Landuse Landcover Analysis and Prediction using Marcov Chain in Parts of Rivers State, Nigeria

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Abstract

Landuse / Landcover changes and its effects on our environment has been a phenomenon of great concern. This study focuses on the need to identify and monitor the Landuse changes within the study area with a view to detect the land consumption rate and the changes that have taken place within a temporal scale of 1989 – 2019. ArcMap 10.1 and Erdas Imagine were deployed for change detection analysis. The prediction of Landuse changes was carried out using Markov Chain analysis. Seven Landuse / Landcover classes were developed. Supervised and post-classification algorithms were employed. Landcover maps were generated and change detection analyses were performed using ArcMap 10.1 and Erdas Imagine software. The statistic evaluation of Landuse Landcover change reveal that built-up areas between 1989 and 1999 increased by 27.44%, the increase was 29.41% between 1999 and 2009 then the increase observed between 2009 and 2019 is 179.4%. The evaluations from the first and last dates reveal that built-up areas, thick forest, bare land and water bodies increased by 360.8%, 127%, 128% and 123.9% respectively while farmland, light forest and swamp decreased by 93%, 33.3% and 20.5% respectively. The overall classification accuracies for 1989, 1999, 2009 and 2019 are 87.00%, 90.00%, 94.53% and 94.14% respectively. The transition probability grid from Markov Chain Analysis reveals that Farm Land and bare Land would be the highest contributors in the Landuse classes to the future increase that would be experienced in the built-up areas in 2029 and 2039.Classified maps from the spatio-temporal Landuse/Landcover changes in the study area would be used as a tool for Land administration, urban planning and environmental management.

Keywords: Landuse, Landcover, Landsat, Image Classification, Change Detection

INTRODUCTION

The rate at which the artificial Landcover features are changing is increasing due to the escalating human population (Giri, 2012). Landcover has an effect on the biophysical processes that occur on the land surface, which in turn influence both the climate system and habitat diversity within that region (Gomez, White &Wulder, 2016). Knowledge of Landcover is vital for geosciences and global change monitoring, as well as for climate change studies, and improving the performance of ecosystem, hydrologic and atmospheric models (Verhulp, 2017).

Population explosion, soil erosion, global warming, pollution and human activities such as deforestation, construction etc. impact the environment and consequently causes Landuse / Landcover changes. Nigeria and specifically Rivers State is also affected by this change phenomenon. Rivers State is regarded as the commercial hub center of the oil and gas industry in Nigeria. The State is characterized by a daily influx of people seeking a pasture especially in the oil and gas industry. Three amongst the prominent Local Government Areas (LGAs) that have experienced urbanization and unprecedented population growth in Rivers State are Obio/Akpor, Port Harcourt City and Ikwerre LGAs.

The aim of this study is to detect Landuse/Landcover trend in part of Rivers State and to predict Landcover changes particularly in the built-up areas for the next 10 and 20 years. The objectives are: a) to classify and analyze the Land changes at four epochs (i.e. 1989, 1999, 2009 and 2019) and to produce Landuse maps of the study area for each epoch, b) to evaluate the Landuse Landcover magnitude of change, rate of change, spatial pattern and trend of change, and c) to predict Landuse changes (using Markov Chain analysis) that may occur in ten (10) and twenty (20) years.

STUDY AREA

The study area covers Obio/Akpor, Port Harcourt City and Ikwerre Local Government Areas of Rivers State with geographical coordinates covering [6°47‘11.90" 7°09’58.50"N][4°41’57.50" 5°14‘59.20"E]. See attached map (Figure 1) of study area.

