Application Of Knowledge-Based Image Classification And Ca - Markov Chain Prediction Model For Landuse / Landcover Change Analysis Of Onitsha And Environs, Anambra State.

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Abstract: Knowledge-based classification have proved to be effective for complex object recognition and for image analysis Therefore, this study was aimed on carried out land use/ land cover change detection and prediction using knowledge-based classification and Cellular Automata (CA)_MARKOV model of Onitsha. Landsat images of 2008, 2013 and 2018 covering the study area was acquired and used to carryout LULC classification and change detection. The change detection was carried out using the matrix union overlay in ERDAS 2014. Result shows that build-up area increased from 39.4% to 43% and from 43% to 45.9% between year 2008 to 2013 and 2013 to 2018 respectively. The water body increased in year 2013 from 6.5% to 7.2%, then decreased in 2018 to 6.8%. While the vegetation keeps decreasing all through the year from 42% in year 2008 to 36.1% in year 2018. CA- MARKOV model was then used to predict the landuse/land cover changes in the study area to year 2025. The result shows that built-up area will increase from 45.9% to 48% and also, decreases in vegetation, open space, sand dunes and water body. The study Recommend that Knowledge based classification should be used as it gives a better understanding and classification for land use / land cover types.

Keywords: Landuse/Landcover, Knowledge-based Classification, Cellular Automata, Change Detection.

1.1: INTRODUCTION

Land use/land cover (LULC) changes are major issues of global environment change. Remote sensing (RS) technology is a valuable tool for extracting LULC information and generating LULC change inventory. The satellite remote sensing data with their repetitive nature have proved to be quite useful in mapping land use/land cover patterns and changes with time. Quantification of such changes is possible through GIS techniques even if the resultant spatial datasets are of different scales/ resolutions (36). (3) Identified the major effect of land use on land cover as deforestation especially of temperate regions. More recent significant effects of land use include Urban sprawl, soil erosion, soil and land degradation, salinization and desertification. Land use changes, together with the use of fossil fuel are the major anthropogenic source of carbon dioxide, a dominant greenhouse gas into the atmosphere (World Bank Environment Development, 1993). In recent years, local government areas in Nigeria have experienced rapid population growth, thus changing population size and commercial needs often necessitate demand for land and change in land use plan (2). Knowledge-based classification procedure integrates remote sensing imagery with ancillary geospatial information from GIS. It has proven to be effective for complex object recognition and for image analysis. (11) States that Knowledge-based systems (KBS) are becoming more and more important in various areas despite the fact that they are still complex to produce. Indeed, acquiring and representing the knowledge of an area is often a tedious process and the multiple steps involved in the creation of the knowledge-base can be very different according to the studied of the area. (24) Suggested a Markov chain (MC) approach for post-classifying the pre-classified image data by traditional methods. This method utilizes expert-interpreted sample data from multiple sources as high-quality sample data in Markov chain model, which takes the pre-classified image data set by a conventional classifier as an auxiliary data set. Therefore, this project is aimed at the Application of Knowledge-based image Classification for Landuse / Landcover Change Analysis between year 2008 and 2018 and

CA – Markov Chain Prediction Model of Onitsha and Environs, to the year 2025.

2.1: The Study Area.

Onitsha and its Environs lies in the north-western part of Anambra State, in South-Eastern Nigeria. The settlements covered by the study include: Onitsha, Obosi, Nkpor, Okpoko and Iyiowa Odekpe. It is located between Latitudes 6° 3’ 00”N to 6° 9’ 00”N and Longitude 6° 45’ 00”E to 6° 48’ 00”E (see figure 1.1) The area is about 3,063 square kilometer. It serves as the gate way between the South-Eastern and South-Western part of Nigeria. The mean annual temperature is between 1,500mm to 2,500mm. South west monsoon harmattan winds are experienced around January, May and September respectively.

