}, and those of the subsoil between 1.56 and 1.92 Mg m^{-3} [49].

Human population of the town grew from 213,630 in 1991 to 359,230 in 2006 and 492,493 in 2017 [54]. Umuahia constitutes a rapidly growing, dense market for the agricultural produce of the surrounding rural areas. The economy of the area is powered by a dual force of agricultural produces (from primary economic activities) and commerce, industrial activities and paid employments (from secondary/tertiary economic activities).

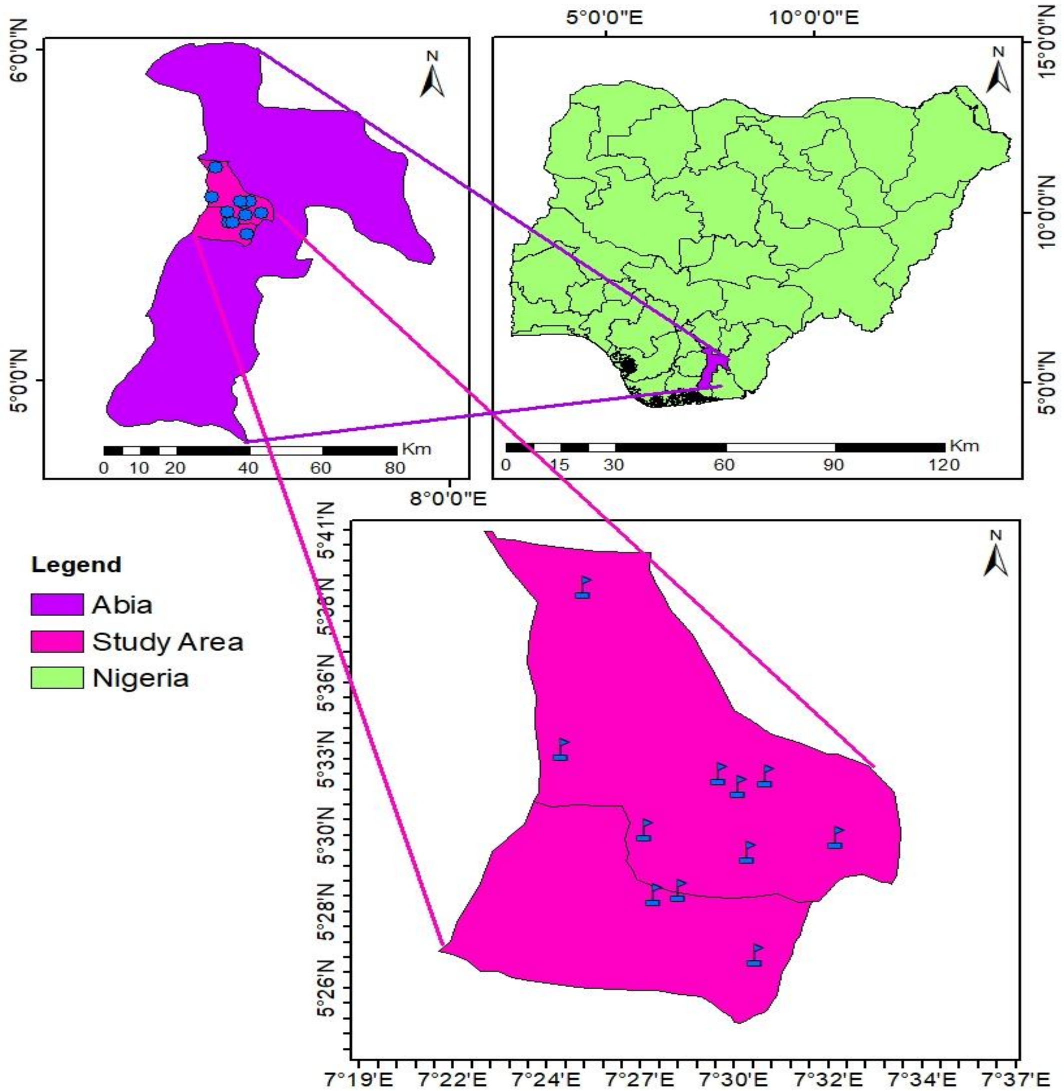

Fig. 1. The study area

2. MATERIALS AND METHODS

2.1 Reconnaissance Survey

Reconnaissance survey was carried out at the beginning of the study to obtain information on various LULC types that characterize the study area. The information generated was used to develop a training data used in classifying the satellite images using ERDAS GIS software.