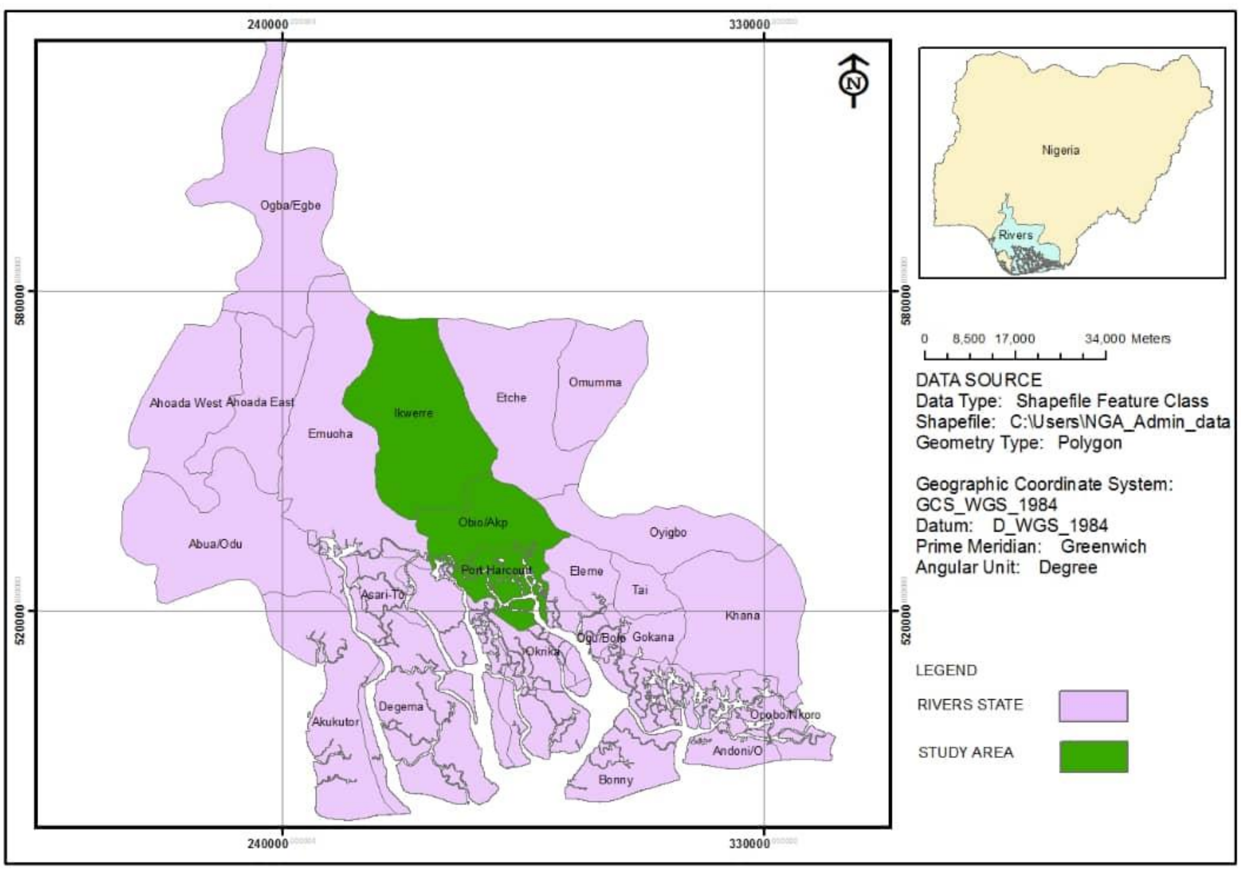

Figure 1: Map of the Study Area.

METHODOLOGY

Dataset

The dataset used in this study are Landsat imageries with characteristics shown in Table 2.

Table 2: Characteristics of the Imageries for the area of Study

S/N	Type of Sensor	Path/row	Resolutions	Year
1	Landsat-5-TM	188/57	30m	1989
2	Landsat-7ETM+	188/57	’	1999
3	Landsat-7ETM+	188/57	’	2009
4	Landsat-8 (OLI)	188/57	’	2019

