SPATIO-TEMPORAL MONITORING AND PREDICTION OF PHYSICAL URBAN DEVELOPMENT OF PART OF NIKE, ENUGU, NIGERIA USING REMOTE SENSING AND GIS

[1]NNAM, V., [1]OKONKWO, U & [2]ONWUZULIGBO, C.

[1]Department of Surveying & Geoinformatics, Enugu State University of Science and Technology, Enugu

[2]Department of Surveying and Geoinformatics, Nnamdi Azikiwe University, Awka

ABSTRACT

One of the major catalysts of physical urban development is the activities of the teeming population of rural-urban migrants. Spatial-Temporal monitoring and prediction of Physical Urban development is the assessment of the rate at which an urban area grows over a period of time. This work monitored the rate of urban development in part of Nike, Enugu East local government area, Enugu state in Nigeria, with focus on its land use/land cover; predicted the future development; and from the results of the study, recommend strategies for the mitigation of the anticipated challenges. Remote sensing and Geographic Information Systems (GIS) techniques were employed in the monitoring of the area for a period of 28 years (1997 to 2018) and a prediction period of 21 years (2018 to 2039) using Statistical Regression Analysis. Supervised (Full Gaussian) classification was applied using the Maximum Likelihood Algorithm in ILWIS Academic 3.2 to generate five main land use/land cover classes for all the remotely sensed images used. The five classes used were built up areas, agricultural areas, light forest, thick forest and water body. The four images (30meters resolution) used were the 1997Landsat 5 TM, 2004 Landsat 7 ETM, 2011 Landsat 7 ETM+ and 2018 Landsat 8. The percentage land cover for built up area in 1997, 2004, 2011 and 2018 were 5.45%, 11.71%, 15.00%, and 39.32% respectively while the regression prediction results for 2025, 2032, and 2039 were66.66%, 104.24% and 150.85%respectively. These results show fast and exponential changes, which serves as an early warning for overflowing slum development. The results are recommended as verified statistics with which government will plan and make policies to mitigate the anticipated slum challenges that will come with the predicted changes in physical urban development in the study area.

KEYWORDS: Remote Sensing**,** GIS, Physical Urban development, Monitoring and Change Prediction.

INTRODUCTION

Sustainable physical urban development is a fundamental part of the civilization of every nation. It is the man-made improvements in the environment, engineered to suite man's habitation purposes. In Africa, rapid developments in urban centers, particularly residential housing, are catalyzed by the teeming population of the rural-urban migrants which is mainly made up of young people who are seeking greener pastures. World Bank (2018) projects that whereas 55% of the global population lives in urban areas today, by 2045, the number of people living in cities will increase by 1.5 times to 6 billion, adding 2 billion more urban residents. With more than 80% of global GDP generated in cities, however, urbanization can contribute to sustainable growth if managed well by increasing productivity, allowing innovation and new ideas to emerge. There is, therefore, a pressing need to assess, monitor and predict the rate of urban development, particularly, in developing African nations where population surge in slums have caused a lot of social ills.

Remote Sensing is the acquisition of spatial/geographic information about an object on the earth's surface without making direct physical contact with the object, converse to

traditional surveying techniques of direct observations and measurements. Geographic Information System (GIS), on the other hand, is a computer based system of software and hardware designed to capture, store, manipulate, analyze and manage geographical related data in order to solve land related problems of humans (Nnam *et al*, 2014). These techniques were employed in this study to assess, monitor and predict physical urban development in Nike sub-urban community in Enugu-East, Nigeria.

This Study was carried out in part of Nike, Enugu East local government area, Enugu state in Nigeria. The population of the sub-urban area is about 50,760 people (Source 2006 Census). It covers an area of 21.749km² radius from coordinate point 6º32′N and 7º32'E, with a population density of 2500/km².

