An Exploratory use of SLEUTH Urban Growth Model in the Spatiotemporal Growth Simulation of Greater Karu Urban Area

MUHAMMAD Asadullah[1], CHINDO Musa Muhammad[2]
Nigeria Customs Service, Abuja Nigeria[1]
Federal Polytechnic Nasarawa, Nasarawa State, Nigeria[2]

Abstract:
SLEUTH is a self-modifying cellular automaton model developed and widely applied to predict urban growth in different cities across the globe. The model as the name implies is calibrated using historical data layers as control. In this study, the model was calibrated for Karu region, which is indeed the first successful calibration of the model in Nigeria. The main objective of the calibration was to find coefficient values that best model urban and related landcover change through time in study area. The calibration was executed in coarse, fine and final phases, with each phase applied datasets of different resolution. The calibration produced initializing coefficient values that best simulate historical growth of Karu and the best fit values were used in the prediction phase. Using average values derived from calibration at full resolution with 100 Monte carlo iterations, year 2012 was set as prediction start date and growth forecasted to year 2073, with probabilistic maps of cells being urbanized in the future produced.

Keywords: SLEUTH, urban growth simulation, urban growth model, cellular automata, Karu.

I. INTRODUCTION

Globally, countries have significantly urbanized since the 1950s and are expected to continue this process through the 21st century (UN-Habitat, 2008). In the year 2001, only 2.9b people (48% of total population) are believed to have lived in urban settlements across the world. But by the year 2016, the figure had risen to 4.034b people (54.5% of total population) and expected to rise to about 5.058b people (60% of total population) by the year 2030 (United Nation, 2016). Thus, urban growths in the 21st century is arguably unprecedented and presents a formidable challenge for urban planners and managers (Masser, 2001). However, with 24 of the world's 31 megacities as at 2016 and all the 10 cities projected to become megacities between 2016 and 2030 located in developing countries, bulk of the urban growth expected will unequivocally take place in the less developed countries (Masser, 2001) (United Nation, 2016).

Urbanization trend in Nigeria indicates Nigeria is one of the countries urban growths are expected to continue unabated. With merely less than 15% of the total population of Nigeria living in urban centers of more than 20,000 inhabitants in 1950, by the year 2000, more than 43.5% of the total population were already living in urban centers of more than 20,000 inhabitant, with some 19 and 40 cities having population of more than one million and close to 500,000 respectively (Thematic Committee, 2001). This unprecedented growth of urban population is certainly not unrelated to the rapid growth of the country's population, and probably rural urban migration as reported by (Oguntoyinbo & Sada, 1981). In fact, in 2015, Nigeria was the only African country, and the most rapidly growing among a list of ten (10) largest countries in the world. Furthermore, Nigeria was ranked second to India on a list of nine countries half of the world's population growth is expected to be concentrated between 2015 and 2050, and is expected to become the third largest by 2050 (United Nations, 2015). This expected population growth will mostly likely be accompanied by further rapid urbanization already estimated by (Adesina, 2005) to have been contributing to loss of about 400,000 hectares of vegetated land cover annually.

Since the relocation of Nigeria's administrative capital from Lagos to Abuja in 1991 for administrative convenience, Karu became one of the fastest growing settlements in Nigeria. This growth is due largely to continued influx of migrants from other parts of the country to Abuja in search of jobs and opportunities, and the failure of Abuja to fully absorb the migrants. In essence, Karu is one of the surrounding cities of Abuja forced to absorb large numbers of people looking for shelter and land that is relatively less expensive than what can be found in the capital city. This has encouraged the development of slums in many neighborhoods; with unsatisfactory urban conditions, indiscriminate waste dumping, inadequate sewage disposal facilities, pollution from motor vehicles and electricity generating machines, environmental degradation, and traffic congestion among other shortcomings in Karu (UN-Habitat, 2012) (Yari, Madziga, & Sani, 2002). Although the growth of Karu being a topical issue, has attracted the attention of researchers who have quantified the growth of Karu over the past decades, projecting the future growth scenario will provide new insights to planners, policy makers and scholars to understand how the Karu might expand and how to actively prepare the settlement for future challenges.

