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**Research Article**

# Pixel-based land transformation study in parts of Rivers, Abia and Akwa Ibom States, Nigeria

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## Abstract

The geospatial technology remains the essential tool for environmental studies, monitoring and mapping. Since land transformation is locational based such land use and land cover (LULC) changes over time could be affected another, hence the need for effective monitoring of these changing land cover types becomes relevant. This study is aimed at Pixel based land transformation study in parts of Rivers, Abia and Akwa Ibom States using medium resolution satellite datasets. For this purpose, land use classification and change detection mapping method were adopted using LANDSAT datasets from two different sensors were processed using spatial analysis tool of resampling, general enhancement, classification and post classification overlay to map the pattern and extent of land transformation for the study area as well as to determine the magnitude of seasonal epochal changes between December 2003 and January 2022. A supervised LULC classification for the studied area using seven classes' namely built-up, bare earth, water body, marine vegetation, other vegetation, plantation and void. A pixel-based cross tabulation was extracted from LULC class pairings for both dates. The kappa coefficients; 0.9824 and 0.9997 for both datasets shows classes that have increased from 2003 to 2022 such as built-up areas 476.00km$^2$ to 820.67 km$^2$; plantation from 1263.90km$^2$ to 4026.55 km$^2$; water body from 3187.14 km$^2$ to 3544.87 km$^2$ and void from 118.56 km$^2$ to 128.60 km$^2$. Similarly, others classes experienced continuous shrinkage such as other vegetation from 2921.18km$^2$ to 763.05km$^2$; marine vegetation from 3353.78km$^2$ to 2110.98km$^2$; bare earth from 87.69sq.km to 23.53km$^2$. From the epochal analyses of deliverables such as land use land cover, it could be inferred that Port Harcourt capital city and Aba metropolis are experiencing radial urban growth over a period of 18 years. However, urban growth should be adequately monitored, mitigating the effect of urbanizing more rural lands.

**Keywords:** Change, Pixel-based, Supervised, Transformation

## Introduction

Remote sensing provides reliable scientific tools for the monitoring and measuring land use land cover transformation using temporal satellite datasets and studying the multispectral space (Bhatta, et al., 2010; Orji and Pepple, 2015; Lechner, et al., 2020). As Remotely sensed data is mostly available in a digital form, computer-assisted interpretation and processing is made. Rimal (2011) identified that irrespective of the specific form in which remotely sensed datasets are obtained, manual data interpretation could be tedious, time-consuming, and in most case dependent on knowledge of the analyst (Barnes et. al, 2001; Prenzel, 2004; Lui and Mason, 2009). By comparison, supervised classification is much faster and requires far lesser amount of human intervention (Story and Congalton, 1986; Ramankutty et. al, 2005; Bhatta, 2009). Lo and Noble (1990) found that a computer-assisted method of analysis of LANDSAT data permits more detailed urban land use information to be extracted, but at an accuracy level of 69% (Zha et al., 2005).

LULC change detection allows for the identification of major processes of change and by inference, the characterization of land use dynamics (Bhatta, 2009). Land-use denotes how human use the biophysical and ecological properties of land (Singh, 1989). It is also seen as the modification or management of land for agriculture, settlement, forestry and other uses including those that exclude human from land as in the designation of nature reserve for conservation (Fazal, 2009). Land use is the function of land, how lands are managed, controlled and regulated which depend upon the land use act of a place. LULC change has been described as the most significant regional anthropogenic disturbance to the environment (Roberts *et. al*, 1998). Land cover refers to the physical material on the surface of the earth; it refers to the vegetation, water, bare rocks, sand, and similar surface and also manmade construction on the earth surface (Lui and Mason, 2009). It should be noted that different LULC classes are continually transformed by land use changes, suggesting that land use is the cause of LULC change and the underlying driving forces remain economical, technological, institutional, and demographical (De-Sherbinin, 2002).

The economic value of land is an important and key factor in sustainable land marketing and information management strategies. Hence, LULC changes are products of prevailing interaction of changes in the physical environment. Therefore, the application of GIS using remotely sensed data for change detection analysis of the study area would definitely enhance effective land monitoring and mapping LULC changes (Esetlili etr al., 2018). Thus, the purpose of this study is to provide a simple application method employing a pixel-based land transformation that can be used in identifying epochal urban expansion, pattern and magnitude of changing LULC classes.