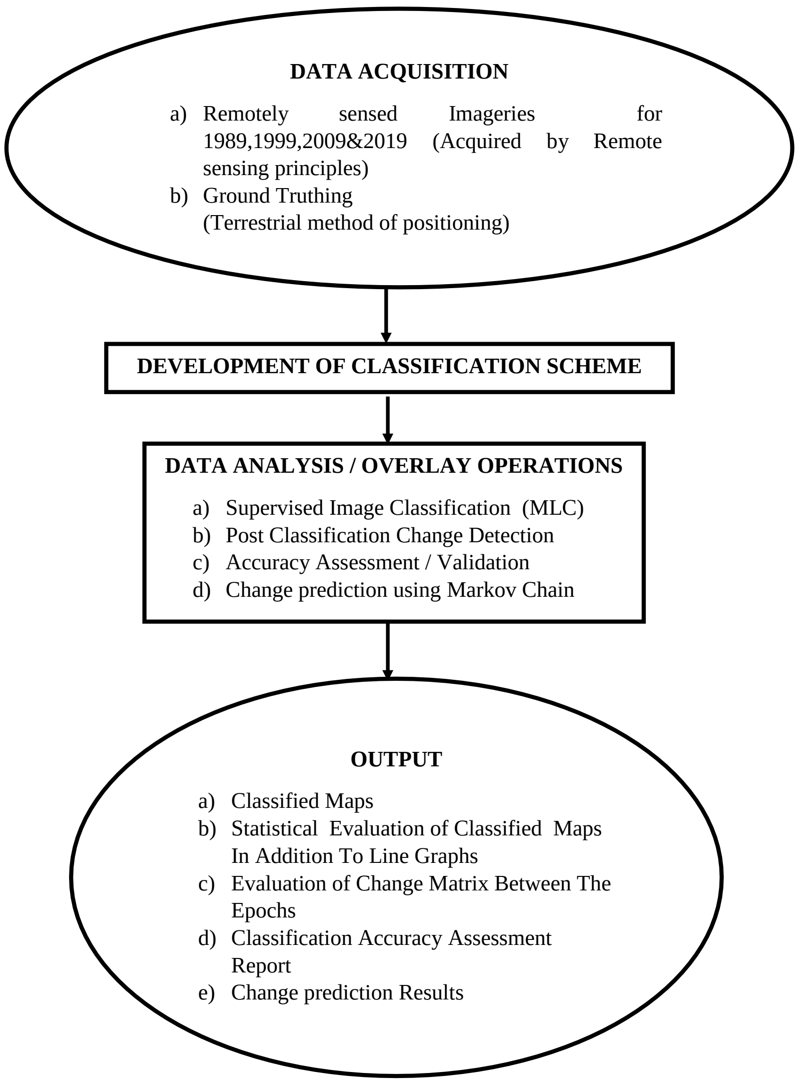

Figure 2: Flow chart diagram of the research method

The research method employed in this study is an integration of remote sensing techniques and geospatial information tool. Landuse/cover classes used in this study are built-up area, farmland, light forest, thick forest, bare land, swamp and water bodies. Two classification algorithms were deployed; Pixel based computer supervised classification and post classification. The statistical evaluation of the LULC distribution derived from the pixel counts were illustrated in tabular form showing the areas and class percentages of each feature class category. The remote sensing (RS) and geospatial information system (GIS) tools deployed for image processing, image classifications, analysis/overlay operations are Arc Map 10.1 and Erdas Imagine. Future change prediction based on each class pixels was carried out by Markov Chain Analysis in Idrisi Taiga software. The procedural steps of methods in this study are encapsulated in the flow chart diagram in Figure 2.

IMAGE CLASSIFICATION PROCESS

The pixel based supervised Classification was carried out using the Maximum Likelihood Classifier (MLC) on the Landsat imageries. It is a classifier that relies on normal distribution of the data in each class. Seven Landuse /cover classes identified for classification are built-up area, farmland, light forest, thick forest, bare land, swamp and water bodies. The classification process yielded classified maps of Landuse Landcover of the study area for each date. See figure 4.

Post classification comparison was also carried out to evaluate the Landuse Landcover change between two consecutive dates which yielded magnitude of change, rate of change and trend of change.

RESULTS AND ANALYSIS

The result analyses in this study include the Landuse / Landcover evaluation of classified imageries, assessment of Landuse changes derived from the post classification comparison which reveals the ‘from – to ‘ changes and future change prediction using Markov chain analysis.

The table 2 revealed that the built up area occupied 9,006.03ha of the study area for the year 1989 which amount to 8.52% of the total Area while the light forest covered an area of 62,262.2ha which is 58.92%. In 1999, the built up area occupied 11,477.5ha of the study area amounting to 10.86% of the total area while the light forest covered an area of 54,440.7ha which is 51.52%. The built up area in 2009 occupied 14,853.1 ha of the study area which amount to 14.06% of the total area while the light forest covered an area of 36,450.8ha which amount to 34.5%.

Again the built up area in 2019 occupied 41,502.8 ha of the study area which is 39.28% of the total area and the light forest covered an area of 41,552hawhich is equivalent to39.32% of the study area. The spatial distribution of Landuse / Landcover classes for the four epochs are represented in table 2 and figure 3 is the histogram representation of the Landuse / Landcover classes. See figure 4 for the classified maps.

Table 2: Statistical Evaluation ofLanduse / Landcover Distribution for 4 Epochs (1989 -2019)

S/N	Class	1989 Evaluation			1999 Evaluation			2009 Evaluation			2019 Evaluation		
		Pixel count	Area (ha)	Class Percentage %	Pixel count	Area (ha)	Class Percentage %	Pixel count	Area (ha)	Class percentage %	Pixel count	Area (ha)	Class percentage %
1	Built Up Area	100067	9,006.03	8.52	127528	11,477.5	10.86	165034	14,853.1	14.06	461142	41,502.8	39.28
2	Farm Land	235250	21,172.5	20.04	128751	11,587.6	10.97	360103	32,409.3	30.67	16385	1,474.65	1.4
3	Light Forest	691802	62,262.2	58.92	604897	54,440.7	51.52	405009	36,450.8	34.5	461689	41,552	39.32
4	Thick Forest	33907	3,051.63	2.89	155207	13,968.6	13.22	12639	1,137.51	1.08	76983	6,928.47	6.56
5	Bare Land	29273	2,634.57	2.49	75658	6,809.22	6.44	162810	1,4652.9	13.87	66748	6,007.32	5.69
6	Swamp	66782	6,010.38	5.69	57901	5,211.09	4.93	64021	5,761.89	5.45	53083	4,777.47	4.52
7	Water bodies	16997	1,529.73	1.45	24136	2,172.24	2.06	4462	401.58	0.38	38048	3,424.32	3.24
Total		1174078	105,667	100	1174078	10,5667	100	1174078	105,667	100	1174078	105,667	100