Urban modelling started since the late 1950s and has evolve over time. Today, progress in remote sensing and geographic information systems technology, and advances in computer science and its application in urban planning have made possible

dynamic modeling for understanding the spatial consequences of urban growth. So far, cellular automata (CA), artificial neural networks, statistical models, multi-agent models and fractal models are some of the documented dynamic models. Among all the aforementioned dynamic models, CA are the famous. This is probably due to their flexibility, simplicity in application and closer ties to remote sensing data and geographic information systems (Rafiee, Salman, Khorasani, Asghar, & Danekar, 2009).

CA were first introduce by John Von Neuman and Stanislaw Ulam in the 1940's as a framework for investigating the biological underpinnings of life (Torrens, 2000). However, the first serious study of CA was initiated by Stephen Wolfram in the early 1980s and that laid the foundation of its applications in many areas of science today (Schiff, n.d). An elementary CA (Cellular Automaton) consist of: cell, state, neighbourhood, transition rule and time as its basic elements. The cellis the basic spatial unit in a cellular space. The statedefines the attributes of the system. The neighbourhoodis a set of cells with which the cell in question interacts.The transition ruledefines how the state of one cell changes in response to its current state and the states of its neighbours. And timespecifies the temporal dimension in which a cellular automaton exists (Liu, 2008).

The application of CA in geographical modeling was originally proposed by Waldo Tobler in 1979 in his paper "The Cellular Geography" and has become the most widely used approach in urban study since the 1980s. Thus far, Dynamic Urban Evolution Model (DUEM) (Batty, 1998), Island model (Engelen, White, Uljee, & Drazan, 1995), SimLand(Wu, 1998), Constrained Cellular Automata Model (Li & Yeh, 2000), and SLEUTH model (Clarke, Hoppen, and Gaydos 1997) are some of the CA-based models of urban growth. However, among the CA-based models, SLEUTH seems to be the most suitable. This is probably because: SLEUTH is a hybrid of the two schools in CA modeling and has the ability of incorporating detailed land use data in modeling urban growth; the shareware availability means that any researcher having the data could perform experiment at no cost; the portability of the model makes it application possible at any geographic system at any extent or spatial resolution; of the presence of a well-established internet discussion board to support any problems and provide insight into the model's application; of the availability of geographic modeling literature that documents both theory and application of the model; and of the ability of the model to project urban growth based on historical trends with urban and non-urban data (Rafiee*et al*., 2009).

