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Investigating Impacts of Urbanization on Agricultural Land in Ikwerre L.G.A., Rivers State Nigeria

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Abstract
Agricultural lands from which food are being produce are regularly threatened by urban expansion. They are degraded by construction of roads, buildings, bridges, railways, airport, terminals, and recreational centers to mention a few. Soil compaction by construction activities destroyed soil fauna and flora available to enhanced productivity of agricultural land. Knowledge of the location and extent of agricultural land in a region is required for possible land planning and management. This paper applied remote sensing and GIS tools to aggregate available agricultural land use and the extent of impacts by urban development in Ikwerre L.G.A., Rivers State, Nigeria. The study adopted supervised classification to derived land use/ cover categories and NDVI to analyzed impact of urbanization on agricultural land use. Land use/ cover categories identified and classified on the remotely sensed Landsat image are water body, built-up, vegetation, wetland and palm tree. Similarly, NDVI maps were classified into five classes to represents land use/ cover types. The study observed increase in urban development and decrease in agricultural land use from 2000 to 2021. Urban expansion increased by 4300.83ha while agriculture land use decreased by 8870.58ha. Also, the maximum NDVI value in 2000 was 0.50 but decreased to 0.30 in 2021, indicating decrease in photosynthetic capability of the leaves due to loss of agriculture land by urban development. Further study should include others vegetation indices in the mapping of agriculture land use.

Keywords: *Agricultural land, Ikwerre L.G.A., Land use/ land cover, NDVI, Supervised classification, Urbanization*

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I. Introduction

Land is a free gift of nature used for cultivation and human settlement. It is an interactive point of biotic and abiotic components of the ecosystem. Land is a delineanable area of the earth's terrestrial surface, embracing all attributes of the biosphere immediately above or below this surface, and also includes soil and terrain, rivers, settlements and animals [1]. The demands for land for cultivation to feed the growing population are on the increase globally. Agricultural land are going to extension in both developed and under developed countries due to urban development. In United State, agricultural land has been converted to urban areas [2]. The conversion is frequent in most metropolitan cities. Also in England, in 2019 over 9.06 million hectares are identified as agricultural land use [3]. They include land used for arable and horticultural crops, grazing land, uncultivated arable land, and grass land. Agricultural land supports the livelihood of the majority of Nigerian population [4]. They are used for the production of food and cash crops in rural and urban areas. Agricultural land is being depleted due to urban expansion created by construction of roads, bridges, railways, estates, residential and industrial buildings, reclamation of wetland, recreational centers etc. Urbanization is the main driver that initiated changes in land use pattern [5] including agricultural land use. According to [6] urbanization leads to reduction of productive agricultural farmlands. In addition, contamination of the soil, water and air are prevalent in urbanized areas which directly or indirectly affecting agricultural land use. According to [7] unregulated conversion of agricultural land to urban can leads to poor yield which can threaten the lives of the rural population. They also observed that urban expansion over agricultural land has increase to 113.32 km2 within the past 13 years in Ethiopia. Also [8] explained the impact of urbanization on agricultural land use in

Nadu, India with a decline in output from 53 per cent in 1950 and 1951 to as low as 16.65 per cent in 2001 and 2002.

Several approaches have been utilized in the characterization and mapping of agricultural land use. Some researchers have demonstrated the use of image classification (supervised or unsupervised) and the applications of vegetation indices (VIs). [9] reviewed the applications of land use/ cover classification and NDVI analysis in identifying agricultural land. The reviews were based on the fact that Landsat data and others satellite datasets can be utilized in mapping agricultural land use. [10] used NDVI computed from Landsat satellite data to map idle (non-productive) from non-idle (productive) agricultural land in Thailand with NDVI value of zero (0) indicates non-productive agricultural land use. Ikwerre is predominantly agrarian tribe of Rivers State and there was no available information on the areal extent and the extent of impact of agriculture land use by urban expansion. This study combined supervised image classification and NDVI analysis to map impact of urbanization on agriculture land for the purpose of agricultural land administration.