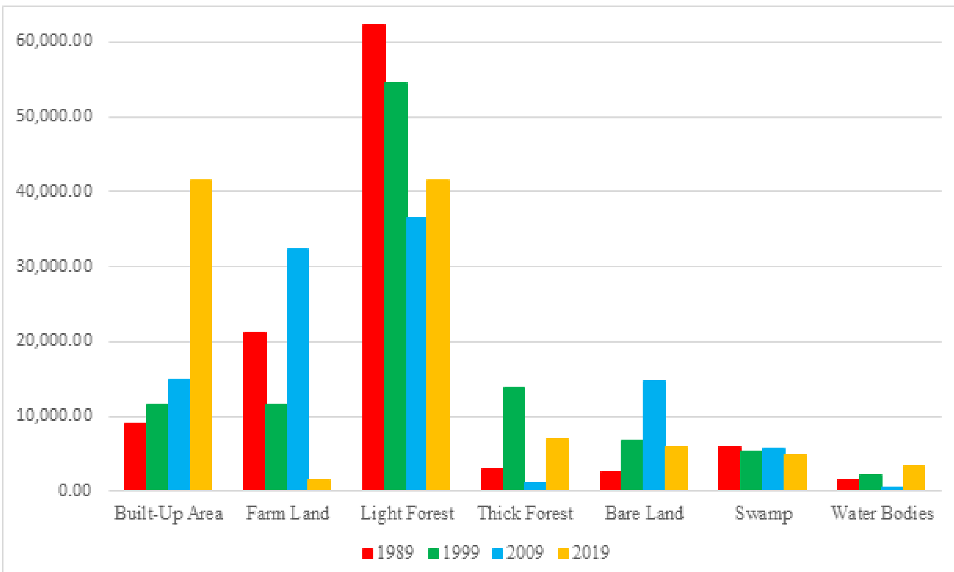

Figure 1: Histogram of Landuse/Landcover classes 1989 – 2019

Evaluation of Change Matrix between Two Consecutive dates.

In the post classification comparison for the year 1989 and 1999 from table 3, observable trend of change shows that the thick forest increased greatly from 3,051.63ha to 13,968.6 ha at a rate of change of 357.74% while the farmland decreased from 21,172.5 ha to 11,587.6 ha at a rate of 45.27%.

Similarly, for the year 1999 and 2009, farmland increased from 11,587.59 ha to 32,409.3 ha at a rate of 179.7% while thick forest decreased from 13,968.63 ha to1, 137.51ha at the rate of change of 91.9%.

Also, the built up area in the year 2009 and 2019 increased from 14,853.06 ha to 41,502.78 ha at the rate of 179.4% while bare land decreased from 14,652.9 ha to 6,007.32 ha at the rate of 59%. See table 3 for the evaluation of change matrix.

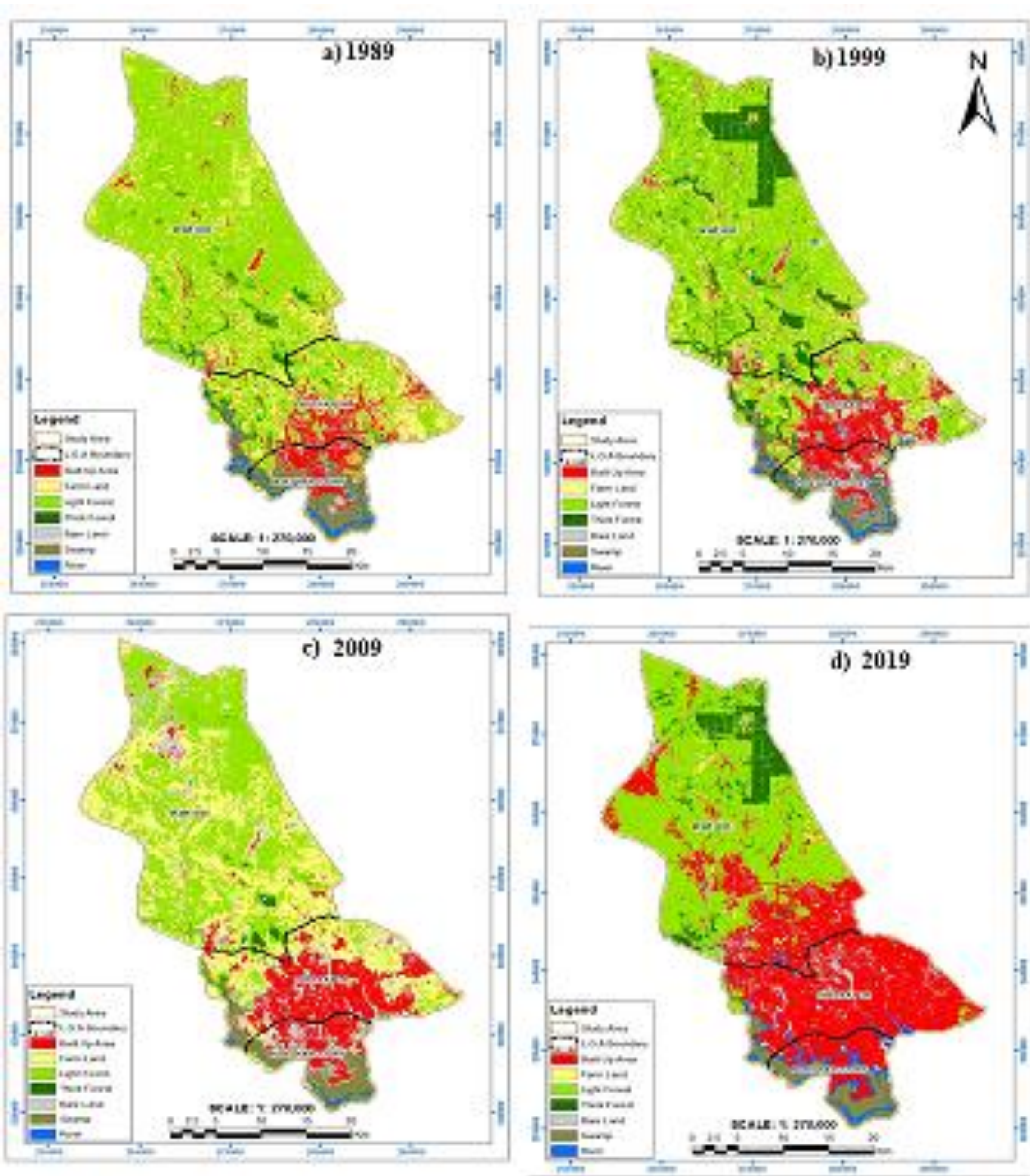

Figure 2: Classified Maps of Landuse Landcover of the study area from a) 1989, b) 1999, c) 2009, and d) 2019.