Study Area
The area under study designated Karu is located at the eastern fringe of Abuja (Nigeria's Administrative Capital) and is defined and delimited by the Boundary of the Greater Karu Urban Area (GKUA), incorporating the settlements of Mararaba, Ado, New Karu, New Nyaya and Masaka in Karu Local Government Area of Nasarawa state as gazette and declared urban by the Nasarawa state government in March 2001, through a law passed by the Nasarawa state House of Assembly (figure 1). The area stretches between latitudes $8^0 43^{'}$N and $9^0 08^{'}$N, and longitudes $7^0 32^{'}$E and $7^0 51^{'}$E; and covers an approximate land area of 704 square kilometers. The area has a gently undulating terrain, dissected by a network of streams, with Uke and Ado Rivers which flows all year round being the prominent ones. The terrain represents a break from the more hilly areas of Nyaya and Abuja municipality. The area is generally between 300 to 500 meters above sea level, with slopes at about 4 to 10 percent gradient except around the stream-beds (Yari*etal*., 2002).
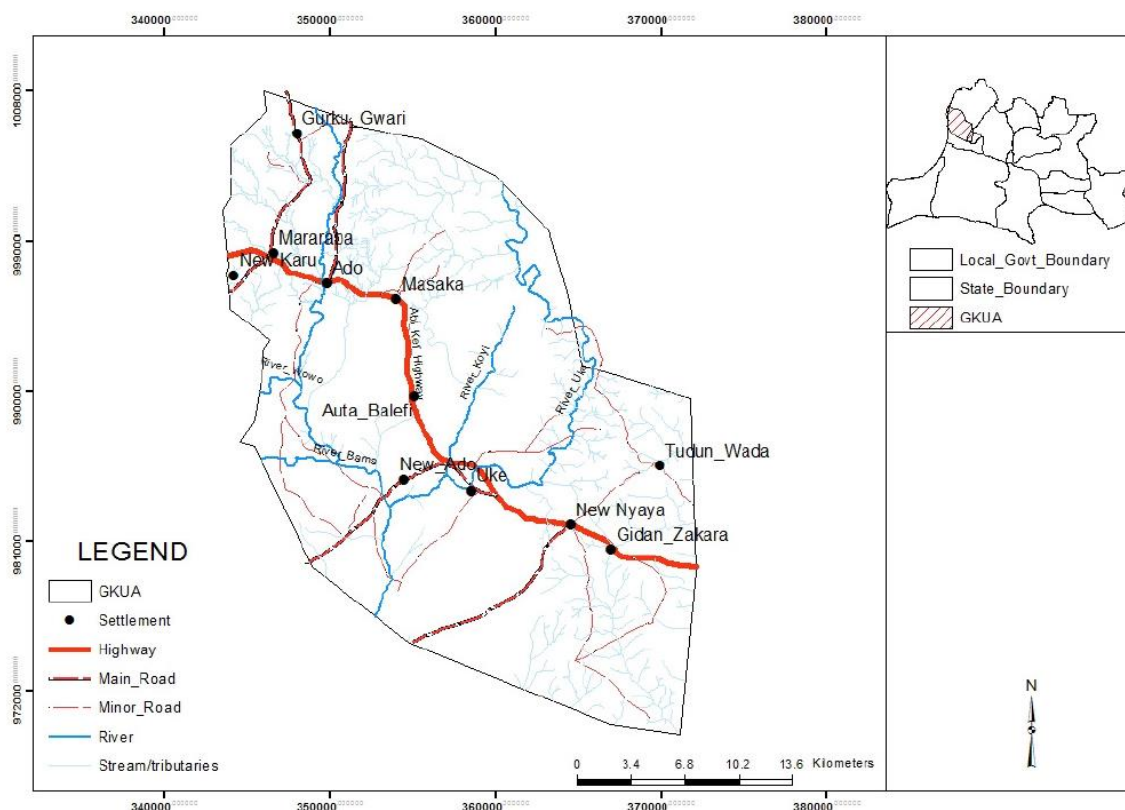
Source: Adopted and modified from topo sheets: 187; Gitata SE, SW & 208; Keffi NE, NW

Figure.1. GKUA, adopted and modified from topo sheets 187 Gitata SE, SW and 208 Keffi NE,NW

Because of the strategic location of Karu as a gateway between Abuja and the eastern regions of Nigeria, it has a cosmopolitan outlook with many different ethnic and tribal groups who migrated to take advantage of the economic potentials of this area living together in harmony. The precise population of Karu urban area is difficult to determine, given that it consists of at least four (4) main settlement areas that sprawl across the Abuja-Keffi expressway. However, available estimates indicates that as at 1991 and 2001 Karu housed about 10,000 and 46,990 people respectively (CASSAD, 2002); and 130,000 people by 2010 (Wards and Target Population in Nasarawa State, 2010).

II. MATERIALS AND METHODS

Sleuth Model

SLEUTH is a dynamic UGM based on CA. it incorporates the original Urban Growth Model (UGM) with Daltatron Land-use Model (DLM) (Brendon, 2007) (Rafiee*et al*., 2009). The model derived it name from the six input data layers: Slope, Land-cover, Exclusion, Urbanisation, Transportation, and Hillshade, required for a successful implementation. It was first developed and applied in the San Francisco Bay area of the United States by (Clarke, Hoppen, & Gaydos, 1997); later it was used to predict urban growth in San Francisco and the Washington/ Baltimore region by (Clarke & Gaydos, 1998); and since then, it has been calibrated and widely used to model urban growth across regions of the United States and the world (Liu, 2008).