1.1 Study Area

Ikwerre Local Governemnt Area, Rivers State, Nigeria is the research location. It is located on latitude 5° 00’ 00”mN – 5° 15’ 00”mN and longitude 6° 45’ 00”mE – 7° 00’ 00”mE in the UTM Zone 32N. It has a total area of 655.71sq.km and total population of 189,726 with its administrative and traditional headquarter’s in Isiokpo. Some semi-urban areas are Igwuruta, Omagwa, Aluu, Isiokpo, and Elele. The demand for land for urbanization in these semi-urban area increases while demand for agricultural land use decline steadily but increases in the rural areas. The inhabitants of Ikwerre are predominantly farmers of various categories. They supply the city with farm produced and other agricultural products and as such effort to identify agricultural land use and the extent of urban encroachment is paramount to this study.

Annual rainfall ranges between 2100mm – 4600mm and mean temperature varies from 30.0°C - 33.0°C [11]. The peak raining season occurred in July while the driest months are January and February each year. Notable land use/ cover in the study area include; buildings including residential and industrial buildings, farmland, roads including dual carriage road like Port Harcourt/ Owerri road, Igwuruta/ Rumuokwrushi road and Igwuruta/ Etche road, major roads, main paths and track roads. Ikwerre was selected for the study because of it contributions to food security of Rivers State, Nigeria.

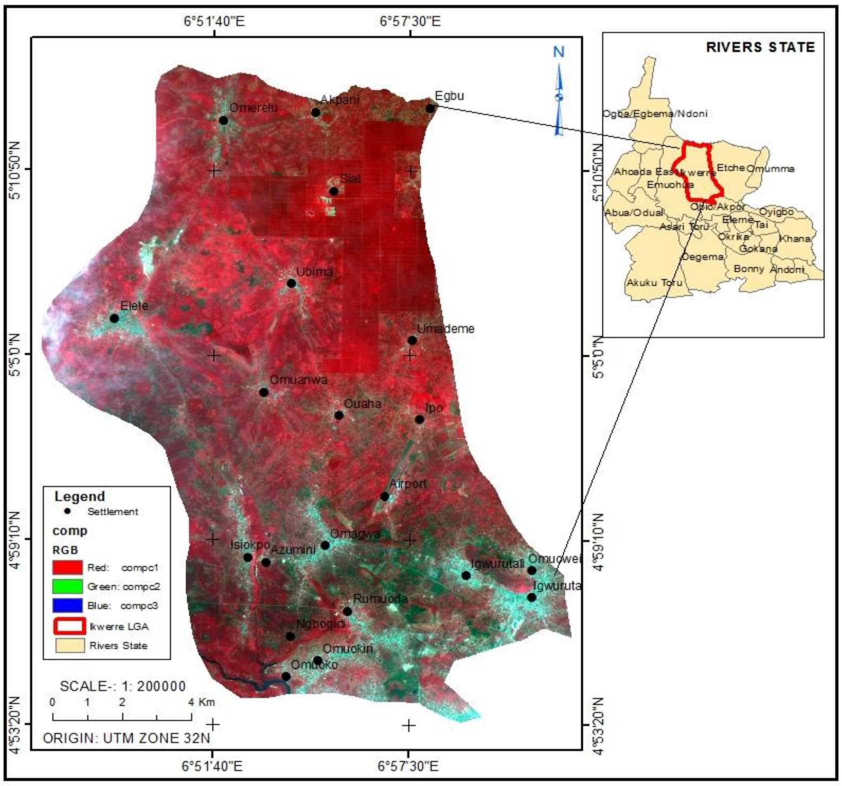

Figure 1.1 Study area map with Rivers State as inset.

2.1 Methodology

The methodology adopted for the study was presented using flow chart in figure 2.1. The dataset used was Landsat images of 2000 and 2021 corrected for radiometric and geometric distortions. The flow chart was divided into two sections, firstly, classification of Landsat data to derived land use/ cover types, secondly, derivation of NDVI. Both results were used for the identification of agriculture land use and impact of urbanization.