Table 3: Evaluation of change matrix

S/N	Classes	From - to change 1989 - 1999					From - to change 1999 - 2009					From - to change 2009 - 2019				
		1989 Area (Ha)	1999 Area (Ha)	Magnitude of change (Ha)	Rate of change (%)	Trend of Change	1999 Area (Ha)	2009 Area (Ha)	Magnitude of change (Ha)	Rate of change (%)	Trend of Change	2009 Area (Ha)	2019 Area (Ha)	Magnitude of change (Ha)	Rate of change (%)	Trend of Change
1	Built-Up Area	9,006.03	11,477.5	2,471.49	27.44	I	11,477.52	14,853.1	3,375.54	29.41	I	14,853.06	41,502.78	26,650	179.4	I
2	Farm Land	21,172.5	11,587.6	-9,584.91	-45.27	D	11,587.59	32,409.3	20,821.7	179.7	I	32,409.27	1,474.65	-30,935	-95.45	D
3	Light Forest	62,262.2	54,440.7	-7,821.45	-12.56	D	54,440.73	36,450.8	-17,990	-33	D	36,450.81	41,552.01	5,101.2	13.99	I
4	Thick Forest	3,051.63	13,968.6	10,917	357.74	I	13,968.63	1,137.51	-12,831	-91.9	D	1,137.51	6,928.47	5,791	509.1	I
5	Bare Land	2,634.57	6.809.22	4,174.65	158.46	I	6,809.22	14,652.9	7,843.68	115.2	I	14,652.9	6,007.32	-8,646	-59	D
6	Swamp	6,010.38	5,211.09	-799.29	-13.30	D	5,211.09	5,761.89	550.8	10.57	I	5,761.89	4,777.47	-984.4	-17.09	D
7	Water Bodies	1,529.73	2,172.24	642.51	42.00	I	2,172.24	401.58	-1,770.7	-81.5	D	401.58	3,424.32	3,022.7	752.7	I
Total		105,667.02	105,667.02				105,667.02	105,667.02				105,667.02	105,667.02			

Trend of Change Legend.
I = Increased, D = Decreased

Figure 5: Evaluation of Landuse/Landcover Change of the Study Area for a) 1989-1999,b)1999-2009,c) 2009-2019

Evaluation of Change Matrix between the First and Last Dates (1989 - 2019)

As part of the post classification comparison, the first and last dates were evaluated to show at a glance the spatial pattern of change in terms of the magnitude, rate and trend.

From Table 3, observable trend of change shows that the built up area increased from 9,006.03ha to 41,502.78 ha at a rate of change of 360.8% while the light forest decreased from 62,262.18 ha to 41,552.01 ha at a rate of 33.3%.

Table 4: Evaluation of Change Matrix between the First and Last Dates (1989 – 2019)

		From - to change 1989 – 2019				
S/N	Classes	1989 Area (Ha)	2019 Area (Ha)	Magnitude of change (Ha)	Rate of change (%)	Trend of Change
1	Built-Up Area	9,006.03	41,502.78	32,497	360.8	I
2	Farm Land	21,172.5	1,474.65	-19,698	-93	D
3	Light Forest	62,262.18	41,552.01	-20,710	-33.3	D
4	Thick Forest	3,051.63	6,928.47	3,876.8	127	I
5	Bare Land	2,634.57	6,007.32	3,372.8	128	I
6	Swamp	6,010.38	4,777.47	-1,233	-20.5	D
7	Water Bodies	1,529.73	3,424.32	1,894.6	123.9	I
	Total	105,667.02	105,667.02			