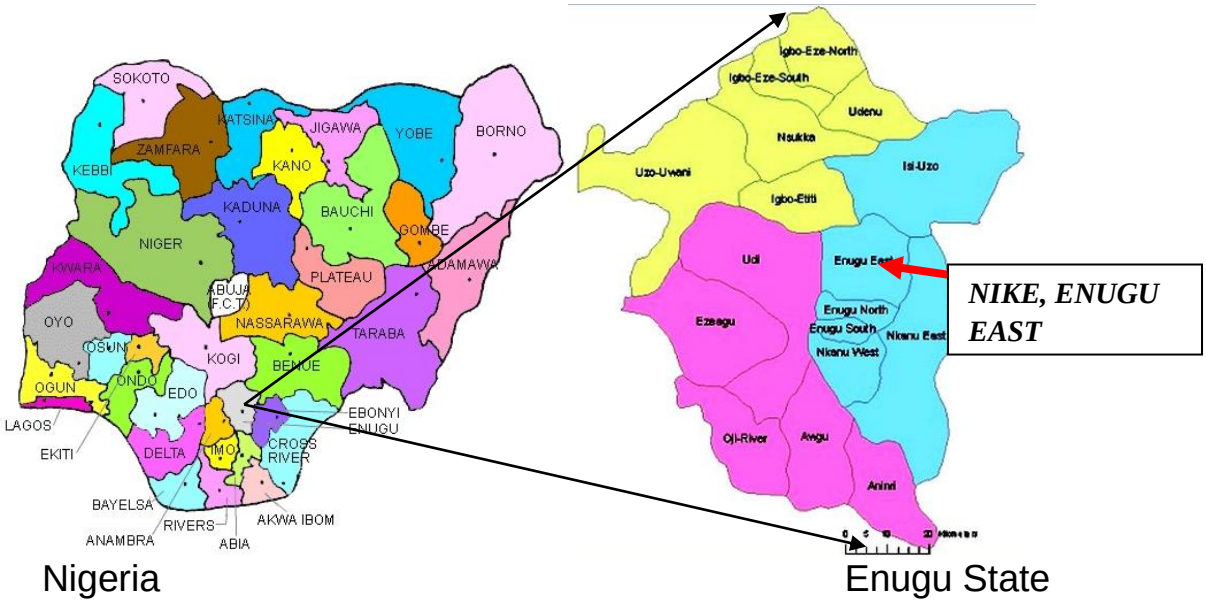


Fig. 1.0: Location maps showing the study area.

Spatial Monitoring of Area

The following archived remotely sensed imageries were openly sourced from Global land cover facility (GLCF) and used; Land sat 5 Thematic Mapper (TM) of 1997 with 30 meters resolution, Land sat 7 Enhanced Thematic Mapper (ETM) 2004 with 30 meters resolution, Land sat 7 Enhanced Thematic Mapper Plus (ETM+) image of 2011 with 30 meters resolution, Land sat 8 with 30meters resolution. The path and row of the study area are P188 and R55 respectively.

ArcGIS 10.1, ILWIS Academic 3.2 and Erdas imagine 9.2 were used for the data processing in the study. Supervised (Full Gaussian) classification was applied, using Maximum Likelihood to generate five main land use/land cover classes, namely, Built-up Area, Farm Lands, Savannah Area, Forests, and Rivers. These land use/land cover classes were derived from the 1997, 2004, 2011 and 2018 imageries of the study area

Three bands (742) were used in color composite operation, the pseudo-color composite were applied where the band 7 was assigned to color red, this is to display the built up area in red color the Near-Infrared band 4 was used to display the spatial distribution of the vegetation in green color and the band 2 was used to display the water body in color blue. The primary color RGB (Red Green Blue) was used as the panel to display the Landsat Scene Information in their various natural colors. The color composite image was resampled using the maximum and minimum coordinate of the area, the pixel size was defined (30m) for the both Landsat TM and ETM+. The same reference system was used in the resampling process. The output image was the subset image to the study area. The image resampling operation enabled registration of multi-date image of the same area.

The pixel based supervised classification scheme was employed where spectral signatures of the classes was adopted and the software assigned each pixel in the image to the cover type. The stages employed in the supervised classification are as following.

i. Location of the 'training sites' in the image and selection of sample set.

ii. Maximum likelihood classification which was employed in the analysis of the classification in which the output image was displayed. A sample set was used as input in the Classification operation.

Change Detection Analysis

The method of change detection used in this study was the Cross Tabulation Method. The Cross Operation performs an overlay of two raster maps. Pixels on the same positions in both images were compared. The occurring combinations of class names, identifiers or values of pixels were stored. These combinations give an output Cross Map, and a Cross Table. The Cross Table of land use/land cover change for the study areas showed Combination Classes in the Change Matrix. The analysis was Area-Based Comparison, so that recorded changes from one class to another represents the actual.