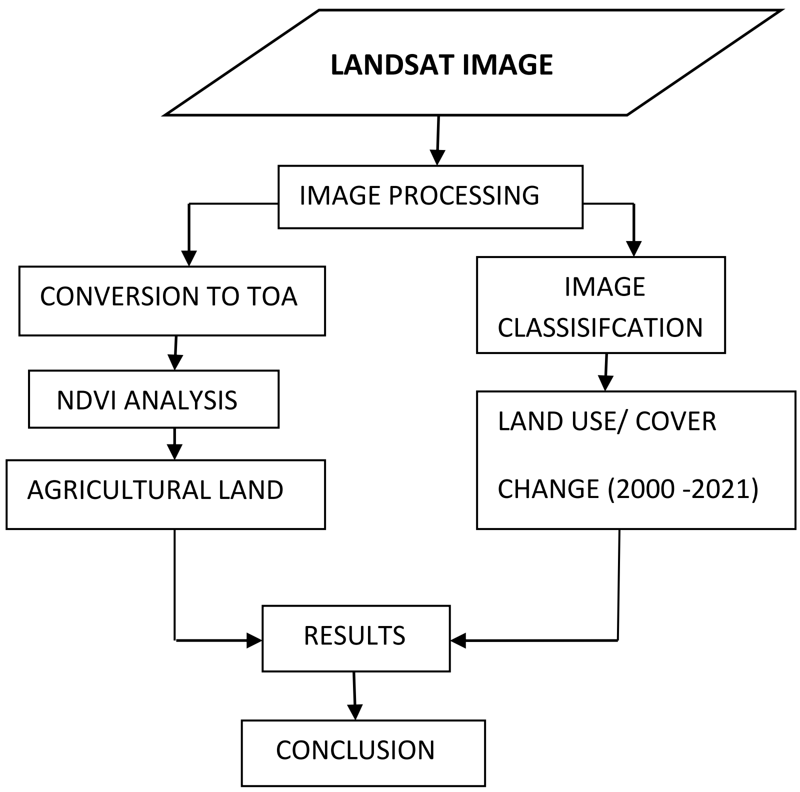

Figure 2.1 Flow chart of the research methodology.

2.2 Dataset and Software

Datasets used for the mapping of agriculture land use are presented in table 2.1. The dataset are mainly from Landsat satellite imagery. Landsat data was selected because it is freely acquired from its website.

Table 2.1 Landsat satellite datasets used for identification of agriculture land use.

Sensor	Path/ Row	Imagery Date	Resolution (m)	Source
Landsat ETM (L7)	188/ 57	17/12/2000	30 x 30	http://glovis.usgs.gov/
Landsat OLI (L8)	188/ 57	18/02/2021	30 x 30	http://glovis.usgs.gov/

Two softwares were used for the processing and analysis of remotely sensed data. Image classification was performed in IDRISI because the software has strength in raster operations. IDRISI TAIGA was developed by Clark University [12]. ESRI's ArcGIS was used for the derivations of NDVI from Landsat data. It was chosen due to the presence of raster calculator that enhances complex raster operations.

2.3 Data Processing

The downloaded Landsat images were the ortho-corrected version which has been corrected for radiometric and geometric distortions [13].The image was clipped to the extent of the study area using shapefile of Ikwerre obtained from the Office of the Surveyor General Rivers State (OSGRV). Image classification was performed in IDRISI TAIGA using Maximum Likelihood Classification (MLC). MLC was selected base on its high accuracy level [14] The image bands used for the study are band 432. The band combination was selected because band 3 is used to monitor vegetation health [15]. During supervised classification minimum of thirty (30) pixels were selected. According to IDRISI user's guide, the minimum pixel selected is given by 10N, where N is the number of bands. The classification scheme adopted was level 1 [16]. The land use/ cover classified are water body, vegetation, built-up, wetland, and palm tree. In addition, classification accuracies were computed for both images (2000 and 2021). Overall kappa was used to compute classification accuracy of the remotely sensed image.

