Original Research Article

INFLUENCE OF URBAN GROWTH ON LANDUSE/COVER IN UMUAHIA, ABIA STATE NIGERIA

ABSTRACT

Understanding land use change (LUC) dynamics is crucial for sustainable land resource management in especially developing countries where the majority of the people depend on natural resources from the landscape for their livelihoods. In this study, moderate resolution Landsat images were freely downloaded from the United States Geological Survey (USGS) archives, analyzed using post classification comparison algorithm using ERDAS Imagine 14 and ArcGIS 10.2 software to examine the LUC change trends from 1991 to 2021 in Umuahia town, which became capital of Abia state of Nigeria in 1991. Key informants interviews and direct field observations were used to identify the key drivers of LUC change in the area. The results show that, the 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 any 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 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.

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Keywords: Umuahia; land use and land cover; urbanization; remote sensing; GIS

INTRODUCTION

Analysis of spatial and temporal processes of LUC change and its driving factors is essential to enable human beings make informed decisions on sustainable land use, enable environmental monitoring and support national reporting on global conventions and frameworks, (Wood et al., 2004; Abd El-Kawy, et al., 2011; Usman, et al., 2015; Leemhuis et al., 2017; Msofe et al., 2019). Human activities, especially urban growth, have significantly altered the natural landscape resulting into remarkable change patterns in the LUC over time (Zubair, 2006; Long *et al.*, 2008; Singh and Khanduri,

Comment [AC4]: Avoid it

2011; Gajbhiye, et al., 2012; Juliev, et al., 2019; Shao et al., 2020). According to the United Nations World Urbanization Prospects (2014), only 30% of the World's population was urban in 1950, but presently, 54% of it currently resides in urban centres, and it is further projected that by 2050, about 66% of the World's population would be residing in urban centres (UN Population Division, 2002). In addition, UN Population Division (2002) stated that towns and cities sheltered nearly half of the world's population (over 2.9 billion people) by 2000, the majority of which were in developing countries. Urbanization at the global levels remains a major development issue but is of particular concern in developing countries where urbanization is more often uncontrolled (Gong et al., 2019; Korah et al., 2019; Xu et al., 2019; Shao et al., 2020).

Assessment of LUC change is extremely important for understanding the relationship between human activities and nature. 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 gather more information on nature, causes and impacts of LUC change. In particular, a number of change detection algorithms have been developed and tested for use in assessing LUC change in many areas, with the selection of an algorithm depending upon the scale of analysis required (Singh, 1989; Dimyati et al., 1996; Lu et al., 2004; Shalaby and Tateishi, 2007; Jin et al., 2013; Zhu and Woodcook, 2014; Mas et al., 2017; Halefom et al., 2018; Seydi, et al., 2020; Chughtai, et al., 2021). 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 (Anil, et al., 2011; Kaul and Sopa, 2012; Zaidi et al., 2017; Islam, et al., 2018; Fahad, et al., 2020; Salem et al., 2020; Tewabe and Fentahun, 2020; Vivekananda et al., 2021).

Comment [AC5]: Mention others than using etc

LUC change is the result of different anthropogenic activities which cause disturbance of biodiversity, water and radiation budgets, affects trace gas emissions and other processes that cumulatively affect climate and biosphere (Rawat and Kumar, 2015). As such, information about the change is increasingly needed to effectively manage environment as well as living conditions 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 (Lambin, 1999; Gautam, et al., 2002; Hathaut, 2002; Ramachandra and Kumar, 2004; Sadaat et al., 2011; Jia et al., 2014; Jin et al., 2017; Roy and Inander, 2019; Chowdhury, et al., 2020; Hussein et al., 2020; Mishra, et al., 2020; Wang et al. 2020;

Comment [AC6]: Rearrange it as follow: regional, state, district and local government

Anitha Selvasofia, et al., 2021; Chugtai, et al., 2021; Hao, et al., 2021; Kemarau, et al., 2021; Rasool et al., 2021).