The study presents a thematic map that shows forty-one (41) land transformation class pairings from two epochs of 18years spacing. Based on the results obtained the direction of urban growth and the size such growth can be examined. The objectives of this study are as follows:

1. Identification and Mapping of different LULC classes of the study area.
2. Monitoring LULC changes over a period of 18 years of the study area.
3. Estimating coverages of paired land transformations of the study area.

The study areas physical boundaries lie between (260292 - 378415) metres East and (550995 - 444210) metres North on the Universal Traverse Mercator (UTM) projected coordinate system which covers an approximate area of $12,614km^2$. Having Port Harcourt City as its administrative capital of Rivers State, Nigeria which lie in central part of the state. Port Harcourt City is the core of the state and having oil and gas resources within her territorial space. The study area as shown in figure 1 includes all of Port Harcourt, Obio/ Akpor, Oyigbo, Tai, Eleme, Gokana, Khana, Opobo/ Nkoro, Andoni, Bonny, Okrika, Ogu/ Bolo, Degema, Akuku Toru, and parts of Asari Toru, Abua/ Odual, Emouha, Ahoada East, Ikwerre, Etche and Omuma local government areas of Rivers State.

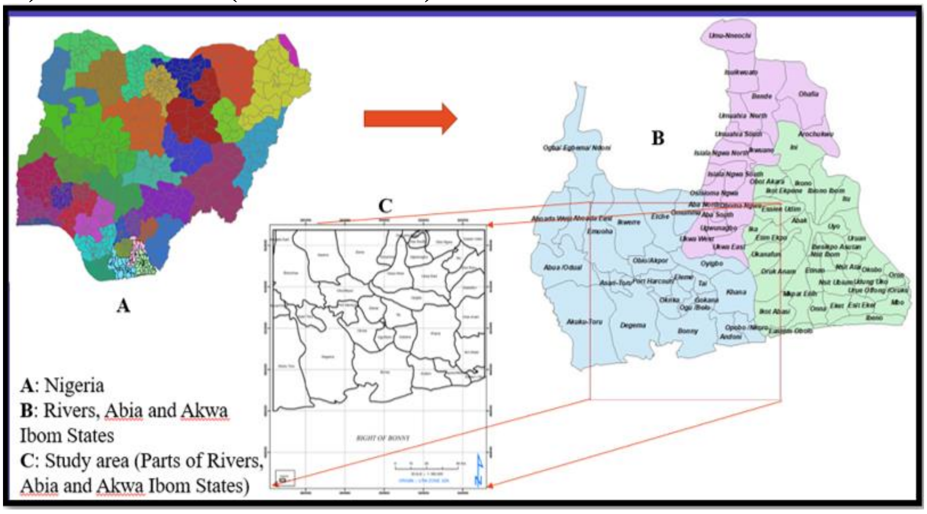


Fig. 1: The study area.

Table 1: Quad-resolution parameters for Path 188 and Row 057 datasets.

| S/N | Platform/ Sensor | Acquired Date (d-m-y) | Temporal separation (y, m, d) | Seasonal Difference (Days) | Temporal Spacing (Days) |
|---|---|---|---|---|---|
| 1 | L7/$ETM^+$ | 17/12/2003 | | | |
| 2 | L8/OLI | 4/01/2022 | 18, 0 & 18 | 18 | 6593 |

The study area includes all of Ukwa East, Ukwa West, Ugwunagbo, Aba South, Aba North and parts of Osisioma Ngwa, Obio Ngwa LGA of Abia State and lastly, Ika LGA and parts of Essien Udim, Etim Ekpo, Ukanafun, Oruk Anam, Ikot Abasi and Eastern Obolo of Akwa Ibom State**.** The distance between Port Harcourt and Aba is approximately 65km as such Aba is predominantly a commercial town that has undergone rapid expansion during the last decade. Topology has been largely responsible for the present shape of Port Harcourt City constraining its growth northwards. Only now, as the landward side of the swamp are being reclaimed thresholding alternative physical opportunities for the town's growth along its coastal fringes.

**Materials and Methods**

Research questions focusing on change and variability require relatively high spatial resolution datasets. Landsat datasets utilized are a standard data for earth observations with an approximate scene size of 170 km north-south by 183 km east-west. Thus, the study used two Landsat datasets, see Table 1 and other in-situ datasets to provide apriori information about the study area. The software's used for this study are ERDAS ER Mapper for data pre-processing, ENVI 4.5 for processing and LULC classifications, and Arc GIS 10.3 for spatial analysis and data presentation. Using spatial and non-spatial datasets, the study integrated remote sensing, geographical information systems and statistical techniques to derive information on LULC and its transformation. Verification of the aforementioned result was possible using coordinate of selected points interest during field completion exercise. The temporal separation is 18 years and 18 days that is an equivalent of 6593 days with both datasets having a spatial resolution of 15m.