Agricultural land in this study refers to land that can be used for the cultivation of food and cash crops. They include vegetation, wetland, and palm tree. Water body and built-up are non-agricultural land use.

Similarly, Normalized Difference Vegetation Index (NDVI) was also computed in other to determined agricultural land use and to compare the results with that of image classification. NDVI is the most popular vegetation indices used in analysis vegetation health and development [17]. It is based on the absorption of red and infrared electromagnetic spectrum by the plant leaves [18] and was first proposed by Reuse et al., 1974 [19]; [17]. NDVI equation is given by

$$NDVI = \frac{\text{Near infrared} - \text{Red}}{\text{Near infrared} + \text{Red}} \quad \text{-- -----------1}$$

NDVI values ranges from -1 to 1 [20], [17]. Higher NDVI value signifies the presence of healthy vegetation and availability of agricultural land.

Prior to the computation of NDVI, Landsat image was first converted to Top of Atmosphere (TOA) radiance image which represents radiating energy from the earth's surface features. The conversion was performed on both Landsat 8 and 7 and the algorithms are given thus;

For Landsat 8, the equation is given by,

$L_\lambda = M_L \times Q_{cal} + A_L$ -- 2

Where, L_λ is spectral radiance in $Wm^{-2}Sr^{-1}$, M_L is radiance multiplicative scaling factor for the band, Q_{cal} is L1 pixel value in DN and A_L is radiance additive scaling factor for the band [21].The bands equivalent of Red and infrared for Landsat 8 are band 4 and band 5 and they were converted to radiance image using the algorithm.

Similarly, the algorithm for the conversion of raw Landsat 7 to radiance image is giving by

$L_\lambda = (LMAX_\lambda – LMIN_\lambda)/ QCALMAX – QCALMIN \times (DN – QCALMIN) + LMIN_\lambda$ -------------3

Where, $LMAX_\lambda$, is maximum spectral radiance for the band, $LMIN_\lambda$ is minimum spectral radiance for the band, QCALMAX is maximum quantize calculated for the band, QCALMIN = minimum quantize calculated for the band and DN is the pixel DN value [22].

For the Landsat 7, red is band 3 and infrared is band 4 [22]. The computed NDVI map was used to identify agricultural land use. [23] also used NDVI derived from Landsat data to mapped agricultural land in Abia State, Nigeria. [24] used NDVI derived from MODIS data to mapped drought impacted agricultural land in India.

3.1 Results and Discussions

The classification maps identified land use/ cover categories in the area. The results of the classification map for the 2000 was shown in figure 3.1a. Total area of built-up was 3920.85ha wetland 39159.99ha vegetation 11505.15ha water body 1168.85ha and palm tree was 8806.70ha. The percentage of built-up was 6.0% and wetland was 60.9%. Similarly, in 2021 built-up increased to 8221.68ha with percentage of 12.8%. Wetland decreased to 26484.12ha representing 41.2% of the total area. Figure 3.1b shows the classification map of 2021.