To determine the percentage of land use/land cover change, the study period 1997-2018 was divided into three sub-periods and the land use/land cover changes of the two sub periods were compared. The first sub-period was from 1997 to 2004 and the second sub period was from 2004 to 2011 and the third one is from 2011 to 2018. The comparative analysis in land use and land cover change focused on the three sub-periods. The spatial distribution of the average (annual) rate of land use/land cover change between two periods was computed by a slightly modified formula used by Long *et al.* (2007).

$$\Delta = \left(\frac{A_2 - A_1}{A_1} \times 100 \right) \div (T_2 - T_1) \qquad (1)$$

Where: Δ = Average annual rate of change
A_1 =Amount of land cover type in Time 1 (T_1)
A_2 =Amount of land cover type in Time 2 (T_2)

Percentage change to determine the trend of change can then be calculated by dividing observed change by sum of area of the particular land use in that period multiplied by 100.

$$\%Trend = \frac{\Delta A \times 100}{\sum A} \qquad (2)$$

Where:

ΔA= (Area of the previous year – Area of the current year)
$\sum A$ = Sum of area (both years)

Result, Analysis and Forecasting

The spatial change pattern of the physical development of the study area from 1997, 2004, 2011and 2018 was assessed, monitored and predicted through land use/land cover change classification of the study area. The results are shown, analysed and discussed below.

Results of Land Cover Classification of the study area in 1997

Table 1: Land use/Cover of the study area in 1997

Trans 1997	Class	Count	Area(m^2)	PCt (%)
1	Built Up Area	1318	1186200	5.45
2	Agricultural Area	2546	2291400	10.54
3	Light Forest	4836	4352400	20.01
4	Thick Forest	15389	13850100	63.68
5	Water Body	76	68400	0.31
Total		**24165**	**21748500**	**100.00**

Results of Land Cover Classification of the study area in 2004

Table 2: Land use/Cover of the study area in 2004

Trans 2004	Class	Count	Area(m^2)	PCt (%)
1	Built Up Area	2830	2547000	11.71
2	Agricultural Area	2574	2316600	10.65
3	Light Forest	10127	9114300	41.91
4	Thick Forest	8232	7408800	34.07
5	Water Body	402	361800	1.66
Total		**24165**	**21748500**	**100.00**

Results of Land Cover Classification of the study area in 2011

Table 3.0: Land use/Cover of the study area in 2011

Trans 2011	Class	Count	Area(m^2)	PCt (%)
1	Built Up Area	3625	3262500	15.00
2	Agricultural Area	6439	5795100	26.65
3	Light Forest	10759	9683100	44.52
4	Thick Forest	3247	2922300	13.44
5	Water Body	95	85500	0.39
Total		**24165**	**21748500**	**100.00**

Results of Land Cover Classification of the study area in 2018

Table 4.0: Land use/Cover of the study area in 2018

Trans 2018	Class	Count	Area(m^2)	PCt (%)
1	Built Up Area	9501	8550900	39.32
2	Agricultural Area	2324	2091600	9.62
3	Light Forest	8268	7441200	34.21
4	Thick Forest	3961	3564900	16.39
5	Water Body	111	99900	0.46
Total		**24165**	**21748500**	**100.00**