This study makes a contribution in this regard by examining LUC change 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.

Comment [AC7]: Where is the objective of the study? Or not clear

STUDY AREA

Umuahia, administratively ~~administravely~~ is divided into two local government areas ~~(~~namely: Umuahia North and Umuahia South~~)~~ and lies between latitude 5°26′06~~.00~~″N to 05°36′04~~.00~~″N and longitude 07°21′50~~.00~~″E to 7°34′03~~.00~~″E (Figure 1), covering a total area of about 70km^2. The study area is located within the coastal plains of Nigeria, dotted with outcrops of sandstones and shales of the Bende-Ameki, of Eocene to Oligocene age consisting of medium-coarse-grained white sand stones (Ukeka, 1992).

Comment [AC8]: 5°26′06 N to 05°41′04N

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The area has a varied and complicated topography of narrow ridges and valleys. The climate of the study area is humid tropical rainforest-KoppenAf (Ochege et al., 2017). Daily average insolation is generally low at 4.8h, nevertheless the area experiences mean annual maximum temperature of 31°C with little daily variations (Iloeje, 2007). Annual mean rainfall averages 2,278 mm (Onyeka et al, 2008), with eight months of precipitation received between early March to late October. There are two main seasons, a very short dry season (November to February) and a longer rainy season (April to October) with two peaks in June and September (Agoha, 1997).

Umuahia which is underlain by sedimentary rocks ~~which~~ have given rise to development of hydromorphic and organic soils along the coast and river floodplains. The top soils are generally sandy loam to sandy clay loam, with the clay content increasing with depth. Topsoil bulk densities are high, varying between 1.34 and 1.55 Mg m^{-3}. Subsoil bulk densities are also high, with values reaching as high as 1.56 to 1.92 Mg m^{-3} in some horizons (Ukeka, 1992).

Comment [AC10]: Is it high this range ?for which soil particle?

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The population of the town grew from 213,630 in 1991 to 359,230 in 2006 and 492,493 in 2017 (Ejenma, 2013). The area is located within the Equatorial Rain Forest belt in Nigeria, with the natural forest landscape now greatly modified into cover of oil palm plantations and secondary vegetation (International Lake Environment Committee, 1993). 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,

Comment [AC12]: How this source could be reference for 2017? Otherwise it should be projection industrial activities and paid employments (from secondary/tertiary economic activities).

MATERIALS AND METHODS

Reconnaissance Survey

A reconnaissance survey was conducted to obtain information on various land uses and land cover that characterize the study area. The information generated was used to develop a training data ~~used in~~for classifying the satellite images using ERDAS and GIS software.

Comment [AC13]: Year and their version

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 of spectral band 3 (0.63–0.69 mm), 4 (0.78–0.90 mm) and 5 (1.55–1.75mm) of Thematic Mapper (TM); band 3 (0.63–0.69 mm) and band 4 (0.77–0.90mm) and band 5 (1.55–1.75 mm) for ETM, and band 3 (0.533–0.590mm), band 4 (0.636–0.673 mm) and band 5 (0.851–0.879mm) of Operational Land Imager (OLI) were obtained from the United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (https://earthexplorer.usgs.gov). The images were used to produce a time series of LULC change on a 10-year interval period. The spatial resolution of the images was 30 m. The selected images were free of signal error from the sensor and were cloud free. Ancillary data was obtained, which included (1) ground truth (reference) data in the form of reference data points (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 toposheet was used to facilitate image geo-referencing and ground features identification, the ground truth data were also used for image classification, validation of the classification results and overall accuracy assessment of the classification results.

Comment [AC14]: It is too long, it is better to break it in to separate sentences

The multi-band satellite imageries for each year were overlaid in one file (single layer) by using the layer stack tool of ERDAS software. Through this way, a False Colour Composite (FCC) image was developed for each year. Extracting and pre-processing ~~the~~of the image of the study area involved three significant steps: geometric rectification, sub-setting, and enhancement. The geo-referenced toposheet was used as reference data for the geometric rectification of the single-layered image. In geometric rectification, the GCPs were detected in both the toposheet and 2021 satellite image. The satellite image was rectified using the total Root Mean Square (RMS) error estimated below one pixel.