Trend of Change Legend
I = Increased, D = Decreased

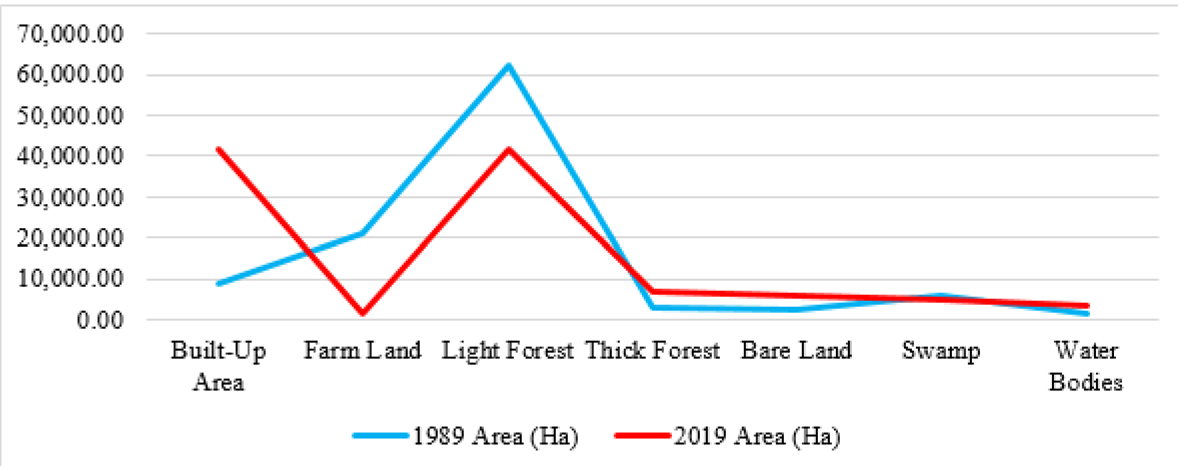

Figure 6: Evaluation of Landuse/Landcover Change between the First and Last Dates (1989 - 2019).

Accuracy Assessment / Validation

The results of the accuracy assessment are in parts; Error matrix, accuracy totals, kappa statistics and conditional kappa for each class category. The accuracy total reveals the producer's accuracy, user's accuracy and overall classification accuracy. The results revealed that the overall accuracy for the classified images were 87%, 90%, 94.53% and 94.14% respectively.

Markov Chain Analysis

The predictive modelling technique used in this study is Markov Chain Analysis. The historical trend of Landuse Landcover changes in two Landcover maps were utilized in the Markov module to create the transition probability matrix (See Table 6) and to simulate future Landuse changes for the year 2029 and 2039 (See Tables 7 and 8). The transition probability matrix (see Table 6) shows records that each Landcover class will change to another class. The transition area matrix shown in percentages in Tables 7 and 8 reveals how much Land is estimated to change from the current date to the predicted dates (2029 and 2039).

Table 5: Accuracy Assessment for 1989,1999,2009 and 2019 Classifications

Land Use/Cover	1989 PA	1989 UA	1999 PA	1999 UA	2009 PA	2009 UA	2019 PA	2019 UA
Built Up Area	100.00	93.00	60.00	100.00	84.62	100.00	96.23	96.23
Farm Land	33.33	50.00	57.14	80.00	96.49	94.83	25.00	50.00
Light Forest	86.67	92.86	96.67	87.88	95.56	86.00	96.97	91.43
Thick Forest	96.55	82.35	71.43	83.33	50.00	66.67	80.00	88.89
Bare Land	57.14	57.14	66.67	100.00	88.89	94.12	77.78	87.50
Swamp	50.00	50.00	100.00	57.14	94.87	94.87	89.66	89.66
Water Bodies	81.82	100.00	100.00	85.71	66.67	100.00	66.67	66.67
Overall accuracy		87.00		90.00		94.53		94.14
Overall Kappa Statistic		0.8342		0.8684		0.9317		0.9242

UA - User's Accuracy, PA - Producer's Accuracy,

Table 6: Transition Matrix of Land Use Change from 2009 to 2019

Classes	Undefined	Built Up Area	Farm Land	Light Forest	Thick Forest	Bare Land	Swamp	River	Total
Undefined	0.5894	0	0	0	0	0	0	0	0.5894
Built Up Area	0	0.0712	0.0359	0.0273	0.0018	0.0038	0.0013	0.0007	0.1421
Farm Land	0	0.0022	0.0223	0.0836	0.0192	0.0001	0	0	0.1274
Light Forest	0	0.0004	0.0147	0.048	0.0057	0.0003	0	0	0.0691
Thick Forest	0	0.0005	0.0093	0.0182	0.016	0.0002	0.0019	0	0.0461
Bare Land	0	0.0009	0.0004	0.0006	0.0001	0.0001	0.0001	0	0.0022
Swamp	0	0	0	0	0.0002	0	0.0097	0.0001	0.01
River	0	0.0007	0	0	0.0001	0	0.0051	0.0076	0.0137
Total	0.5894	0.0759	0.0826	0.1776	0.0431	0.0047	0.0182	0.0085	1

Table 7: Markov Chain Prediction of Land Use Classes from 2019 To 2029

Transition Probabilities Grid

Given : Probability of changing to :

	Built Up Area	Farm Land	Light Forest	Thick Forest	Bare Land	Swamp	River
Built Up Area	0.9384	0.0291	0.0051	0.0061	0.0114	0.0002	0.0097
Farm Land	0.4345	0.2694	0.1780	0.1130	0.0046	0.0002	0.0003
Light Forest	0.1536	0.4708	0.2700	0.1022	0.0033	0.0000	0.0000
Thick Forest	0.0425	0.4451	0.1320	0.3706	0.0021	0.0046	0.0031
Bare Land	0.8122	0.0299	0.0738	0.0506	0.0199	0.0038	0.0097
Swamp	0.0722	0.0001	0.0013	0.1047	0.0063	0.5335	0.2819
River	0.0842	0.0000	0.0005	0.0035	0.0039	0.0092	0.8987