Spatial representation of the Land Use/Land Cover Changes

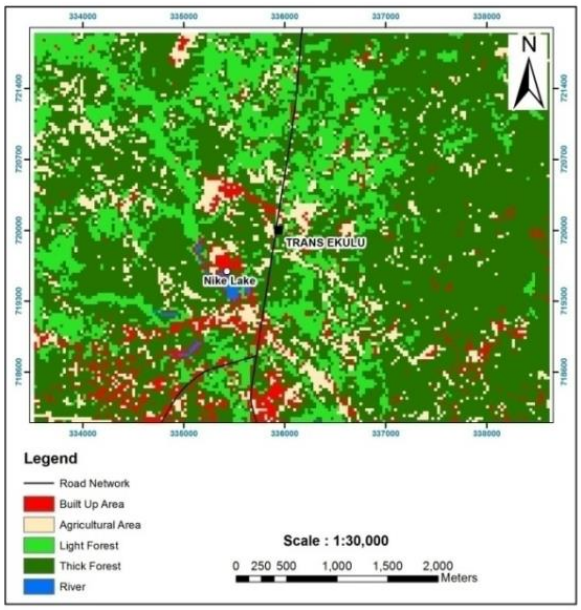


Figure 2.0 Land cover of the study area 1997

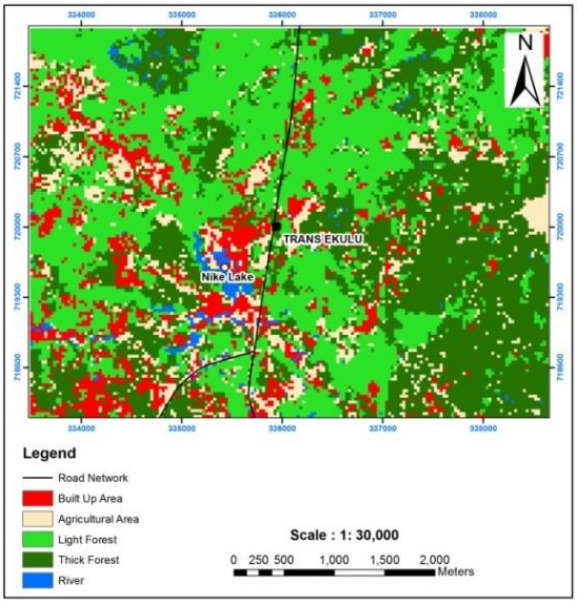


Figure.3.0 Land cover of the study area 2004

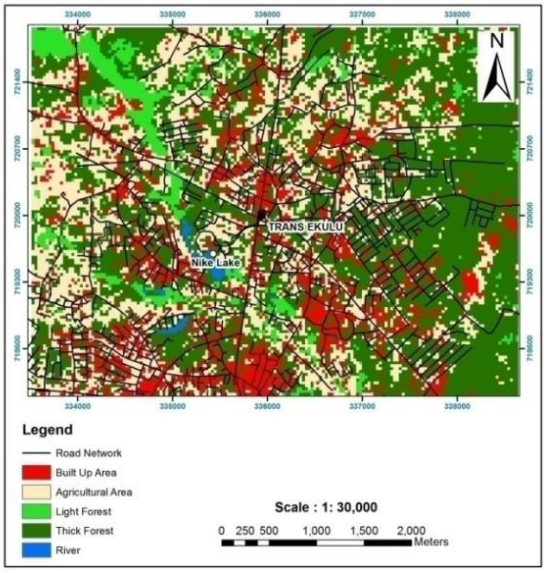


Figure 4.0 Land cover of the study area 2011

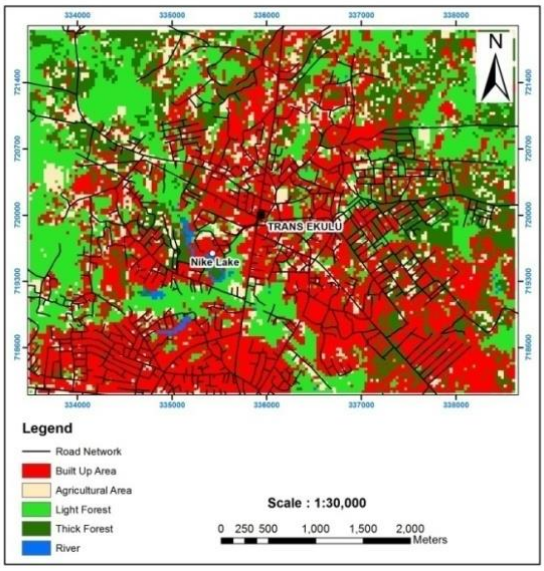


Figure. 5.0 Land cover of the study area 2018

Comparative analysis of the Land Use/ Land Cover Changes

Table 5: Evaluation of land use/Cover change of the study area from 1997 to 2004

		Land use/Cover (1997)		Land use/Cover (2004)		Change between 1997 and 2004			
Value	Classes	Area (m^2)	PCT (%)	Area (m^2)	PCT (%)	Area 2004 - Area 1997 (m^2)	% 2004 - % 1997	(%) of change	Evaluation of changes
1	Built Up Area	1186200	5.45	2547000	11.71	1360800	6	1.18	Increased

2	Agricultural Area	2291400	10.54	2316600	10.65	25200	0	0.02	No Change
3	Light Forest	4352400	20.01	9114300	41.91	4761900	22	4.12	Increased
4	Thick Forest	13850100	63.68	7408800	34.07	-6441300	-30	-5.57	Decreased
5	Water Body	68400	0.31	361800	1.66	293400	1	0.25	Increased
Total		**21748500**	**100**	**21748500**	**100**	**0**	**0**	0.00	