The satellite images were pre-processed in ERDAS imagine for geo-referencing, mosaicking and sub-setting of the image on the basis of Area of Interest (AOI) for classification. For image processing and performing supervised classification of the satellite imageries, layer stacking of ERDAS Imagine 14v software was used to convert the bands into a single layer. Then resultant shape-file of the study area produced through delineation process was used to clip the imageries using ArcGIS 10.2.2. The clipped ~~were~~ images were then re-projected to Universal Transverse Mercator (UTM) and resampled to 30m spatial resolution. The overall objective of the image classification procedure is to automatically categorize all pixels in an image into land cover classes or themes. 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 (Anderson et al., 2002). For each of the predetermined classes, polygons were drawn around representative sites which described minimal confusion among the land covers to be mapped. The maximum likelihood algorithm was used for supervised classification of the imagery.

Comment [AC15]: Mention UTM zone and WGS

Comment [AC16]: If the spatial resolution of the images is uniformly 30m, therefore, what is need to resample to 30m??

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). Kappa statistics along with total accuracy of the classified images were also performed to measure the extent of classification accuracy from the report section of ERDAS Imagine 14v.

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Classification accuracy assessment

After generating the classified images, the accuracy of the classified images was determined using the ERDAS Imagine 14 software. Classification accuracy assessment is an essential step after image classification. The accuracy assessment tool of the supervised classifier randomly generated reference points through stratified random sampling of the classified images. Each point had a specific color and pixel value, which were automatically identified by the software. The classes in the classified image were considered as reference classes. The randomly-generated points were then identified, and the corresponding class was assigned by the user manually. The error matrix and kappa statistics for the two classified images were generated from the self-generated report section of ERDAS Imagine 14. The rows of the matrix represent the classes resulting from the classified image, whereas the columns represent the classes identified by the user from the reference values. The diagonal cells of the error matrix indicate the total number of correctly identified pixels for each class of the reference and classified data. The off-diagonal cells represent the incorrectly identified pixels, which indicate the error between reference data and classified data.

RESULTS AND DISCUSSIONS

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 expansion of the built up area 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~~ as the capital seat of Abia state created in 1991. It is well known that urban growth promote massive development in built-up infrastructure (Abass et al., 2010; Screenivasulu and Bhaskar, 2010; Hassan and Nazem, 2015).

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.

Comment [AC18]: It contradicts each other, check it

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 bare land LUC was 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.

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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.

Foody (2002) has shown that the most common method of performing classification accuracy assessment for any application of remote sensing is creating an error matrix. In this study, an error matrix was generated to evaluate the produced LUC maps resulting from the integration of visual interpretation with the classification results. 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.

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 this in turn could ~~go a long way in~~ promot~~ing~~ climate change mitigation in long term period, as well as human health and comfort in the town. It ~~Is quite~~is quite obvious that though urbanization remains a key driver of LUC changes as it is taking over agricultural and forest lands, it ~~is~~ 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 that boost development in urban woodlands. Studies are ~~particularly~~ needed particularly to monitor soil health and quality in the study area to develop mitigation and ameliorative measures towards controlling water pollution levels and other negative environmental impacts of urban growth.