2.1.1 Image classification and change detection

Signal error, shade and cloud free decadal (February 1991, 2001, 2011 and 2021) Landsat (5, 7 and 8) satellite images with 30m spatial resolution covering the area were downloaded from the USGS Website (USGS-EROSC, at https://earthexplorer.usgs.gov). The bands downloaded include band 3 (0.63–0.69 mm), 4 (0.78–0.90 mm) and 5 (1.55–1.75mm) of Thematic Mapper (TM). Others include bands 3 (0.63–0.69 mm), 4 (0.77–0.90mm) and 5 (1.55–1.75 mm) for ETM, and bands 3 (0.533–0.590mm), 4 (0.636–0.673 mm) and 5 (0.851–0.879mm) of Operational Land Imager (OLI).

Ancillary data was obtained, which included (1) ground truth (reference) data in the form of Ground Control Points (GCPs) for the LULC classes obtained from Geographical Positioning System (GPS)-assisted field surveys, and (2) 1:50,000 topographic sheet of the area produced by the Federal Surveys of Nigeria. While the topographic sheet was used to facilitate image geo-referencing and ground features identification, the ground truth data were utilised for image classification, validation of the classification results and overall accuracy assessment of the results of digital image classification.

Using layer-stack tool of ERDAS software, the multi-band satellite imageries for each year were overlaid in one file to form a single data layer to obtain a False Colour Composite (FCC) image for every year. The geo-referenced topographic sheet was used as reference data for the geometric rectification of the single-layered image. To carry out the geometric rectification of the satellite images, the GCPs were detected in both the topographic sheet and 2021 satellite image, following which the rectification was carried out using the total Root Mean Square (RMS) error, which was estimated at below one pixel. As is usual with digital image processing, the downloaded satellite images were first subjected to pre-processing to correct radiometric and geometric distortions typically associated with raw images. To carry out this, mosaicking and sub-setting were carried out to extract (i.e sub-set) from the geometrically rectified images the Area of Interest (AOI) for this study.

Maximum-likelihood supervised classification procedure was employed to classify the rectified images into LULC classes of interest to this study. The area was classified into seven (Built-up, Agriculture, Water Body, Bareland, Woodland, Uncultivated Farmland, Burned Woodland) main classes, developed based on standard classification schemes [55]. To carry out the classification, layer-stacking module of the ERDAS Imagine 14v software was employed and the resultant shape-file of the study area produced through delineation process was used to clip the imageries using ArcGIS 10.2.2. The clipped images were then re-projected to Universal Transverse Mercator (UTM) 32 and resampled to 30m spatial resolution. LUC statistics generated for the years 1991, 2001, 2011 and 2011 were used to compute 3 sets decadal change scenarios (1991-2001, 2001-2011 and 2011-2021).

2.1.2 Classification accuracy assessment

Classification accuracy assessment is regarded as an essential activity to undertake after image classification has been completed. To carry this out, the accuracy assessment tool of the supervised classification module of the ERDAS Imagine software used was used to randomly generate reference points on the classified images. The points chosen were those with clearly indefinable landmark features on the ground (for example, road intersections or river/road crossing). The classes into which every randomly-generated point was classified were noted. FCC image of 2021 and training data collected during the reconnaissance survey were used to generate information on 'correctly' and 'wrongly' classified classes. Using self-generated report module of the ERDAS Imagine 14 software, error matrix and kappa statistics were generated for the classified images. Accuracy error matrix typically has rows and columns, with the rows representing the classes obtained from the digital image classification while the columns represent the classes identified by the accuracy assessor from the reference values [56]. The diagonal cells of the error matrix typically indicate the total number of pixels that were correctly identified for each class of the reference and classified data. On the other hand, the off-diagonal cells represent the pixels that have been classified incorrectly, which will indicate the extent of error between the reference data and classified data. Through this way, the accuracy of the digital classification carried out was assessed in this study.

3. RESULTS AND DISCUSSIONS

Table 1 shows the statistics on land area (in Km2 and %) covered by each LULC in the study area. Fig. 2 present the distribution of every LULC over the study area. Table 2 on the other hand gives change statistics showing how every LULC has undergone change on decadal basis between 1991 and 2021. Figure It could be seen from the table that built-up area occupied about 28km^2 (representing 8% of the total land area) in 1991, which increased to about 40km^2 in 2001, 56km^2 in 2011 and 93km^2 in 2021. Between 1991 and 2021, the LUC on the overall increased by about +233%. The consistent increase in the area covered by the built up in the study area over the 1991 to 2021 period could be linked to increase in development of infrastructure needed to meet the demands of settlement, commercial, industrial and institutional landuses as Umuahia continues to play its role at the capital seat of Abia state created in 1991. It is well known that urban growth promote massive development in built-up infrastructure [57-59].

In 1991, the total area occupied by agricultural land was about 115km^2 (32% of the total). This decreased to about 96km^2 in 2001 and 97km^2 in 2011 and 86km^2 in 2021. The overall change over the 1991 and 2021 period was -29km^2 (a decrease by about 25%) which could however be regarded as low when one considers how urbanisation brings about massive destruction of agricultural land. The low level of overall decrease in the area occupied by agricultural land in the area could be a reflection of the fact that many residents of the town have not completely abandoned their farming profession, the transformation of Umuahia into a state capital notwithstanding.