Table 5 shows that, from 1997 to 2004 the built up area has increased from 5.45% to 11.71%, the percentage of change at 1.18% for built up area shows that the change was not significant in 2004, the agricultural increased from 10.54 % to 10.65%, the percentage of change in agricultural area at 0.02% shows that they is little change in the agriculture area within the period of study, this was due to the low growth of the population density and urbanization. The Light forest has increased considerably from 20.01% to 41.91% at change rate of 4.12% due to reforestation and climate change phenomenon. The thick forest has decreased from 63.68% to 34.07% at negative change rate of -5.57%. The change in water body can be seasonal. It had a slight increase from 1999 to 2004 at the rate of 0.25% from 0.31% to 1.66%.

Table 6 shows that, from 2004 to 2011 the built up area increased from 11.71% to 15 %, the percentage of change at 0.62% for built up area shows that the change was not significant in 2011, the agricultural increased from 10.65% to 26.65%, the percentage of change in agricultural area at 3.01% shows that they is improve change in the agriculture area within the period of study, this was due to the growth of the population density and urbanization. The Light forest has increased considerably from 41.91% to 44.52% at change rate of 3%. The Thick forest has decreased from 34.07% to 13.44% at negative change rate of -3.88%. These deforestations may be due to pressure of human activities. Water body has decreased from 1.66% to 0.39% at very non significant negative rate of -0.24.

Table 6: Evaluation of land use/Cover change of the study area from 2004 to 2011

		Land use/Cover (2004)		**Land use/Cover (2011)**		**Change between 2004 and 2011**			
Value	**Classes**	**Area (m^2)**	**PCT (%)**	**Area (m^2)**	**PCT (%)**	**Area2011 - Area 2004**	**% 2011-% 2004**	**% Δ**	**Evaluation of Changes**
1	Built Up Area	2547000	11.71	3262500	15	715500	3	0.62	Increased
2	Agricultural Area	2316600	10.65	5795100	26.65	3478500	16	3.01	Increased
3	Light Forest	9114300	41.91	9683100	44.52	568800	3	0.49	Increased
4	Thick Forest	7408800	34.07	2922300	13.44	-4486500	-21	-3.88	Decreased
5	Water Body	361800	1.66	85500	0.39	-276300	-1	-0.24	Decreased
Total		**21748500**	**100**	**21748500**	**100**	**0**	**0**	0.00	

Table 7 shows that, From 2011 to 2018 the built up area has increased from 15% to 39.32 % , the percentage of change at 4.57% for built up area shows that the change was more prominent in 2011. The agricultural decreased from 26.65% to 9.62%, the percentage of change in agricultural area was negative (-3.01%) implying that urbanization has affected the agricultural area. Many agricultural areas have been converted to built up area for human settlement and activities. The Light forest has decreased considerably from 44.52 % to 34.21% at the rate of -1.20%. The Thick forest has increased from 13.44% to 16.39% at change rate of 0.56%. These afforestations may be due to government policy and awareness of population against deforestation.

Table 7.0: Evaluation of land use/Cover change of the study area from 2011 to 2018

		Landuse/Cover (2011)		**Landuse/Cover (2018)**		**Change between 2011 and 2018**			**Evaluation of changes**
Value	**Classes**	**Area (m^2)**	**PCT (%)**	**Area (m^2)**	**PCT (%)**	**Area 2018 - Area 2011**	**Δ 2018 - Δ 2011**	**Δ(%)**	
1	Built Up Area	3262500	15	8550900	39.32	5288400	24	4.57	Increased
2	Agricultural Area	5795100	26.65	2091600	9.62	-3703500	-17	-3.20	Decreased
3	Light Forest	9683100	44.52	7441200	34.21	-2241900	-10	-1.94	Decreased
4	Thick Forest	2922300	13.44	3564900	16.39	642600	3	0.56	Increased
5	Water Body	85500	0.39	99900	0.46	14400	0	0.01	No Change
Total		**21748500**	**100**	**21748500**	**100**	**0**	**0**	0.00	

Results of the Regression analysis

To predict the land use/land cover changes, the regression analysis were run in Microsoft excel using the tables5.0, 6.0 and 7.0 above and the results are in Table 8.

The summary table shows that the polynomial second order equation which was used for forecasting as the R Square is0.956 this equation is the best fit for prediction. To determine the polynomial equation the following coefficients in the summary table were used to formulate the prediction equation: Intercept= 80105905019, X Variable 1= - 80129832.24, X Variable 2= 20038.77551

Prediction equation is therefore: $Y = 20038.77551X^2 - 80129832.24X + 80105905019$

This equation was used in computing the prediction table where Y is the predicted Land use/land cover and X is the predicting Years.