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Table 1: LUC statistics for the various years

LUC Type	Area in Km² and % for each year							
	1991		2001		2011		2021	
	Km²	%	Km²	%	Km²	%	Km²	%
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: LUC 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. Km²	P.C. %	Diff. Km²	P.C. %	Diff. Km²	P.C. %	Diff. Km²	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

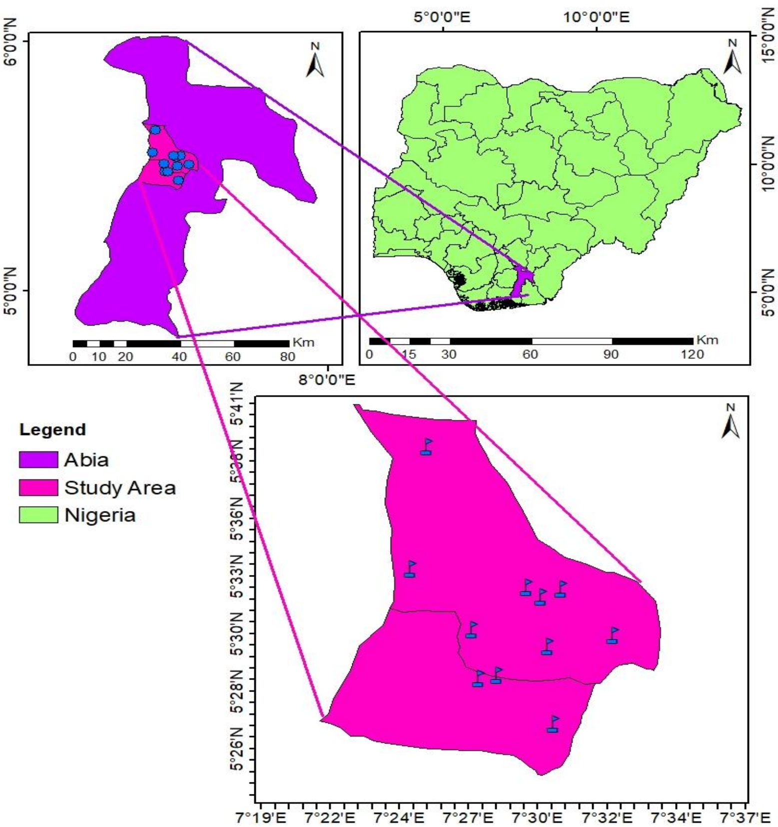

Figure 1: The study area

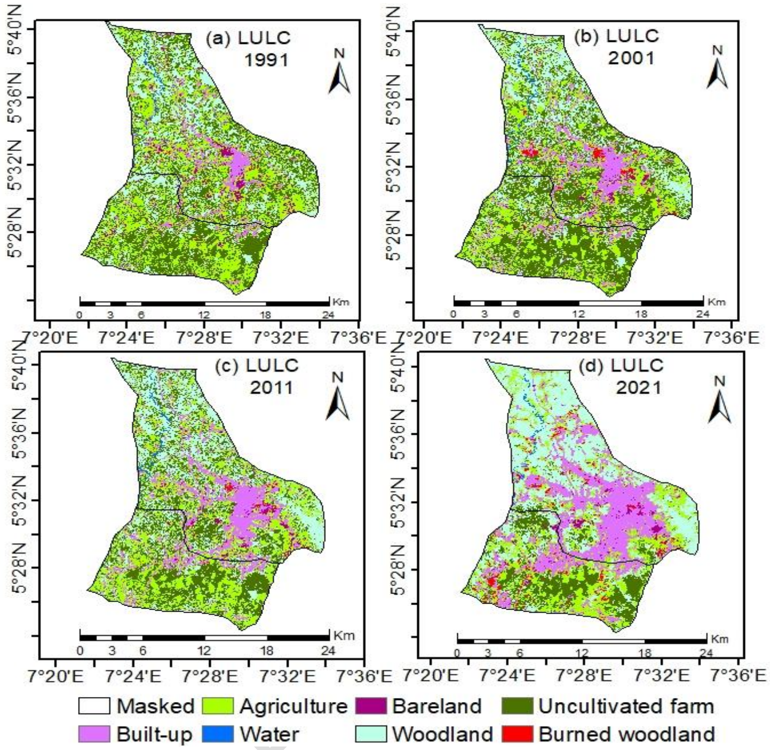

Figure 2: Distribution of the mapped LUC for the years 1991, 2001, 2011 and 2021