The area covered by water body in all the years between 1991 and 2021 remained at about 2km^2 (representing about 0.3% of the total land area. Consequently, on the overall, there was no change in size of the area covered by the LUC. The no-change scenario exhibited by water body in the area over the 1991 to 2021 period is surprising especially when one considers that phenomena like climate change, erosion and siltation are known to be causing massive alterations in surface water bodies in the world.

Bareland occupied a land area of about 13km^2 (about 4% of total) in 1991. This decreased to about 9km^2 in 2001, about 8.5km2 in 2011 and 8.7km^2 in 2021. On the overall, the LUC decreased by about 34% over the 1991 to 2021 period. The decrease in lands that have been bare in the study area over the study period is expected, as more lands are taken up for development of infrastructure over the period under consideration.

The area under woodland was about 82km^2 in 1991 (23% of the total), which decreased slightly to about 80km^2 in 2001. In 2011, it increased to about 97km^2 and to 119km^2 in 2021. On the overall, the LUC increased by about 45% over the 30 year (1991 to 2021) period. The increase in area covered by woodland in the study area, especially between 2011 and 2021, could be a reflection of massive urban greening embarked upon by the Abia state government to improve shade and urban aesthetics in the town.

In 1991, uncultivated farmlands occupied an area of about 120km^2 (33% of the total). This increased to about 131km2 in 2001 but decreased to about 98km2 in 2011 and 45km^2 in 2021. The overall change over the 1991 to 2021 period showed a decrease of about 75km^2, representing about 62% decrease in the size of the LUC. The overall decrease in the area of this LUC is expected as urban growth is very well known to be causing decline in areas under farming activities [60-71].

In this study, the error matrix generated and used to assess the accuracy of the classification carried out involved an integration of visual interpretation with the results of digital image classification. The integration process carried out has helped to increase the classification accuracy for the 1991, 2001, 2011 and 2021 classified images from 89%, 84%, 85%, and 82% to approximately 94%, 97%, 93%, and 96%, respectively. In particular, the lands under agriculture, bare lands, water boy and uncultivated farmland were characterized by the highest classification accuracy levels.

Table 1. LULC statistics for the various years

LUC Type	Area in Km^2 and % for each year							
	1991		2001		2011		2021	
	Km^2	%	Km^2	%	Km^2	%	Km^2	%
Built-up Area	27.99	7.8	40.47	11	56.42	15.6	93.27	25.8
Agriculture	115.04	31.9	96.02	27	97.21	26.9	85.79	23.8
Water	1.86	0.5	1.87	0.5	2	0.6	1.9	0.5
Bareland	13.19	3.7	9.09	2.5	8.53	2.4	8.7	2.4
Woodland	81.83	22.7	80.37	22	97.48	27	118.66	32.9
Uncultivated Farmland	120.27	33.3	130.9	36	98.19	27.2	45.46	12.6
Burned Woodland	1.01	0.3	2.51	0.7	1.31	0.4	7.38	2
Total	**361.19**	**100**	**361.2**	**100**	**361.1**	**100**	**361.17**	**100**

Table 2. LULC change statistics over the 30 year (1991 and 2021) period

LUC Type	Change statistics for the three decades						Overall change statistics for 1991 - 2021		Direction of Overall Change
	1991-2001		2001-2011		2011-2021				
	Diff. Km^2	P.C. %	Diff. Km^2	P.C.%	Diff. Km^2	P.C.%	Diff. Km^2	P.C.%	
Built-up Area	12.48	25.4	15.95	23.2	36.85	28.67	65.28	233.23	Increase
Agriculture	-19.02	-38.7	1.19	1.7	-11.42	-8.88	-29.25	-25.43	Decrease
Water	0.01	0.02	0.13	0.2	-0.1	0.08	0.04	2.15	Static
Bareland	-4.1	-8.3	-0.56	0.8	0.17	0.13	-4.49	-34.04	Decrease
Woodland	-1.46	-3	17.11	24.9	21.18	16.48	36.83	45.01	Increase
Uncultivated Farmland	10.59	21.5	-32.67	47.48	-52.73	41.03	-74.81	-62.2	Decrease
Burned Woodland	1.5	3	-1.2	1.7	6.07	4.72	6.37	630.69	Increase

Note: Diff (differences in land area between one date to another); P.C. (Percentage change in an LUC over two dates being compared); Negative values of Diff and P.C indicates decrease in LUC