Five factors: diffusion factor (dff), breed coefficient (Brd), spread coefficient (Sprd), slope resistance factor (Slp) and road gravity factor (RG), control the behavior of the system. The diffusion factor determines the overall outward depressiveness of the distribution; the breed coefficient specifies how likely a newly generated detached settlement is to begin its own growth cycle; the spread coefficient controls how much organic expansion occurs from existing settlements; the slope resistance factor influences the likelihood of settlement extending up steeper slopes; and the road gravity factor attracts new settlements toward and along roads. Consequently, four types of growth: spontaneous, diffusive, organic, and road influenced growth, are defined in the model. Spontaneous growth is when a randomly chosen cell falls very close to already urbanized cell, simulating the influence of urban areas on their surroundings. Diffusive growth emphasizes the urbanization of cells which are desirable locations for development, even if they do not lie near an already established urban area. Organic growth emphasizes spreads outward from existing urban centers, representing the tendency of cities to expand. Road influenced growth is when urbanized cells develop along the transportation network replicating increased accessibility (Clarke, et al., 1996)(Clarke, Hoppen, & Gaydos, 1997)(Clarke & Gaydos, 1998). Generally, SLEUTH model is implemented in two phases: a calibration phase, in which the model is trained to replicate historic development trends and patterns; and a prediction phase, in which historic trends are projected into the future. However, Implementation of SLEUTH in a new region is done in five steps: model compilation, data input preparation, calibration, prediction and result output (Yang & Lo, 2003).

Data preparation

Five (5) sets of satellite images (table 1) specifically from Landsat Multispectral Scanner (MSS), Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper + (ETM+) of 1973, 1986, 1990, 2003 and 2013, of the Karu area were acquired and classified using the supervised maximum likelihood image classification method. Urban extend were then derived by reclassifying the land cover maps obtained from the aforementioned image classification. Road layers of 1991 was prepared from Nigeria topo-sheets 187 (Gitata south-east and south-west) and sheets 208 (Keffi north-east and north-west), and 2013 from Digital Ortophoto obtained from the Nasarawa Geographic Information Services (NAGIS). Slope and hillshade layer were prepared from Shuttle Radar Topographic Mission (SRTM) Digital Elevation Modem (DEM). In this, the input layers were resampled into three spatial resolutions i.e. 120m Coarse phase, 60m fine phase, 30m final phase with corresponding image sizes of 238 by 322, 476 by 644 and 951 by 1288 pixels respectively for calibration purpose.

Table.1. Data source

Dates	Data type	Sources
1990	Topographic Map	Nigeria topo-sheets 187(Gitata SE and SW) and 208 (Keffi NE and NW)
2013	Ortho photo image	NAGIS
1973	Landsat MSS LANDSAT 1	U.S. Geological Survey
1986	Landsat MSS LANDSAT 5	U.S. Geological Survey
1990	Landsat TM LANDSAT 4	U.S. Geological Survey
2003	Landsat ETM LANDSAT 7	U.S. Geological Survey
2013	Landsat ETM LANDSAT 7	U.S. Geological Survey
2000	SRTM DEM	U.S. Geological Survey

Model Compilation:

Varied data sets were acquired from various sources as per the requirement of this research. Specific data acquired included: Landsat imageries of 1973, 1986, 1990, 2003 and 2013; USGS Digital Elevation Model (DEM); Topo map of 1990 depicting the Karu area; and 2013 ortho photo image of Karu area. To prepare and analyze all the relevant data, ArcGIS 10.5, Erdas imagine and SLEUTH3.0_beta were used. A temporary database was first created for Karu area in ArcGIS 10.5. This was used to assemble and manage historical data sets. The final data created (figure 2) included: slope, landuse used to derive urban extent, roads, excluded areas where urban growth can't take place, and a hill shaded background used for visualization.
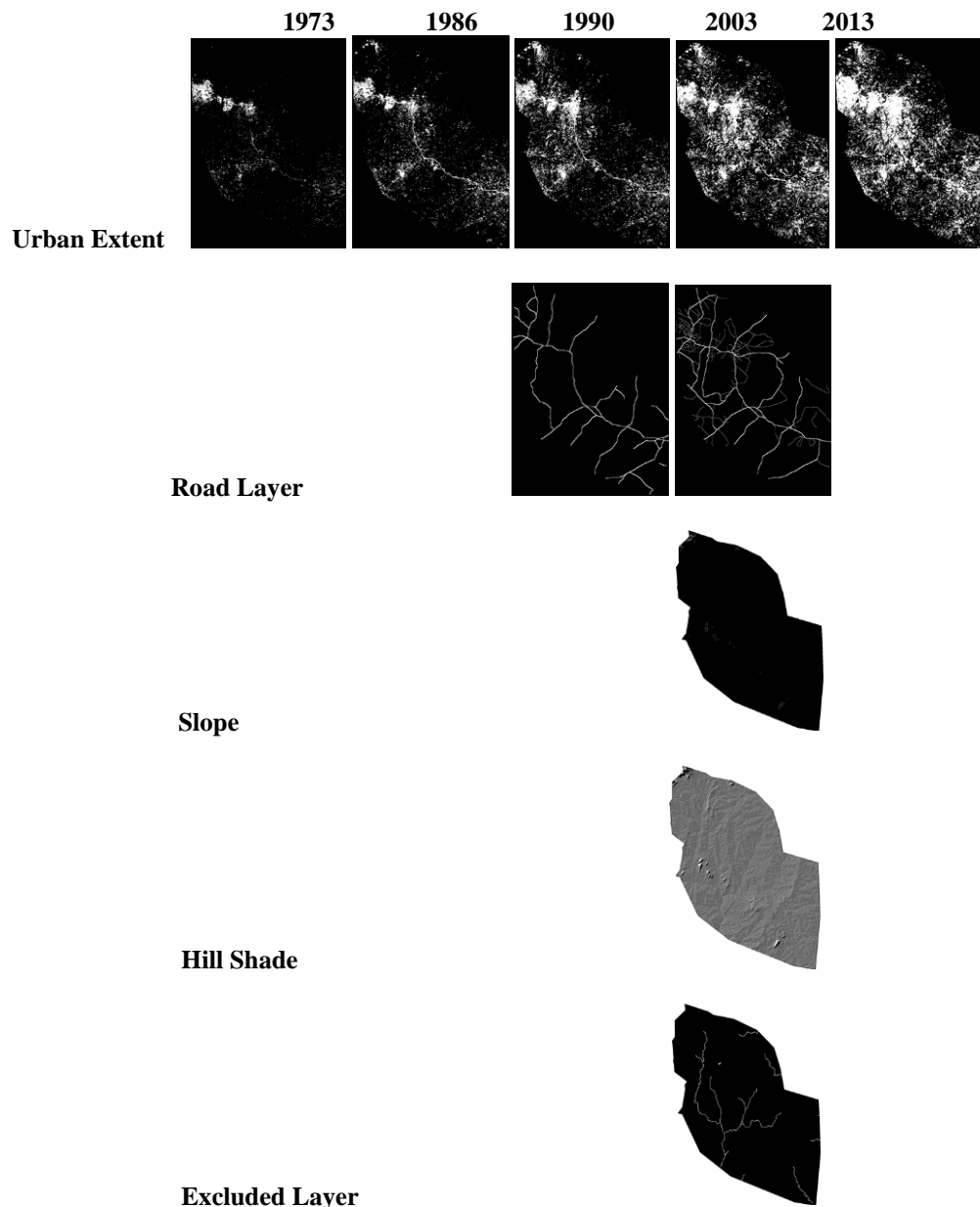
Figure.2. Input data layers of study area

Calibration

The main objective of the calibration mode is to find coefficient values that best model urban and related landcover change through time. Calibration requires many thousands of single simulations of landcover change. Therefore output requirements can greatly add to the total application. Calibration was executed in three phases: coarse, fine and final, based on the procedure of SLEUTH version 3.0 beta program. It involves the use of grey scale gif images at different resolution which corresponds to the three phases of calibration of each calibration stage.