Table 8:The Statistical Summary of Regression Analysis

Regression Statistics	
Multiple R	0.977960812
R Square	0.95640735
Adjusted R Square	0.869222051
Standard	1166824.992

Error								
Observations	4							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	2	2.99E+13	1.49E+13	10.96982	0.208789			
Residual	1	1.36E+12	1.36E+12					
Total	3	3.12E+13						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	80105905019	4.8E+10	1.669469	0.34357	-5.3E+11	6.9E+11	-5.3E+11	6.898E+11
X Variable 1	-80129832.24	47804164	-1.67621	0.34244	-6.9E+08	5.27E+08	-6.9E+08	527279658
X Variable 2	20038.77551	11906.38	1.683029	0.341304	-131246	171323.6	-131246	171323.65

Table 9: Prediction of urban Development (Built up Area)of the Area.

Study	**Years**	**Area(m^2)**	% Coverage
Year of Study	1997	1186200	5.45
	2004	2547000	11.71
	2011	3262500	15.00
	2018	8550900	39.32
Prediction	2025	14498559	66.66
	2032	22670919	104.24
	2039	32807079	150.85

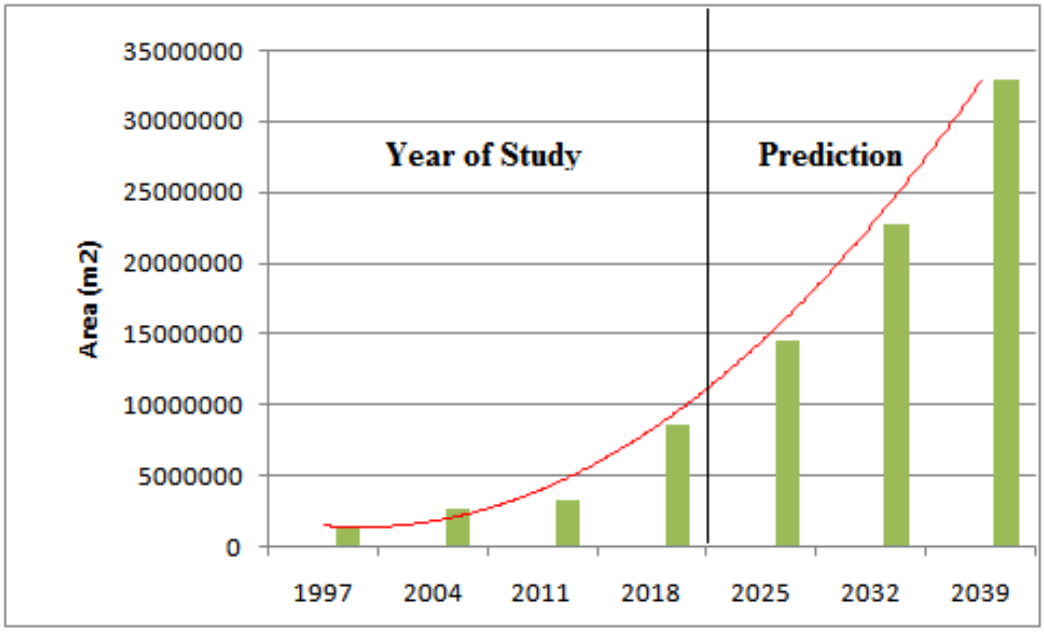


Figure 6.0: Histogram and trend line of urban area/ Prediction.

CONCLUSION

This study has analyzed the physical urban development pattern and developmental activities that has occurred in the study area within a period of 28 years by studying the land use/land cover changes. It also made a prediction through regression analysis of the possible state of the area by the year 2025, 2032 and 2039 respectively.

Considering the rate of urban development demonstrated in this study and its prediction, it is expected that by 2039, if not controlled, the will be a total overflow of built up areas and inhabitants of the area will be faced with challenges such as traffic jams, increased crime rates, land litigations, juvenile delinquencies and more.

With the total elimination of all other classes of land use as shown by the prediction, comes all the negative effects of climate change. Without vegetation, the production of oxygen (O_2) and consumption of the Carbon IV Oxide (CO_2) by the trees would be impossible. Since the water bodies would be lost, people would resort to excessive borehole drilling and this would bring about the weakening of the substructure of the area and excessive removal of water from the underground aquifers which would possibly lead to subsidence especially for large structures.