**Methods**

**Data Pre-processing and Processing**

The study area was clipped out from the stalked bands of the image scenes and the image was processed for further analysis by projecting to World Geodetic System (WGS) 1984. $ETM^+$ bands (1 to 5, 7 and 8) and OLI/TIRS bands (1 to 9) stacked to form multi-spectral image set were pre-processed using ERDAS ER Mapper and further resampled to a 15m resolution using the panchromatic band (band 8) so as to enhance the resolution of the data. The study identified and matched twenty-four (24) control points (GCPs) on raw data approximately six for each year under review. The brightness value of the Landsat images was enhanced by the balanced contrast enhancement technique (BCET). The BCET technique that matches histogram was adopted for this study because of its flexibility and better output over similar techniques.

**Estimating LULC transformation**

To achieve the aforesaid Land Use Land Cover Classification (LULC) and Change Detection or transformation, the datasets used for the study were carefully inspected taking into consideration their resolutions and minimum mapping unit (Lillesand and Kiefer, 1994). The modified US Geological Survey Classification System was adopted and a supervised classification was carried out on the LANDSAT datasets for seven classes namely built-up, bare earth, water body, marine vegetation, other vegetation, plantation and void. Statistics for 2003 and 2022 were generated based on the LULC classes and maps of change detection were generated for further analysis.

## Results

### Results of objective One

***Identification and Mapping of different LULC classes of the study area.***

The modified US Geological Survey Classification System was adopted and a supervised classification was carried out on the LANDSAT datasets for seven classes namely built-up, bare earth, water body, marine vegetation, other vegetation, plantation and void.

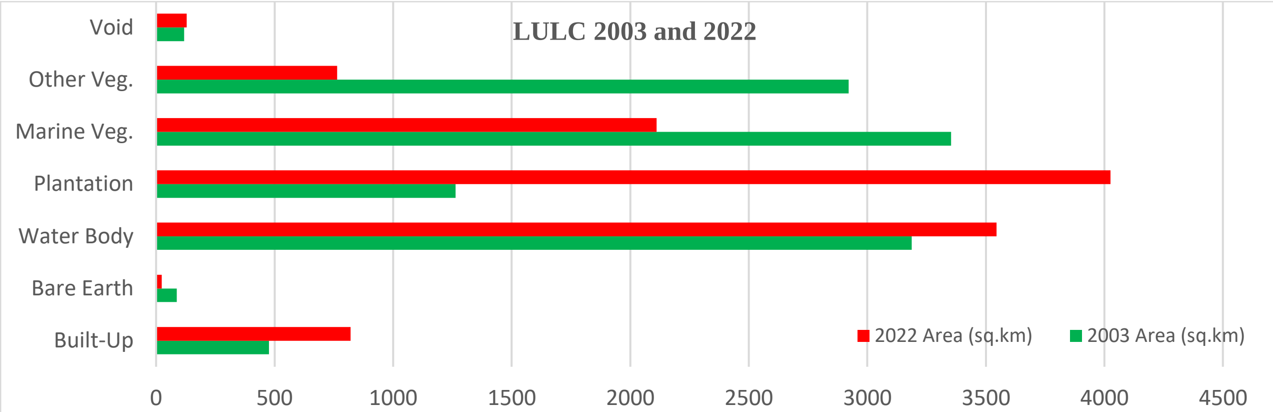


Fig. 2: Cross Classification chart for 2003 and 2022

Table 2: Legend and title of LULC

| Class ID | Colour | Class Code | Class Name |
|---|---|---|---|
| 1 | R | BU | Built-Up |
| 2 | G | BE | Bare Earth |
| 3 | B | WB | Water Body |
| 4 | Y | OV | Other Vegetation |
| 5 | C | MV | Marine Vegetation |
| 6 | M | PL | Plantation |
| 7 | BL | VD | Void |

*Where R = Red, G = Green, B = Blue, Y = Yellow, C = Cyan, M = Magenta and BL = Black*

Table 3: LCLU summary for 2003 and 2022 with change rate and directional remark.