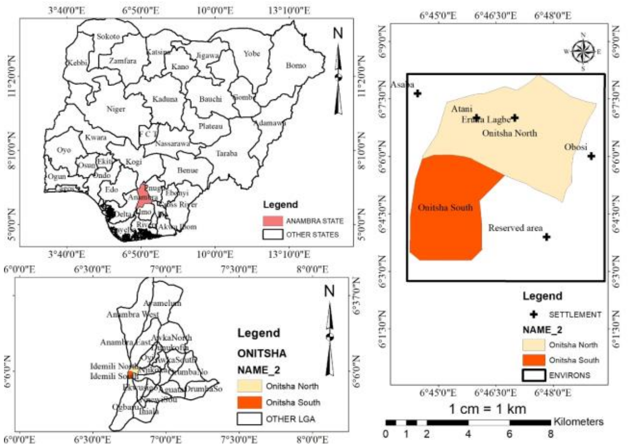

***Figure 1:1**. Showing Study Area map*

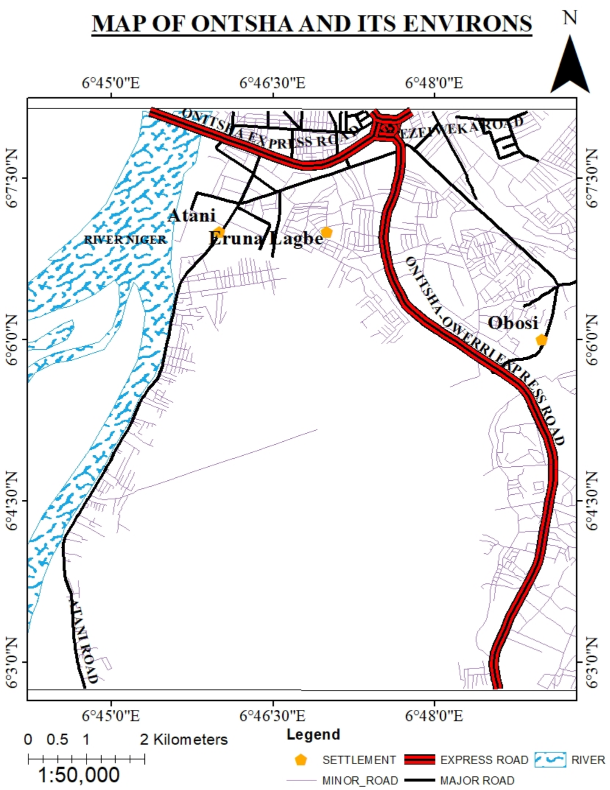

***Figure 1:2**. Showing Study Area map*

3.1: Methodology

The methodology of this study was composed of five phases: (a) Image processing (data pre-processing and indices calculation), (b) Image classification, (c) Change detection and (d) Prediction using CA-Markov.

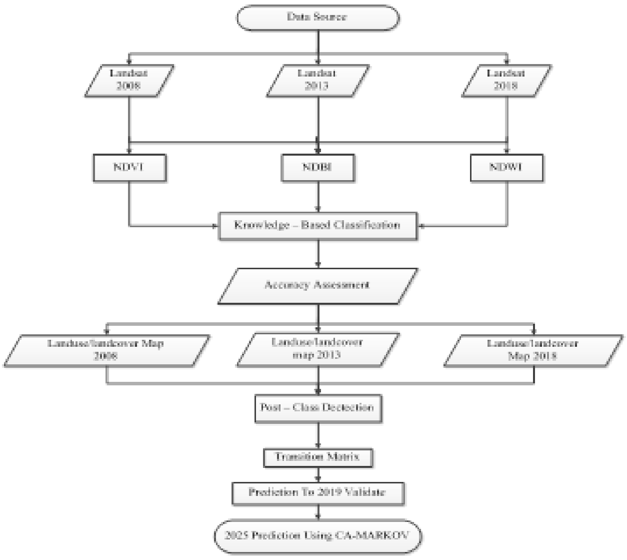

***Fig 2** Flowchart of methodology adopted*

A. Data Pre-processing

The underlisted data were obtained for the purpose of this research. Boundary of the study area was obtained from a Google earth image. A 30 meters resolution of Landsat 7 and Landsat 8 was downloaded from United State Geological Survey (USGS) www.earthexplorer.usgs.gov.