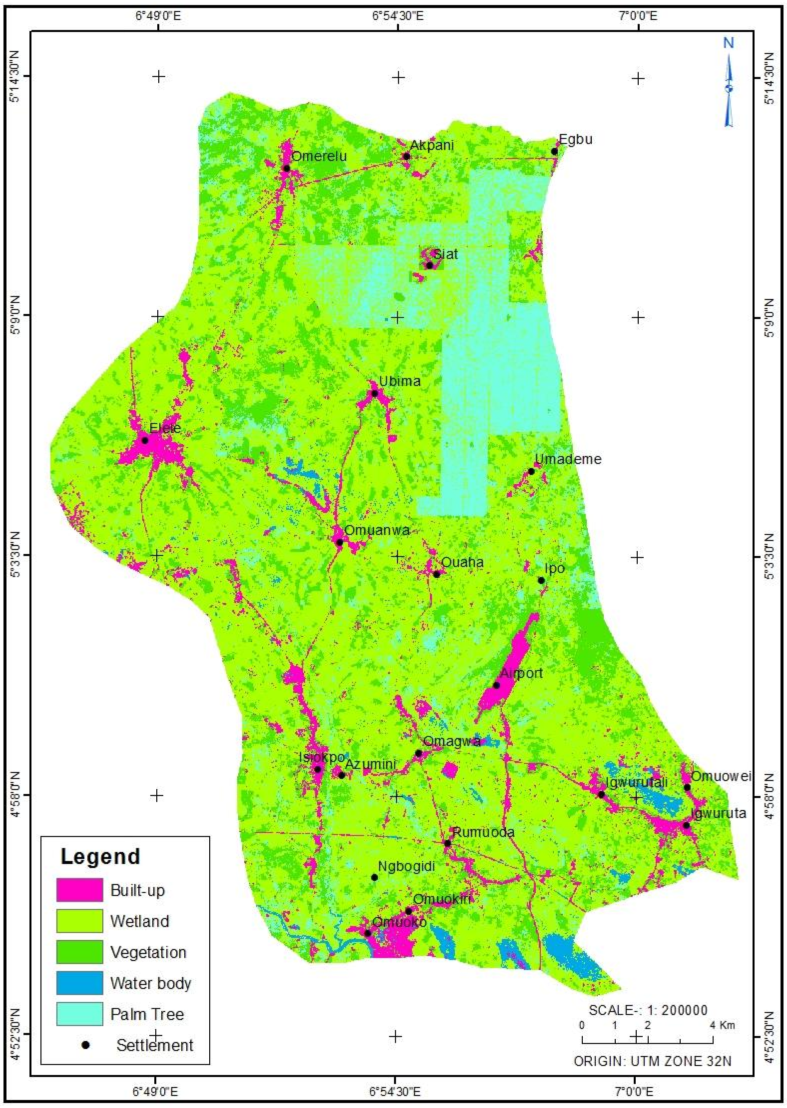

Figure 3.1a Classification map of 2000.