| S/N | LCLU Class | Classified 2003 (C1) | | Classified 2022 (C2) | | Difference | | Remarks |
|---|---|---|---|---|---|---|---|---|
| | | Area (Km²) | Area (%) | Area (Km²) | Area (%) | C2 - C1 (Km²) | Annual Change rate (Km²) | |
| 1 | Built-Up | 475.997 | 4.169 | 820.670 | 7.187 | 344.673 | 19.149 | Gain |
| 2 | Bare Earth | 87.691 | 0.768 | 23.531 | 0.206 | -64.160 | -3.564 | Loss |
| 3 | Water Body | 3187.138 | 27.913 | 3544.871 | 31.046 | 357.733 | 19.874 | Gain |
| 4 | Plantation | 1263.903 | 11.069 | 4026.552 | 35.264 | 2762.649 | 153.481 | Gain |
| 5 | Marine Veg. | 3353.781 | 29.372 | 2110.975 | 18.488 | -1242.806 | -69.045 | Loss |
| 6 | Other Veg. | 2921.182 | 25.583 | 763.051 | 6.683 | -2158.132 | -119.896 | Loss |
| 7 | Void | 128.559 | 1.126 | 128.601 | 1.126 | 0.042 | 0.002 | Gain |
| | Total | 11418.250 | 100.000 | 11418.250 | 100.000 | 0.000 | 0.000 | |

Tables 3 and 4 shows the interpretative legend that shows clearly the class identities (1, 2, 3, 4, 5, 6, and 7), class codes (BU, BE, WB, OV, MV, OL and VD) and class names (Built-Up, Bare Earth, Water Body, Other Vegetation, Marine Vegetation, Plantation and Void).

### Results of Objective Two

***Monitoring LULC changes over a period of 18 years.***

Table 3 shows statistics for 2003 and 2022 where Built-Up changed from 475.997km$^2$ to 820.670km$^2$ in 2003 - 2022 with a 344.673km$^2$ change to its area extent with an annual change rate 19.149km$^2$ having a class gain inference. Bare Earth also changed from 87.691km$^2$ to 23.531km$^2$ in period under review with a -64.160km$^2$ change to its area extent with an annual change rate -3.564km$^2$ having an inference of a class loss. Water body changed from 3,187.138km$^2$ to 3,544.871km$^2$ in 2003 and 2022 with a class change of 357.733km$^2$, annual rate of change of 19.874km$^2$ having a class gain inference.

Furthermore, other notable changes were observed and recorded as follows; Plantation from 1,263.903sq.km to 4,026.55sq.km with a 2,762.649km$^2$ change to its area extent with an annual change rate 153.481km$^2$ having a class gain inference, Marine vegetation class changed from 3,353.781sq.km to 42,110.98sq.km with a -1,242.806km$^2$ change to its area extent with an annual change rate -69.045km$^2$ having a class loss inference.

Lastly, other vegetation class changed from 2,921.182sq.km to 763. 05sq.km with a -2,158.132km$^2$ change to its area extent with an annual change rate -119.896km$^2$ having a class loss inference while Void class changed from 128. 559 km$^2$ to 128. 60 km$^2$ for 2003 and 2022 with a 0.042km$^2$ change to its area extent with an annual change rate 0.002km$^2$ having a class gain inference.

**Results of objective Three**

***Estimating coverages of paired land transformations of the study area.***

Table 4 shows the output cross table statistics after generating the land transformation output for the pair datasets, sequel to this change map was generated for 2003 and 2022 datasets. A total of forty-one (41) class pairings were retrieved from a possible forty-nine (49) parings, if all class pairings exist. Column one (1) indicating the serial number of the class pairing, column two (2) shows the corresponding coverage in square kilometres and column three (3) shows the corresponding pairing use in estimating coverages of paired transformations such as same class, grouped class and no change class parings.