B. Indices calculation

The three main indices used in this study were Normalized Difference Vegetation Index (NDVI), Normalized Differential Built-up Index (NDBI), and Normalized Difference Water Index (NDWI). NDVI is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum, and is adopted to analyses remote sensing measurements and assess whether the target being observed contains live green vegetation or not. NDVI was calculated from equation 1. As given by Prarthna at el., (2017)

$$NDVI = NIR – RED / NIR + RED \qquad (1)$$

NDBI is the numerical indicator that uses the short wave infra-red and near infra-red bands of electromagnetic spectrum for mapping built-up areas. NDBI is calculated from equation 2. As given by Prarthna at el., (2017)

$$NDBI = SWIR – NIR / SWIR + NIR \qquad (2)$$

The NDWI is an index of water which make use of reflected near – infrared radiation and visible green light to enhance the presence of such features while eliminating the presence of soil and terrestrial vegetation features. Activity which can be calculated from equation 3. As given by Prarthna at el., (2017)

$$NDWI = (GREEN - NIR) / (GREEN + NIR) \qquad (3)$$

C. Classification

The results obtained from NDVI, NDWI and NDBI for 2008, 2013 and 2018 were used as ancillary data for knowledge-based classification to produce the landuse land cover image of 2008, 2013 and 2018, the following classes were obtained as shown in table 1.1.

TABLE: 1.1: CLASSIFIED CLASS TYPES AND DESCRIPTION.

S/No	Class	Description	Colour assigned
1	Water bodies	Water related features such as fresh water, lakes, rivers and streams.	Blue
2	Built-up areas	Includes all residential, commercial and industrial development.	Red
3	Open space	Includes bare earth or soil, unpaved roads and excavation sites.	Yucca yellow
4	Sand dunes	Includes all the areas where sand are been gathered or hip which may be gotten from the river.	cantaloupe
5	Vegetation	Includes all vegetation features such as evergreen, farm land, deciduous, shrub and forest.	Leaf green

4.1: Results and Discussion

The land use land cover distribution for each study year are presented in table

TABLE 2.1: LAND USE LAND COVER DISTRIBUTION (2008, 2013, 2018)

LANDUSE/ LAND COVER CATEGORIES	2008		2013		2018	
	AREA (Ha.)	AREA (%)	AREA (Ha.)	AREA (%)	AREA (Ha.)	AREA (%)
WATER BODY	710.1416	6.5	788.2396	7.2	744.8604	6.8
BUILT-UP LAND	4370.7258	39.4	4815.2738	43	5281.2140	45.9
OPEN S PACE	1273.8398	11.5	936.9219	8.5	1171.1231	10.6
SAND DUNES	68.2596	0.6	105.2645	1	70.6165	0.6
VEGETATION	4664.9164	42	4442.1298	40.3	4019.9695	36.1
TOTAL	11087.8296	100	11087.8296	100	11087.8296	100

The figures presented in table 2.1 represents the area of each land use land cover category for each study year. Water body seems not to have much changes only an increase in 2013 and then still decreased in 2018. Built-up in 2008 has 39.4% of the total classes, in 2013 which increased to 43% and in 2018 buildup still increased to 45.9% this is to show that there is massive development in Onitsha and environs. Open space seems to also be decreased from 11.5% in 2008 to 10.6% in 2018 that is to show that open spaces are also been transited to buildup area. Vegetation (which comprises of farm land, low forest shrubs etc.) seems to be decreasing, from 42%, 40.3% and 36.1% in 2008, 2013 and 2018 respectively. The classified image is been showed in fig 3.1, 3.2 and 3.3