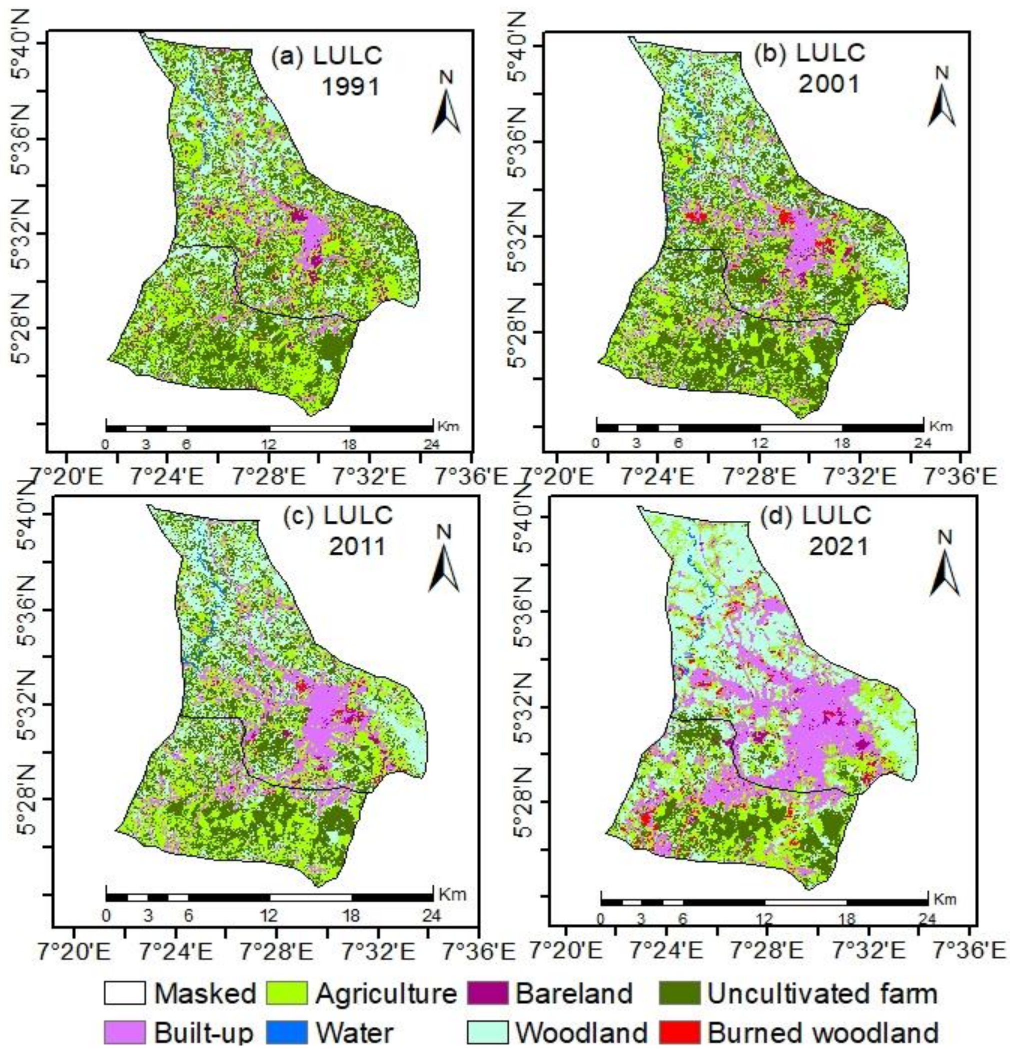

Fig. 2. Distribution of the mapped LUC for the years 1991, 2001, 2011 and 2021

4. CONCLUSION

The results obtained in this study indicate that Umuahia town has undergone significant LUC changes since its designation as Abia state capital in 1991. The extent changes for the various LUCs over the 30 year period (1991 to 2021) have been Built-up (+233%), Bareland (-34%), Woodland (45%), Uncultivated Farmland (-62%), Burnt Woodland (630%) and Agricultural land (-25%). Water Body did not undergo change over the period. These particularly indicate that there are massive expansion of burnt woodland, built-up and woodland, and corresponding decreases in areas under Bareland, uncultivated farmlands and agricultural lands. Though these confirm once again that urban growth has promoted some degradation trends in Umuahia area, it has however promoted increases in urban woodland areas which could go a long way in promoting climate change mitigation, as well as human health and comfort in the town. Is quite obvious that though urbanization remains a key driver of LULC changes in the study area, as it is taking over agricultural and forest lands, it has however created some trends that could promote improvement in biodiversity and ecosystem services that could help improve conditions for human well-being in the area. There is thus the need to promote deliberate reforestation efforts boost development in urban woodlands. Studies are particularly needed to monitor soil health and quality in the study area to develop mitigation and ameliorative measures towards controlling pollution levels and negative environmental impacts of urban growth.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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