Table 4: Cross-table area statistics for 2003 and 2022

| S/No | Coverage (Sq.km) | Parings |
|---|---|---|
| 01 | 273.3696000 | 1 \| 1 |
| 02 | 8.9820000 | 2 \| 1 |
| 03 | 49.8843000 | 3 \| 1 |
| 04 | 92.2680000 | 4 \| 1 |
| 05 | 230.6484000 | 5 \| 1 |
| 06 | 165.5172000 | 6 \| 1 |
| 07 | 6.9327000 | 1 \| 2 |
| 08 | 1.2681000 | 2 \| 2 |
| 09 | 1.0611000 | 3 \| 2 |
| 10 | 3.4326000 | 4 \| 2 |
| 11 | 6.1983000 | 5 \| 2 |
| 12 | 4.6377000 | 6 \| 2 |
| 13 | 80.3862000 | 1 \| 3 |
| 14 | 10.3005000 | 2 \| 3 |
| 15 | 3142.6056000 | 3 \| 3 |
| 16 | 12.7530000 | 4 \| 3 |
| 17 | 270.4419000 | 5 \| 3 |
| 18 | 27.7200000 | 6 \| 3 |
| 19 | 0.6633000 | 7 \| 3 |
| 20 | 54.1287000 | 1 \| 4 |
| 21 | 41.9265000 | 2 \| 4 |
| 22 | 0.2241000 | 3 \| 4 |
| 23 | 939.2076000 | 4 \| 4 |
| 24 | 897.6978000 | 5 \| 4 |
| 25 | 2093.3676000 | 6 \| 4 |
| 26 | 57.2832000 | 1 \| 5 |
| 27 | 17.4465000 | 2 \| 5 |
| 28 | 3.2382000 | 3 \| 5 |
| 29 | 34.8975000 | 4 \| 5 |
| 30 | 1831.5468000 | 5 \| 5 |
| 31 | 166.5630000 | 6 \| 5 |
| 32 | 3.8961000 | 1 \| 6 |
| 33 | 7.7670000 | 2 \| 6 |
| 34 | 179.9199000 | 4 \| 6 |
| 35 | 111.3282000 | 5 \| 6 |
| 36 | 460.1394000 | 6 \| 6 |
| 37 | 0.1242000 | 3 \| 7 |
| 38 | 1.4247000 | 4 \| 7 |
| 39 | 5.9193000 | 5 \| 7 |
| 40 | 3.2373000 | 6 \| 7 |
| 41 | 117.8955000 | 7 \| 7 |

**Discussion and Conclusion**

The resultant effect of land transformation changes has been documented by human activities in the study area over the last decade due to increase in built up areas, industrial settlements and other urban land practices.Figure 3 shows land transformation map for 2003 and 2022 were generated based on the LULC classes and change detection analysis.

Table 5 shows same class pairings such as 1/1, 2/2, 3/3, 4/4, 5/5, 6/6, and 7/7 implies that no change was recorded for such class matching of the both dates. Thus, the figure shows the extent of same class Pairing and their corresponding coverage reveals that Water Body/ Water Body (3/3) had the highest coverage of 3,142.606km$^2$ followed by Marine Vegetation/ Marine Vegetation (5/5) with 1,831.547km$^2$, Other Vegetation/ Other Vegetation (4/4) with a total of 939.208km$^2$, Plantation/ Plantation (6/6) with 460.139km$^2$, Built-Up/ Built-Up (1/1) with 273.370km$^2$, Void/ Void (7/7) with 117.896km$^2$ and Built-Up/ Built-Up (2/2) which occupies the lowest geographical extent of 1.268km$^2$. Similarly, Table 6 shows the missing class pairing and it indicates that class 3 (Water Body) has no missing class, all other classes have one missing class except column 6 (Other Vegetation) and 7 (Void) that have two (2) missing class.