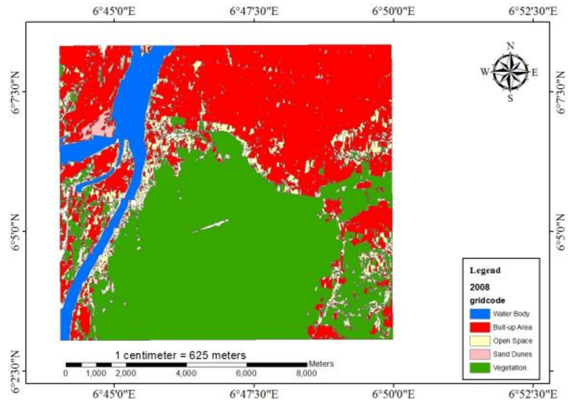

***Fig 3.1**: Classified image of Onitsha and environs 2008.*

The classified image of 2008, 2013 and 2018 are made up of five classes which are: water body, built up, open space, sand dunes and vegetation where the Blue represent the Water Body, Red represent the Built-up, Yucca yellow represent the Open Space, cantaloupe represent the Sand Dunes and Green represent the vegetation.

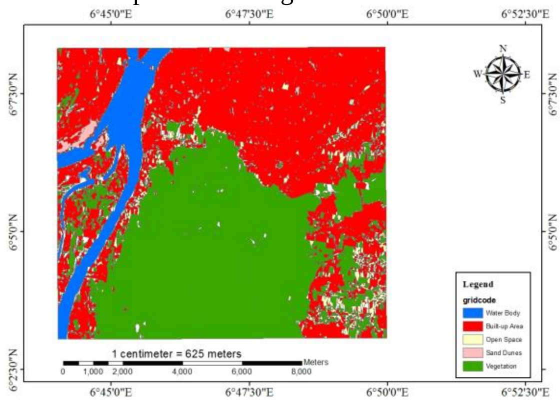

***Fig 3.2**: classified image of Onitsha and environs 2013*

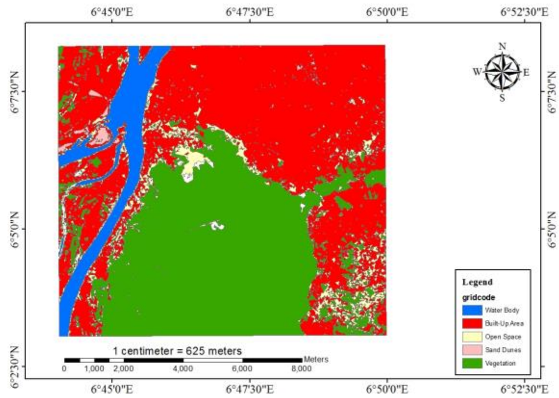

***Fig 3.3**: classified image of Onitsha and environs 2018*

***TABLE 3.1**: NATURE AND LOCATION OF CHANGE IN LAND USE LAND COVER*

LANDUSE/ LAND COVER CATEGORIES	2008 – 2013			2013-2018		
	Changed Area (Ha.)	Change Extent (%)	Rate of Change (%/yr.)	Changed Area (Ha.)	Change Extent (%)	Rate of Change (%/yr)
WATER BODY	78.098	11	2	- 43.3792	- 6	- 1
BUILT-UP LAND	444.548	10	2	465.9402	10	1
OPEN SPACE	- 336.9179	- 26	-5	234.2012	25	5
SAND DUNES	37.0049	54	11	-34.6481	- 33	- 7
VEGETATION	-222.7866	- 5	- 1	- 422.1603	- 10	- 2

The nature of change and location is been gotten using the following formula:
Total area (TA)
Change area (CA)
Change rate of change (CR)
1) CA = TA (T2) – TA (T1)
2) CE = CA/TA (T1)
3) CR = CE/ (T2-T1)

Where T1 and T2 are the beginning and ending time of the landuse study. From table 3.1, the negative change is as a result of the reduction in open space and vegetation between year 2008 and year 2013. Between year 2013 and 2018 open space increased while vegetation still decreased. This may be as a result of development in Onitsha and more populations. There are no much changes in buit-up area while both water body and sand dunes land both increased between year 2008 and 2013 then decreased by 1% and 7% respectively between year 2013 and 2018.