III. RESULTS

Leesalee matrix was used to evaluate the performance of the model at each phase of calibration. The top three scores from Leesalee matrix determined the range of values to be used at the next phase of calibration. Each phase is applied a dataset of different resolution. For this study, coarse phase was applied to a

120m resolution dataset, fine phase had 60m and final phase had 30m resolution. The calibration produced initializing coefficient values (table 2) that best simulate historical growth of the study area, the best fit values were also used in the prediction phase. The low diffusion coefficients indicate karu has a dense form of growth, with urbanization occurring near the existing urban areas. Therefore, the growth of new urban areas near the existing urban area through spontaneous growth was very unlikely to occur. The breed coefficients are low, thus indicating low probability of dispersed urban growth which in turn responsible for some of the compact urban growth in karu. Moderate spread coefficients reflects a medium term probability of urbanization outward of the existing urban area. The slope resistance coefficients were high that implied the topography was a limiting factor for urban sprawl. The high road gravity coefficient showed urban growth has been affected by road network significantly.

Table.2. Calibration results

Coarse Calibration

compare	pop	edges	cluster	Leesalee	slope	xmean	ymean	diff	Brd	sprd	slp	RG
0.80	0.98	0.34	0.98	0.65	0.99	0.29	0.47	25	100	50	100	75
0.79	0.98	0.33	0.98	0.65	0.99	0.07	0.56	75	75	50	100	100
0.79	0.98	0.33	0.98	0.65	0.99	0.13	0.51	75	50	50	100	75

Fine Calibration

compare	pop	edges	cluster	leesalee	slope	xmean	ymean	diff	Brd	sprd	slp	RG
0.76	0.95	0.58	0.99	0.51	0.96	0.00	0.59	13	19	41	76	100
0.78	0.95	0.59	0.99	0.51	0.96	0.00	0.55	1	13	41	76	70
0.75	0.97	0.71	0.99	0.51	0.98	0.00	0.73	1	19	41	51	60

Final Calibration

| compare	pop	edges	cluster	leesalee	slope	xmean	ymean	diff	brd	sprd	slp	RG
0.90	0.95	0.99	0.22	0.34	0.29	0.21	0.00	1	13	40	40	24
0.91	0.95	0.99	0.21	0.34	0.29	0.21	0.00	1	25	40	40	24
0.91	0.95	0.99	0.21	0.34	0.29	0.22	0.00	1	25	40	40	47

Prediction

Models are often judged by their predictive power (Silvia & Clarke, 2007), thus the urban extent for the year 2013 (figure 3) was predicted by setting a prediction start date of 2012 as the initializing date. This was achieved using average values (table 3) derived from calibration at full resolution with 100 monte carlo iterations and growth was forecasted to 2073 (figure 4).