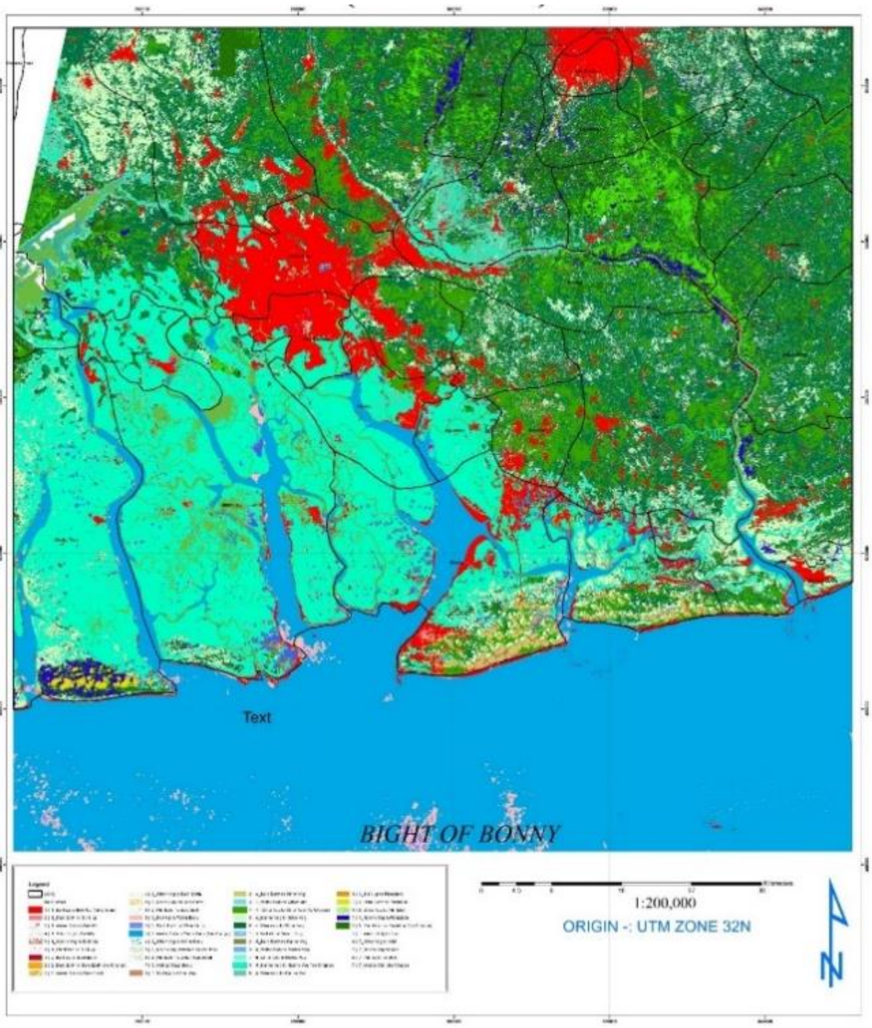


Fig. 3: Cross Classification Output of 2003 and 2022

Table 5: Same class Pairing

| Class ID | Pair ID | Class Name Paring | Area (km²) |
|---|---|---|---|
| 1 | 1/1 | Built-Up/ Built-Up | 273.370 |
| 2 | 2/2 | Bare Earth/ Bare Earth | 1.268 |
| 3 | 3/3 | Water Body/ Water Body | 3,142.606 |
| 4 | 4/4 | Other Veg./ Other vegetation | 939.208 |
| 5 | 5/5 | Marine Veg./ Marine vegetation | 1,831.547 |
| 6 | 6/6 | Plantation/ Plantation | 460.139 |
| 7 | 7/7 | Void/ Void | 117.896 |

Table 6: Missing class Pairing

| S/No | Class ID | Class Name | Pair ID | Class Name Pairing |
|---|---|---|---|---|
| 1 | 1 | Built-Up | 7/1 | Void/ Built-Up |
| 2 | 2 | Bare Earth | 7/2 | Void/ Bare Earth |
| 3 | 4 | Other Veg. | 7/4 | Void/ Other Vegetation |
| 4 | 5 | Marine Veg. | 7/5 | Void/ Marine Vegetation |
| 5 | 6 | Plantation | 3/6 | Water Body/ Plantation |
| 6 | 6 | Plantation | 7/6 | Void/ Plantation |
| 7 | 7 | Void | 1/7 | Built-Up/ Void |
| 8 | 7 | Void | 2/7 | Bare Earth/ Void |

Table 7 shows the rate at which changes occurred within the Built-Up grouped class pairings, it was revealed that Marine Vegetation/ Built-Up (5/1) had the highest transformation with a total of 230.638km$^2$ followed by Plantation/ Built-Up (6/1) with a total of 165.517km$^2$, Other Vegetation/ Built-Up (4/1) with a total of 92.268km$^2$, Water Body/ Built-Up (3/1) with a total of 49.884km$^2$ and Bare Earth/ Built-Up (2/1) which has the lowest transformation of 8.982km$^2$ in coverage.