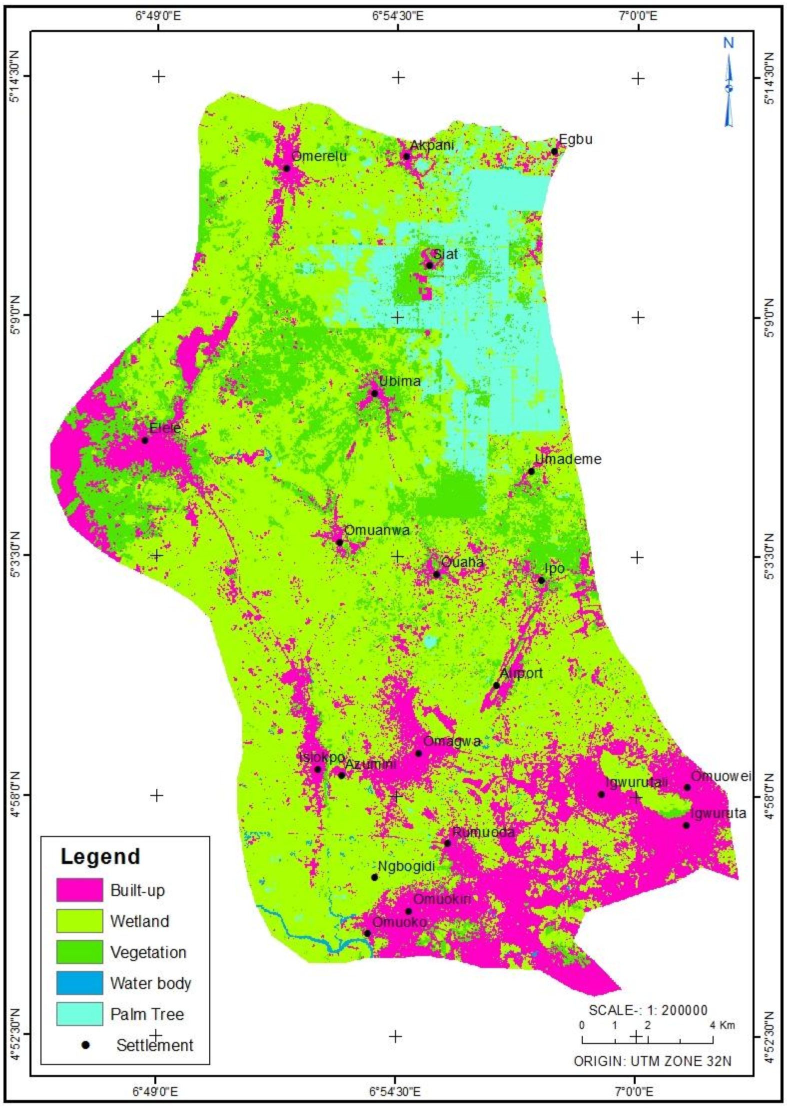

Figure 3.1b Classification map of 2021.

Total area of the classification maps of 2000 and 2021 are presented in table 3.1. The table shows the area of each land use/ cover expressed in hectare and their percentages. Table 3.2 shows the classification accuracy of the image data. It was computed using overall kappa and the results obtained was above the standard of 0.85%. In 2000 the overall kappa was 0.936 and in 2021 it was 0.999.

Table 3.1 Total area per class in land use/ land cover calculated in hectares.

Lulc Type	**2000**		**2021**	
	Area (ha.)	**% (ha.)**	**Area (ha.)**	**% (ha.)**
Built-up	3920.85	6.0	8221.68	12.8
Wetland	39159.99	60.9	26484.12	41.2
Vegetation	11505.15	17.9	12697.65	19.7
Water body	1168.65	1.8	5696.64	8.9
Palm tree	8606.70	13.4	11219.49	17.4
Total	**64261.34**	**100**	**64261.34**	**100**

Table 3.2 Results of the classification accuracy.

Classification Map	Overall Kappa
2000	0.936
2021	0.999

The results of the NDVI maps were also computed and used to investigate agricultural land use in the study. The computed maps were reclassified into five classes ranging from poor to very good agricultural land depending on the range of NDVI value. Figure 3.2a is the NDVI map of 2000 and the value varies from minimum -0.06 to maximum 0.50. The first class ranges from -0.06 to 0.05 and they represent water body - classified here as non-agriculture land. The second class ranges from 0.05 to 0.16, represented by pink and is the built-up areas also non-agriculture land. The third class ranges from 0.16 to 0.27 which represents bare land within neighbourhood of built-up. The fourth and fifth class ranges from 0.27 to 0.38 and 0.38 to 0.50. The fifth class was mostly located outside built-up areas with presence of green and healthy vegetation. They are very good agricultural land use indicated by moderate NDVI values.

Figure 3.2b shows 2021 NDVI map with values varies between minimum -0.16 to maximum 0.30. The first class ranges from -0.16 to -0.07, second class -0.07 to 0.03 representing built-up areas. The third class ranges from 0.03 to 0.12 located in the neigbourhood of built-up. Fourth and fifth class ranges from 0.12 to 0.21 and 0.21 to 0.30 respectively. The fifth class is mostly located within the palm tree plantation in the south-east of the map. NDVI value decreased from maximum 0.50 in 2000 to maximum 0.30 in 2000, indicating decrease in green and healthy agricultural land use.