The 104.24% and 150.85%prediction values for years 2032 and 2039 respectively, indicates that by those years, having attained a complete spread of the study area, there will not just be a horizontal slum, there would also be a vertical slum. The number of high rise buildings would increase by over 50% by 2039 and with this comes poor circulation of air, over use of social amenities, and eventually an increased mortality rate.

Sustainable development in Africa can only be achieved if urban development is periodically and continuously assessed, monitored, predicted and controlled with strong urban development planning policies based on such scientific methods as applied in this study.

Recommendations

In order to forestall the impending slum development in Nike Enugu, it is strongly recommended that the leadership of Nike community and Enugu State Government moves in quickly and create a master plan for the development of the area under review.

That the master plan, so designed, be used for the continuous assessment, monitoring and control of the area in order to curb violations. If adequately policed, the impending loom so discovered in this area would be averted.

It is further recommended that the Enugu State Government and Nigeria in general adopts this approach of Remote Sensing and GIS for the planning, management and control of newly developing areas in order to improve the livelihood and health standards in such places.

REFERENCES

Burdekin, R. (1979) A dynamic Spatial Urban Model: a generalization of Forrestser's Urban Dynamics model. Urban 4:93-120.

Carleer, A. P. and Wolff, E., (2006). Urban land covers multi-level region-based classification of VHR data by selecting relevant features. *International Journal of Remote Sensing,* 27(6), pp. 1035–1051.

Coppin, P., Jonckheere, I., Nackaerts, K. and Muys, B. (2004). Digital change detection methods in ecosystem monitoring: a review. *International Journal of Remote Sensing,* 25 (9): 1565-1596.

Despotakis, Vassilios K., and Maria Giaoutzi.(1996) Spatial Modeling of Urban Dynamics. Paper read at 1996International System Dynamics Conference, at Cambridge, Massachusetts.

Graham, AlanK. (1974) Understanding Urban Dynamics: An Analysis of Garn's Interpretation. In Rreading in Urban Dynamics, Edited by N. J. Mass. Cambridge MA; Productivity Press.

IgbokweJ. I., OgunladeS O, Ejikeme J Oand IgbokweE C (2016): Mapping and monitoring deforestation in ondo state using remote sensing techniques for forest resource management. Nigeria. Nigerian Journal of Surveying and Geoinformatics, Vol 5. No 1.

IgbokweJ. I., IbeU C, EjikemeJ O, Igbokwe E C (2016): Spatio-temporal mapping and analysis of agulu-nanka gully erosion site in Anambra, Nigeria. Nigerian Journal of Surveying and Geoinformatics, Vol 5. No 1.

Jensen, J.R.,(1996), Introductory digital image processing: a remote sensing perspective, Upper Saddle River, NJ: Prentice Hall, (second edition).

Long, H.G., Tang, G., Li, X., and Heilig, G.K. (2007): Socio-economic driving forces of land use change in Kunshan, the Yangtze River Delta Economic Area of China. *Journal of Environmental Management* 83 (3): 351-364

Nnam V.C , Maduako I., Nnam G. U, Onwuzuligbo C., Eze M. A.(2014): Assessment ofSpatial Urban Dynamics in Enugu City Using GIS and Remote Sensing. Presented at the technical session, paper 6908. FIG Congress 2014, 16 – 21 June 2014,Kuala Lumpur,Malaysia.

Nnam G. U , Ndukwu R. N, Nnam V.C , Onwuzuligbo C., Nnam J. O.(2015): Comparison of Pixel Based and Object Oriented Image Classification for Mapping Urban Greenery in Uwani Enugu. Peer reviewed paper 7557,presented at the technical session,.FIG Congress 2015, 17 – 21 May 2015, Sofia, Bulgaria.

Sanders P. and Sanders F., (2012): Spatial Urban Dynamics; A vision on the Future of Urban Dynamics: Forrester Revisited. PDF accessed online 20-10-2013.

Singh, A. (1989): Digital change detection techniques using remotely-sensed data. International Journal Remote Sensing, 10 (6): 989-1003.

Statistics: Enugu, Nigeria (2010): The Weather Network.(PDF) Retrieved 2012-06-23.

World Bank (2018): Urban Development. Accessed through www.worldbank.org,20-09-2018