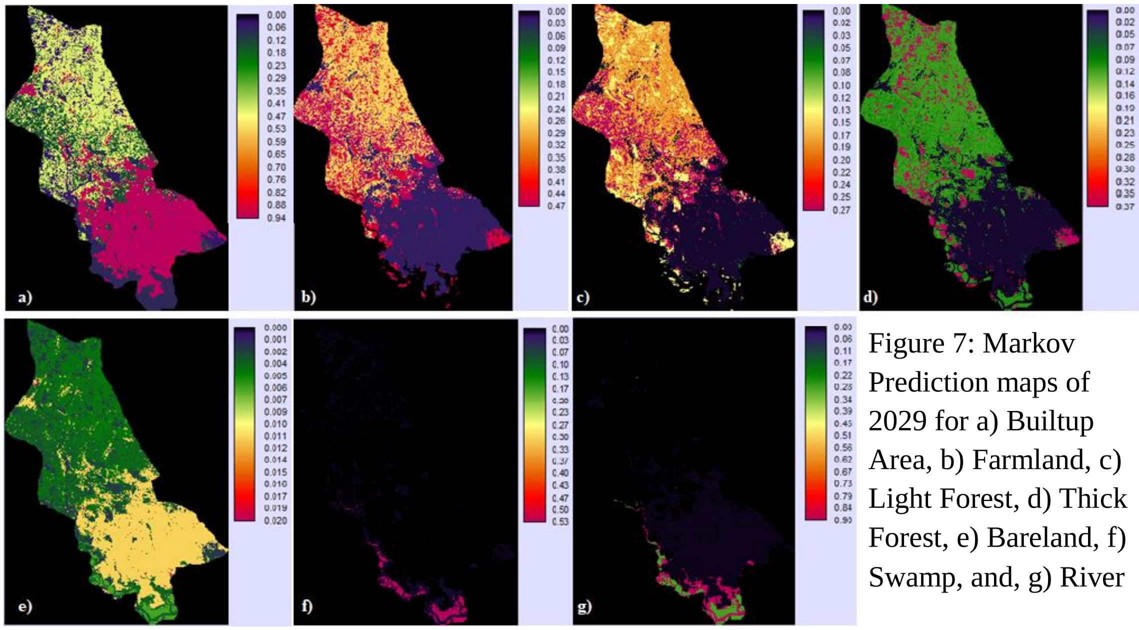

Figure 7: Markov Prediction maps of 2029 for a) Builtup Area, b) Farmland, c) Light Forest, d) Thick Forest, e) Bareland, f) Swamp, and, g) River

Table 8: Markov Chain Prediction of Land Use Classes from 2019 To 2039

Given : Probability of changing to :

	Built Up Area	Farm Land	Light Forest	Thick Forest	Bare Land	Swamp	River
Built Up Area	0.9044	0.0407	0.0130	0.0125	0.0111	0.0004	0.0180
Farm Land	0.5607	0.2195	0.1135	0.0935	0.0071	0.0008	0.0050
Light Forest	0.3972	0.3040	0.1712	0.1198	0.0051	0.0006	0.0020
Thick Forest	0.2716	0.3483	0.1642	0.2020	0.0038	0.0043	0.0058
Bare Land	0.8059	0.0896	0.0376	0.0361	0.0102	0.0026	0.0180
Swamp	0.1398	0.0496	0.0159	0.0965	0.0056	0.2878	0.4049
River	0.1587	0.0044	0.0018	0.0062	0.0046	0.0132	0.8111

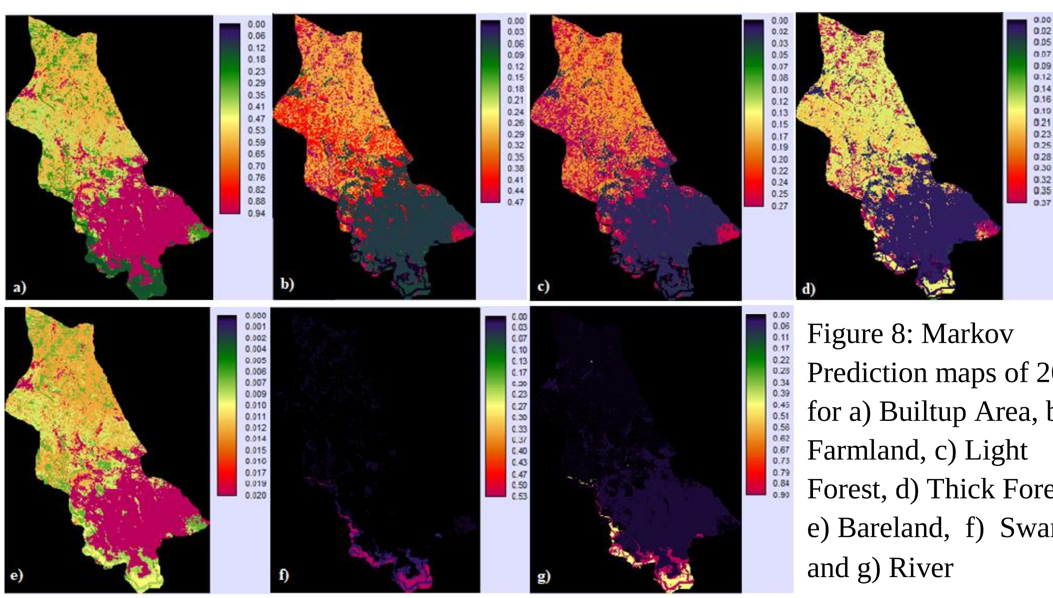

Figure 8: Markov Prediction maps of 2039 for a) Builtup Area, b) Farmland, c) Light Forest, d) Thick Forest, e) Bareland, f) Swamp, and g) River