Class Statistic table

***TABLE 4.1** CLASS STATISTIC TABLE 0F THE CHANGES BETWEEN CLASS 2008 AND 2018*

Landuse/ Land Cover Categories	Changed Area 2008 (Ha.)	Changed Area 2018 (Ha.)	Diff in change Area 2008/2018 (%)	Total Area 2008 (%)	Total Area 2018 (%)	Diff in Total Area 2008/2018 (%)
Water Body	0.12	0.11	-0.00	6.5	6.8	0.3
Built-Up Land	0.67	0.84	0.17	39.4	45.9	6.5
Open Space	0.21	0.18	-0.03	11.5	10.6	-0.9
Sand Dunes	0.01	0.01	0.00	0.6	0.6	0.0
Vegetation	0.69	0.56	-0.13	42	36.1	-5.9

From the Statistic table the changes between 2008 and 2018 is presented in fig 4.1

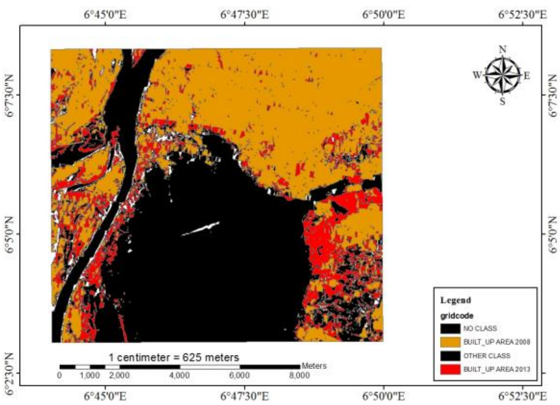

***Fig 4.1** Derived from the overlay of 2008 and 2018 Land use land cover map*

The overlay built-up map between year 2008 to year 2018, shows the difference between built-up area of 2008 to 2018 as mentioned earlier. The area verged black are no class area and other class area, the area verged red are the built-up area of year 2018 and the area verged electron gold are the built-up areas in year 2008.

Transition Probability Matrix

The transition probability matrix shows the probability of how each of the land cover will change to each other. The transition probability matrix is repented in the 5 x 5 matrix table below, the rows represent the older land cover categories and the column represents the newer categories. Two landuse/landcover maps of 2008 and 2013 were used to create the transition probability matrix.

***TABLE 5.1** TRANSITIONAL PROBABILITY TABLE DERIVED FROM THE LAND USE LAND COVER MAP OF 2008 AND 2018.*

CLASSES	WATER BODY	BUILT-UP AREA	OPEN SPACE	SAND DUNES	VEGETATION
WATER BODY	0.889365	0.068611	0.009434	0.032590	0.000000
BUILT-UP AREA	0.005386	0.949132	0.034710	0.007929	0.002843
OPEN SPACE	0.016714	0.653295	0.287488	0.000000	0.042502
SAND DUNES	0.164948	0.515464	0.061856	0.257732	0.000000
VEGETATION	0.000000	0.079377	0.129889	0.000433	0.790302