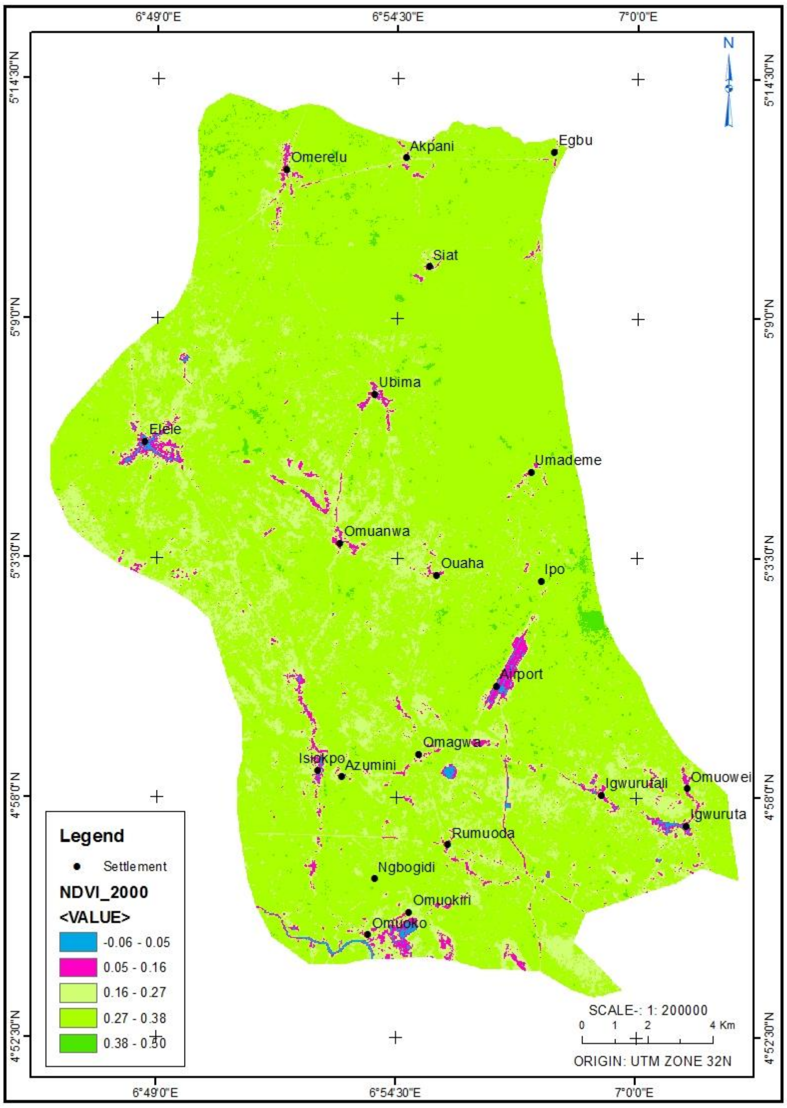

Figure 3.2a NDVI map of 2000.