Table 7: Built-Up grouped class Pairing

| Class 1 | Pair ID | Class Name Pairing | Area (km²) |
|---|---|---|---|
| Built-Up | 2/1 | Bare Earth/ Built-Up | 8.982 |
| | 3/1 | Water Body/ Built-Up | 49.884 |
| | 4/1 | Other Vegetation/ Built-Up | 92.268 |
| | 5/1 | Marine Vegetation/ Built-Up | 230.638 |
| | 6/1 | Plantation/ Built-Up | 165.517 |
| | | **Total** | **547.299** |

Table 8: Bare Earth grouped class Pairing

| Class 2 | Pair ID | Class Name Pairing | Area (km²) |
|---|---|---|---|
| Bare Earth | ½ | Built-Up/ Bare Earth | 6.933 |
| | 5/2 | Marine Vegetation/ Bare Earth | 6.198 |
| | 6/2 | Plantation/ Bare Earth | 4.638 |
| | 4/2 | Other Vegetation/ Bare Earth | 3.433 |
| | 3/2 | Water Body/ Bare Earth | 1.061 |
| | | **Total** | **22.263** |

Table 9: Water Body grouped class Pairing

| Class 3 | Pair ID | Class Name Pairing | Area (km²) |
|---|---|---|---|
| Water Body | 1/3 | Built-Up/ Water Body | 80.386 |
| | 4/3 | Other Vegetation/ Water Body | 12.753 |
| | 5/3 | Marine Vegetation/ Water Body | 270.442 |
| | 6/3 | Plantation/ Water Body | 27.720 |
| | 7/3 | Void/ Water Body | 0.663 |
| | | **Total** | **391.964** |

Table 10: Other Vegetation grouped class Pairing

| Class 4 | Pair ID | Class Name Pairing | Area (km²) |
|---|---|---|---|
| Other Vegetation | 1/4 | Built-Up/ Other Vegetation | 54.129 |
| | 2/4 | Bare Earth/ Other Vegetation | 41.927 |
| | 3/4 | Water Body/ Other Vegetation | 0.224 |
| | 5/4 | Marine Vegetation/ Other Vegetation | 897.698 |
| | 6/4 | Plantation/ Other Vegetation | 2093.368 |
| | | **Total** | **3087.346** |

Table 11: Marine Vegetation grouped class Pairing

| Class 4 | Pair ID | Class Name Pairing | Area (km²) |
|---|---|---|---|
| Marine Vegetation | 1/5 | Built-Up/ Marine Vegetation | 57.283 |
| | 2/5 | Bare Earth/ Marine Vegetation | 17.447 |
| | 3/5 | Water Body /Marine Vegetation | 3.238 |
| | 4/5 | Other Veg./ Marine Vegetation | 34.898 |
| | 6/5 | Plantation/ Marine Vegetation | 166.563 |
| | | **Total** | **279.429** |

Table 8 shows the transformation within the Bare Earth grouped class pairings, it was revealed that Built-Up/ Bare Earth (1/2) had the highest transformation with a total of 6.933km$^2$ followed by Marine Vegetation/ Bare Earth (5/2) with a total of 6.198km$^2$, Plantation/ Bare Earth (6/2) with a total of 4.268km$^2$, Other Vegetation/ Bare Earth (4/2) with a total of 3.433km$^2$ and Water Body/ Bare Earth (3/2) which has the lowest transformation of 1.061km$^2$ in terms of the geographical extent occupied.

Table 9 shows the transformation within the Water body grouped class pairings, it was revealed that Marine Vegetation/ Water Body (5/3) had the highest transformation with a total of 270.442km$^2$ followed by Built-Up/ Water Body (1/3) with a total of 80.386km$^2$, Plantation/ Water Body (6/3) with a total of 27.720km$^2$, Other Vegetation/ Water Body (4/3) with a total of 12.753km$^2$ and Void/ Water Body (7/3) which has the lowest transformation of 0.663km$^2$ in terms of the geographical space occupied.

Table 10 shows the transformation within the Other Vegetation grouped class pairings, it was revealed that Plantation/ Other Vegetation (6/4) had the highest transformation with a total of 2,093.368km$^2$ followed by Marine Vegetation/ Other Vegetation (5/4) with a total of 897.698km$^2$, Built-Up/ Other Vegetation (1/4) with a total of 54.129km$^2$, Bare Earth/ Other Vegetation (2/4) with a total of 41.927km$^2$ and Water Body/ Other Vegetation (3/4) which has the lowest transformation of 0.224km$^2$ in terms of the geographical extent occupied.

Table 11 shows the transformation within the Marine Vegetation grouped class pairings, it was revealed that Plantation/ Marine Vegetation (6/5) had the highest transformation with a total of 166.563km$^2$ followed by Built-Up/ Marine Vegetation (1/5) with a total of 57.238km$^2$, Other Vegetation/ Marine Vegetation (4/5) with a total of 34.898km$^2$, Bare Earth/ Marine Vegetation (2/5) with a total of 17.447km$^2$ and Water Body/ Marine Vegetation (3/5) which has the lowest transformation of 3.238km$^2$ in terms of the geographical extent occupied.