Row represent land use land cover classes in 2018 while column represent the later projected landuse/ land cover image of 2025 classes. The transition matrix in table 5.1 showed that water body has a probability of 0.889365 to be remained same as water body in 2025 and 0.068611 probability to be changed into built-up area, 0.009434 to open space, 0.032590 to sand dunes, and 0.00000 to vegetation. Similarly, the built-up area has a probability of 0.949132 to be remained as built-up in the projected year of 2025, 0.068611 changes into water body, 0.034710 to open space, 0.007929 to sand dunes and 0.002843 to vegetation. Open space has a probability of 0.287488 to be remained as open space in year 2025, 0.0164714 changed to water body, 0.515464 changed into the built-up area, 0.00000 into the sand dunes and 0.042502 to vegetation. Sand dunes has a probability of 0.257732 to be remained as sand dunes in year 2025, 0.164948 changed to water body, 0.515464 changed into the built-up area, 0.061856 into an open space and 0.00000 to vegetation. Vegetation has a probability of 0.790302 to be remained as vegetation in year 2025, 0.00000 changed to water body, 0.079377 changed into the built-up area, 0.129889 into an open space and 0.000433 to sand dunes. Hence built-up area has the maximum probability to remain in same class follow by the vegetation and sand dunes shows minimum probability to remain in same class.

***TABLE 6.1** PROJECTED LAND USE LAND COVER FOR 2025.*

LAND USE LAND COVER CLASSES		WATER BODY	BUILT-UP AREA	OPEN SPACE	SAND DUNES	VEGETATION
2025	AREA IN HECTARES	1247.152	8462.324	1925.213	184.543	5709.342
	AREA IN PERCENTAGE	7	48	11	1	33

Table 6.1 shows the area of land use land cover projection for 2025. Showing the percentage representations of table 6.1 and table 2.1, there exist similarities in 2008 to 2018, particularly in 2018. Therefore in table 6.1 above, shows that built-up area still remain the highest position in the class while sand dunes will still be the least position.

Vegetation will be second in the highest of the class, followed by open space and finally, water body.

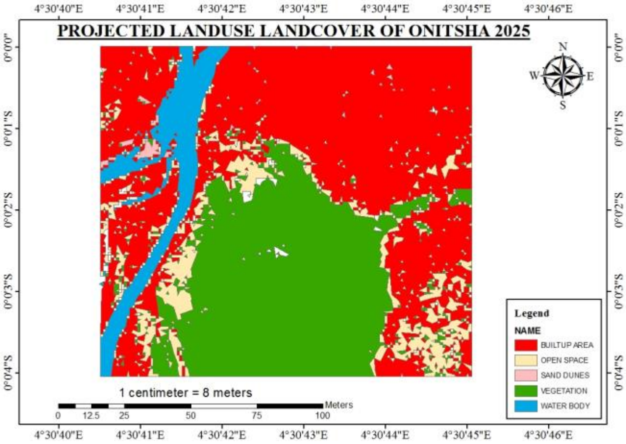

Fig: 5.1 *CA-Markov projected land cover map of 2025*

5.0: CONCLUSION AND RECOMMENDATION

5.1: Conclusion

Landuse change conceptualize the relationship between different classes of land cover and their uses. Different disciplinary concepts can assist in the analysis of landuse change in specific situation. The conventional surveying techniques is time consuming, the use of Landsat imageries in modelling and mapping of landuse and land cover changes is an important approach. It structures the model around the human environment relationship which can be improved using Cellular Automata. Landuse land cover when carried out in the rightful other can be used to assist relevant Government agencies in the planning of the study. This study has been able to use knowledge-based technique to classify landuse/landcover changes in Onitsha and Environs. Markov Chain Model was used to predict the changes to the year 2025. The study has been able to demonstrate the effectiveness of GIS and Remote Sensing techniques in classification and prediction of landuse / landcover changes.

5.2: Recommendations

i. Knowledge based classification should be used, for image classification since it gives a better understanding and better classification for land use / land cover mapping.
ii. Modeling and mapping of land use and land cover changes using cellular Automata and Markov chain should always be carried out and ensure a successful implementation.
iii. Further studies should be carried out on modeling and mapping of land use and land cover for sustainable development.

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