The phase produced probabilistic maps of cells being urbanized in the future

Table.3. Prediction best fit values

DIFF	BRD	SPRD	SLP	RG
7	13	40	1	70

URBAN GROWTH

2013 ACTUAL   2013 MODELED
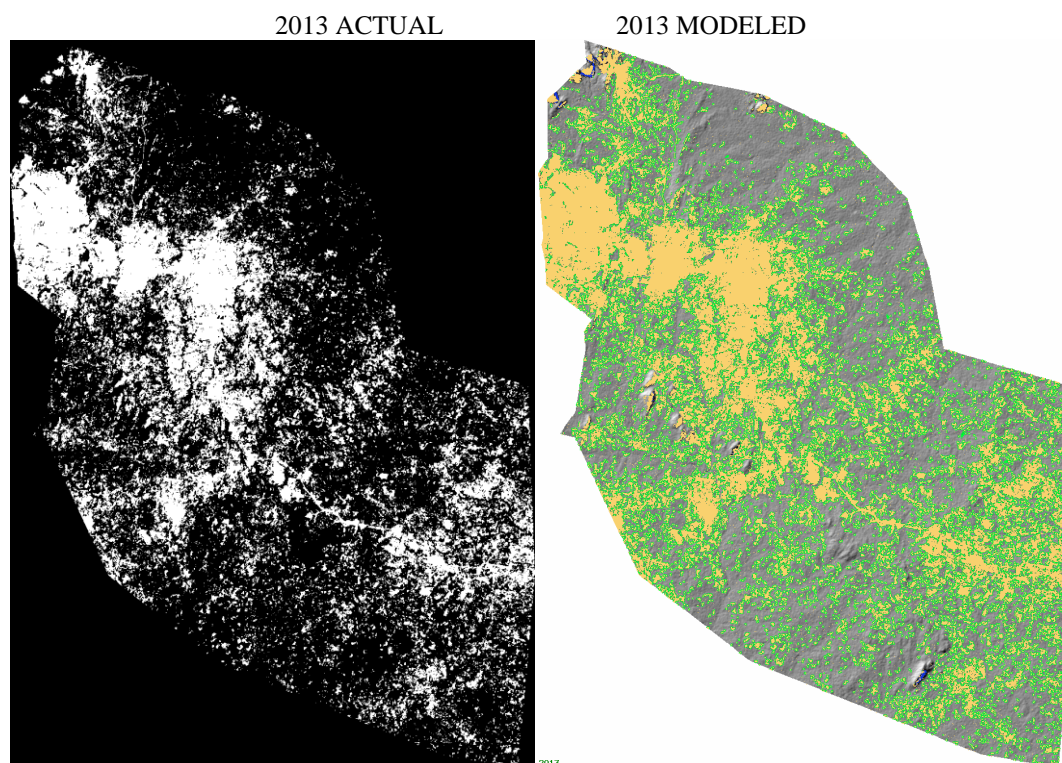
Figure.3. comparison of actual and modelled urban growth of the study area
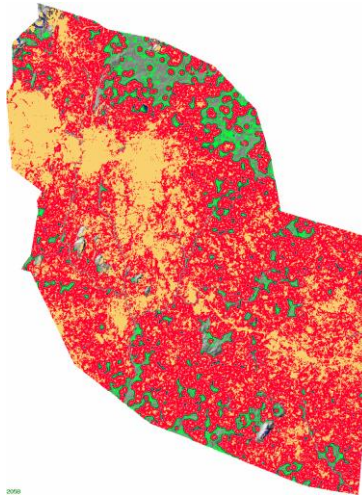
2028 MODELLED   2043 MODELLED

2058 MODELLED   2073 MODELLED

Figure.4. Simulation of urban growth (2028, 2043, 2058 and 2073)

Going by the visual interpretation of (figure 3) of the modelled urban extent with the actual urban extent, it appears the model was able to generate the urban extent of karu successfully. The forecast is based on a scenario where Karu's historical urban extent is allowed to expand with no limitation i.e. without the influence of policy making. However the urban growth rate and pattern would change with a master plan implemented strictly.

IV. CONCLUSION

Our research explored the combined and integrated application of remote sensing and SLEUTH urban model, which brings about a novel approach to the study spatiotemporal growth with 100years of spatial growth pattern analysis in karu, Nigeria. The model indicated a moderate spread coefficient and a very high road gravity coefficient, thus indicating moderate to low organic urban growth, whereas urban growth in the study area is highly road influenced. Lastly SLEUTH is a very sensitive model, thus the quality of the input data, cell size, consistent historic dataset and selection of optimal parameter ranges should be considered carefully to improve calibration.

V. REFERENCES

[1]. Adesina, F. A. (2005). Geo information and Natural Resources exploitation in Africa; United Nations Economic and Social Council Paper. Fourth meeting of the committee on Development Information. Addis Ababa 23 - 28.

[2]. Batty, M. (1998). Urban evolution on the desktop: simulation with the use of extended cellular automata. Environment and Planning A(30), 1943–67.

[3]. Brendon, M. W. (2007). The SLEUTH Urban Growth Model as Forcasting and Decision-Making Tool. Stellenbosch University.