Table 12: Plantation grouped class Pairing

| Class 6 | Pair ID | Class Name Pairing | Area (km²) |
|---|---|---|---|
| Plantation | 1/6 | Built-Up/ Plantation | 3.896 |
| | 2/6 | Bare Earth/ Plantation | 7.767 |
| | 4/6 | Other Vegetation/ Plantation | 179.920 |
| | 5/6 | Marine Vegetation/ Plantation | 111.328 |
| | | **Total** | **302.911** |

Table 13: Void grouped class Pairing

| Class 7 | Pair ID | Class Name Pairing | Area (km²) |
|---|---|---|---|
| Void | 4/7 | Other Vegetation/Void | 1.425 |
| | 3/7 | Water Body/Void | 0.124 |
| | 5/7 | Marine Vegetation/Void | 5.919 |
| | 6/7 | Plantation/Void | 3.237 |
| | | **Total** | **10.705** |

Table 14: Rate of LULC transformation

| Class ID | Class Code | Class Name | Area (km²) |
|---|---|---|---|
| 1 | BU | Built-Up | 547.299 |
| 2 | BE | Bare earth | 22.263 |
| 3 | WB | Water body | 391.964 |
| 4 | OV | Other vegetation | 3,087.346 |
| 5 | MV | Marine vegetation | 279.429 |
| 6 | PL | Plantation | 302.911 |
| 7 | VD | Void | 10.705 |
| | **Total** | | **4,641.917** |

Table 12 shows the transformation within the Plantation grouped class pairings, it was revealed that Other Vegetation/ Plantation (4/6) had the highest transformation with a total of 179.920km$^2$ followed by Marine Vegetation/ Plantation (5/6) with a total of 111.328km$^2$, Bare Earth/ Plantation (2/6) with a total of 7.767km$^2$ and Built-Up/ Plantation (1/6) which has the lowest transformation of 3.896km$^2$ in terms of the geographical space occupied.

Table 13 shows the transformation within the Void grouped class pairings, it was revealed that Marine Vegetation/ Void (5/7) had the highest transformation with a total of 5.919km$^2$ followed by Plantation/ Void (6/7) with a total of 3.237km$^2$, Other Vegetation/ Void (4/7) with a total of 1.425km$^2$ and Water Body/ Void (3/7) which has the lowest transformation of 0.124km$^2$ in terms of the geographical space occupied.

Table 14 reveals that other Vegetation grouped paring had the highest coverage or area of transformation with a total of 3,087.346km$^2$ followed by Built-Up with a total of 547.299km$^2$; Water Body with a total of 391.964km$^2$; Plantation with a total of 302.911km$^2$; Marine Vegetation with a total of 279.429km$^2$; Bare Earth with a total of 22.263km$^2$ while Void grouped paring had the lowest coverage or area of transformation of 10.705km$^2$.

**Conclusion**

This research study made use of geoinformatics techniques in estimating and mapping accurate information on pixel-based land transformation and the spatial distribution of locations of these changing LULC classes over time. The capabilities of the aforesaid techniques have been used in analysing meaningful, useful datasets of medium and small-scale coverage of the geographical terrain.

This study demonstrates the usefulness of satellite data for the preparation of accurate and up-to-date LCLU transformation maps depicting classes of Built-Up, Bare Earth, Water Body, Marine Vegetation, Other Vegetation, Plantation and Void for analysing the change pattern for the study area for 2003 - 2020 by the utilization of digital image processing techniques.

Adeniyi and Omojola (1999) stated that studies of this nature will be essential in formulating meaningful plans, land policies and extract, evaluate land use land cover information based on the past to achieve a balance and sustainable development in the study area. Therefore, man's quest for most habitable lands among others tend to increase the exigency for human settlement thereby standing as a wellspring of the incessant increase in built up and a stepwise decline in vegetation.

Consequently, the following recommendations are made for this study;

- There should be proper distribution of industries to other sub urban area to mitigate the concentration of sites for factories and oil and gas installations.
- There should be a development control to closely monitor and measure land transformation activities so that, it does not

continue to annex agricultural land as this will have serious repercussions on food production.

- An integrated assessment of LCLU change mapping and spatio-temporal modelling works should be done while marine vegetation protection should be adequately enforced.

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