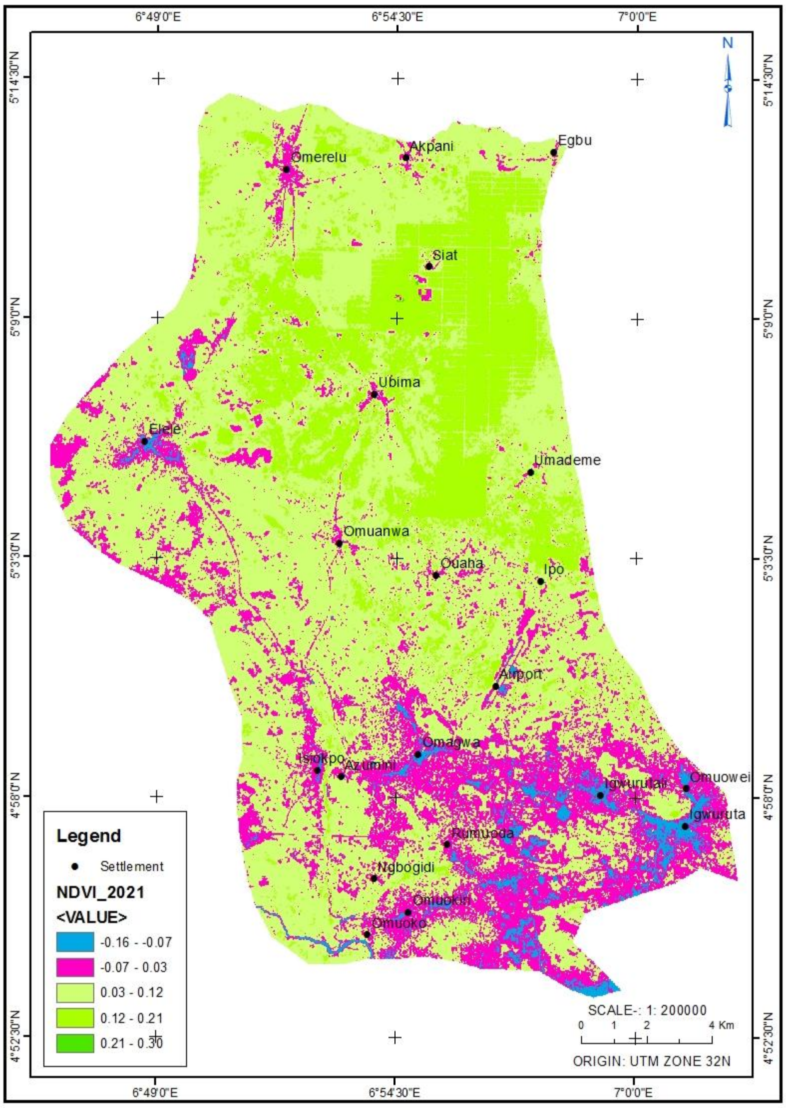

Figure 3.2b NDVI map of 2021.

3.2 Discussions

There was an increase in built-up areas from 2000 to 2021 with total area of increase as 4300.83ha. The increase was more in the southern part, indicating increase in urban development at the expense of agricultural land. As urbanization increase, vegetation and wetland which are agricultural land are decreasing in areal extent. In 2000 map, agricultural lands were available in the southern and northern part of the map but gradually lost due to urban expansion in 2021. This was evidence by aggregating total agricultural land (vegetation, wetland and oil palm) in 2000 to be 59271.84ha but in 2021 it reduces to 50401.26ha. This represents 8870.58ha lost in agricultural land within eleven (11) years. Collaborating the lost in agricultural land using land use/ cover image classification was the NDVI analysis which shows non-agricultural land with decrease NDVI values. In 2000 NDVI map, agricultural land was located in two NDVI ranges. They are 0.27 to 0.38 which are shrubs and meadows and 0.38 to 0.50 which represent tropical forest. [23] in their study identified agriculture land use within NDVI range of 0.45 to 0.55. Over 60 percent of the map in 2000 was potential agricultural land and was located in the south, mostly around Omagwa, Igwuruta and Aluu and in the north around Ubima, Omerelu, Akpani and Siat plantation. In 2021 NDVI map, agricultural land decreased which was evidence by the decrease in NDVI values. The shrubs and meadows are restricted to Siat plantation with NDVI value ranges from 0.21 to 0.30. The reduction in the values of NDVI was an indication of lost of agricultural land due to urbanization. For instance, there was an increase in built-up in 2021 with NDVI value ranges from -0.07 to 0.03 covering large area of the map.

4.1 Conclusion and Recommendation

The degradation and loss of valuable agricultural land are mostly urban driving. Besides lost of agricultural land, urbanization may leads to food insecurity when most of the land available for cultivation has been converted to urban development. It is problems experienced by develop and under develop nations. In a bid to curb food insufficiency, is it necessary to have database of agricultural land use which guarantee land use planning. Ikwerre L.G.A in Rivers State, Nigeria as an agrarian people does not have such database which prompted this study. The study used Landsat satellite data and GIS software (ESRI's ArcGIS 10.3 and IDRISI TAIGA 16.0) to mapped agricultural land using land use/ cover types and NDVI analysis. The study observed that urbanization was the main driver of agricultural land extinction and that the impacts are more in semi-urban and urban than in rural areas. For further study, the numbers of Landsat epoch can be increase from two to four by adding 1980 and 1990. The limitation of the study was the inability to calculate the area of agricultural and non-agricultural land from the NDVI maps.

Disclosure of Conflict of Interest

The authors involved in this articles have unanimously agreed and declared that no conflict of interest with any person or organization.

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