[4]. Clarke, K. C., & Gaydos, L. J. (1998). Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. int. j. geographical information science, 12, 699-714.

[5]. Clarke, K. C., Hoppen, S., & Gaydos, c. (1997). A Self-Modifying Cellular Auto Mata Model of Historical Urbanization in The San Francisco Bay Area. Environment and Planning B: Planning and Design, 27, 247-261.

[6]. Clarke, K. C., Hoppen, S., & Gaydos, L. J. (1996). Methods And Techniques for Rigorous Calibration of a Cellular Automaton Model Of Urban Growth. Urban Dynamics.

[7]. Engelen, G., White, R., Uljee, I., & Drazan, P. (1995). Using cellular automata for integrated modelling of socio-

environmental systems. Environmental Monitoring and Assessment(34), 203-14.

[8]. Hir, J. (2012). Karu: Nasarawa's untapped goldmine. Daily Trust. Retrieved 01 01, 2018, from https:// www. dailytrust. com.ng/sunday/index.php/business169-karu-nasarawas-untap ped -goldmine

[9]. Kreibich, V. (2003). Urbanisation: Peasants and 'Yuppies' – Unconnected. KAAD Conference: Worlds Apart: Local and Global Villages. From Villagization to Globalization in One Generation. Nairobi.

[10]. Li, X., & Yeh, A. G. (2000). Modelling sustainable urban development by the integration of constrained cellular automata and GIS. International Journal of Geographical Information Systems(14), 131–52.

[11]. Liu, Y. (2008). Modelling Urban Development with Geographical Information Systems and Cellular Automata. Newyork: CRC Press, Taylor & Francis Group.

[12]. Masser, I. (2001). Managing our urban future: the role of remote sensing and geographic information systems. Habitat International(25), 503–512. Retrieved December 18, 2017, from http://www.Elsevier.com/locate/habitatint

[13]. Oguntoyinbo, J. S., & Sada, P. O. (1981). Urbanization Processes and Problems. Ibadan: University Press.

[14]. Rafiee, R., Salman, A. M., Khorasani, N., Asghar, A. D., & Danekar, A. (2009). Simulating urban growth in Mashad City, Iran through the SLEUTH model (UGM). Cities, 26, 19–26.

[15]. Schiff, J. L. (n.d). Introduction to Cellular Automata.

[16]. Shlomo, A., Stephen, S. C., & Daniel, C. L. (2005). The Dynamics of Global Urban Expansion. The World Bank, Department of Transport and Urban Development, Washington D.C. Retrieved December 22, 2017, from http:// www. williams. edu/ Economics/UrbanGrowth/DataEntry.htm.

[17]. Torrens, P. M. (2000). How Cellular Models of Urban System Works (1. Theory). Center for ADvance Spatial Analysis Working Paper Series Paper 28. CASA, UCL. Retrieved from http://www.casa.ucl.ac.uk/working_papers.htm

[18]. UN-Habitat. (2008). Meeting the Urban Challenges: UN-Habitat Donors meeting. Seville: United Nations.

[19].UN-Habitat. (2012). Nigeria: Karu Urban Profile. Nairobi.

[20]. United Nation. (2016). The World's Cities in 2016: Data Booklet. United Nation.

[21]. United Nations. (2015). World Population Prospects: The 2015 Revision, Key Findings and Advance Tables. Working Paper No. ESA/P/WP.241., Department of Economic and Social Affairs, Population Division, New York.

[22]. Wu, F. (1998). SimLand: a prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rules. International Journal of Geographical Information Science(12), 63–82.

[23]. Yang, X., & Lo, C. P. (2003). Modeling urban growth and landscape changes in the Atlanta metropolitan area. International Journal of Geographical Information Science, 17, 463–488.

[24]. Yari, K., Madziga, B., & Sani, M. (2002). Karu Governance and Management Institutions, Land use Management and Urban Services Management. UN-HABITAT, Karu Cities Alliance Initiative; Component of Karu Development Strategy