Results versus objectives

I. Statistical analysis and evaluation of each Landuse Landcover for each date yield the extent of the area and percentage area for each feature class. The statistical analysis and evaluations presented in tabular form in Table 2 and the graphical representation by histogram (Figure 3) in addition to the production of the classified maps (See Figure 4) for each epoch (1989, 1999, 2009 and 2019) met our first objective which is to classify, analyze the Landuse changes at four epoch (1989, 1999, 2009 and 2019) and produce the Landuse map for each year.

II. Post classification comparisons enable us to evaluate the Landuse Landcover change between two consecutive dates which yielded the rate of change, spatial pattern and trend of change. This evaluation shows the "from – to" change of each feature class in two consecutive dates which is also graphically represented by histogram for visual interpolation. This assessment met the second objective of the study which is "to evaluate the Landuse Landcover rate of change, spatial pattern and trend of change".

III. The third objective of the study is to predict Landuse changes that may occur in 10 and 20 years (2029 and 2039 respectively). To this end, Markov Chain model was adopted. The Markov Chain process utilized the LULC data sets of 2009 and 2019 to yield transition probability matrix (Table 6) which in turn was used to predict future Landuse changes for 2029 and 2039 (Tables 7 and 8). The provision of the transition probability matrix, the transition area matrix showing the changes from each Land cover type to every other land cover type and the transition maps all met our third objective of Land use change prediction.

DISCUSSION

The findings of this study show that the built-up area has been on a steady increase from the first date; 1989 to the last date; 2019. The primary factor for the increase witnessed in the built-up areas is due to population growth. The issues of the ever changing Landuse and Landcover are predominant in the urban/built up areas. This was corroborated by Zubair, (2006) in his work on Landuse and Landcover change detection in Ilorin and it's environ. The effects of population on land use are essential to analyze the pressure of population on Landuse development. Population growth influences land use changes by placing high demand on Land purchase for residential and economic purposes. Ardalan, (2013) in his work on Landuse /Landcover change detection in the Iraqi province of Sulaimaniah using remote sensing highlights major dynamics in LULUC as it relates to the growing population and consequently increase in economic activities. This has some similarity with Zubair (2006) who looked at population indices as a measure of growth rate. The increase in demand consequently makes Land scarce and price skyrocket especially within the highly developed areas. The farm land has been converted to built-up areas while some forest has been destroyed for expansion of farm land. The need for timber for construction and the burning of bush for hunting activity has highly affected the forest. The deforestation has impacted the study area adversely by chasing away different types of animals and eroding different species of vegetation.

CONCLUSION

The study of multi-date Landuse Landcover of the study area has proven that GIS and Remote sensing techniques are efficient tools for monitoring and evaluation of Landuse changes. The study revealed that the built-up areas have been on steady increase since 1989 to 2019. The built-up areas have significantly increased from 9,006.03 ha in 1989 to 41,502.78 ha in 2019 with a positive magnitude change (change extent) of 3,2497ha which amounted to a rate of change of 360.8%. This is as a result of population growth in the study area which puts a demand on Landuse for various activities such as housing, road construction etc. The increase in built-up areas has advert effect on farmland feature class which has drastically reduced from 21,172.5ha in 1989 to 1,474.65 ha in 2019 which is at a rate of 93%. This Landuse change is particularly pronounced in Obio/Akpor LGA and Port Harcourt city LGA. The issues of insecurity generally experienced in the state are a contributory factor to the sharp drop in the farm Land feature class. Some part of the swamp areas are also eaten up (6,010.38 ha in 1989 and 4,777.47 ha in 2019) by built-up areas by people who build houses in swamp areas and on water courses. This causes a decrease in the swamp areas but consequently causes the water bodies to increase (1,529.73 ha in 1989 and 3,424 ha in 2019) in addition to the issues of the climate change experienced around the world. The over saturation of the built up areas in Obio/Akpor LGA has caused the Ikwerre LGA to witness a spread of growth from the common boundary shared with Obio/Akpor LGA. This is the consequence of the heterogeneous nature of the area of study. The increase in thick forest between the first and the last dates in view is as a result of the abandonment of farmland which consequently resulted to an observable Landcover change. Light forest experienced a decreased between the first and the last dates. The decrease observed in light forest class can be adduced to loss to built-up area.

The Markov Chain analysis also show that the present development observed in the built-up areas of the study area will continue till 2029 and 2039. The most important reason for this is the continual migration from rural areas to urban areas. Rural-urban migration causes the abandonment of farmland which invariably changes the Landcover classification into forest. Moreover, the climate pattern of the region is very suitable for forestation. We have more period of rainy season in Rivers State than the dry season which can also alter the Landcover type experienced.

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