Environmental Technology & Science Journal
Vol. 9 Issue 1 June 2018

Scenario Simulation and Prediction of Land Use Changes in Metropolitan Kano, Based on the Markov-Cellular Automata Model (CA-MARKOV)

Duchi, Fidelis C. and Habila, Sunday Kazahshii
Department of Urban and Regional Planning, Faculty of Environmental Design, Ahmadu Bello University, Zaria-Nigeria.
fidelisduchi@yahoo.com

Land use models are essential for analyzing Land use change and predicting land use requirements and are valuable for guiding reasonable land use planning and management. However, each Land use model has its own advantages and constraints. Spatially explicit land use/cover models are indispensable for sustainable land use planning, particularly in African countries that are experiencing rapid land use changes. The study simulated future land use changes of Kano Metropolis up to 2035 based on a Markov-cellular automata model that integrates Markovian transition probabilities computed from satellite-derived land use/cover maps and a cellular automata spatial filter. A multicriteria evaluation (MCE) procedure was used to generate transition potential maps from biophysical data. The model's overall simulation success was 69% for 2005 simulated land use map and 83% for 2015 simulated land use map. Based on the 2005 calibration scenario, the Markov-cellular automata model simulated future land use/cover changes (up to 2035) under the 2015 calibration scenario, predicting a continuing downward trend in Open Space areas and an upward trend in Residential areas. Future land use simulations indicated that if the current land use trends continue in the study area without holistic sustainable development measures, severe land degradation and possibly land fragmentation will ensue.

Keywords: Changes, Land use, Markov-cellular, Models, Simulation, Sustainable development.

Introduction

Land use involves the management and modification of natural environment into built environment such as settlements, semi-natural habitats and spatial distribution of city functions such as residential areas, industrial, commercial, institutional, recreational functions. Changes in land use are often nonlinear and might trigger feedbacks to the system, distress living conditions and threaten vulnerability of people (Kasperson et al., 1995). Land use change has caused and will continue to cause dramatic changes in the structure and function of urban areas (Meyer and Turner, 1994). Projections of future land uses are needed to evaluate the implications of human action for the future of urban areas (Turner et al., 1995). Simulation of land use change is an essential way to the projections of future land use change patterns; it is needed to evaluate the implications of human action on the natural environment. It is also regarded as an efficient way to understand the driving forces of land use change. The land use models may help in representing spatial patterns of change which is essential in the selection, planning and implementation of land use schemes intended to meet the increasing demands for basic human needs and also determine possible environmental impacts. It is also essential to evaluating the consequences of current and recent land use trends, so as to avoid the future fragmentation of the urban land.

In this study, CA-Markov was chosen to simulate land use change based on the following requirements: dynamic simulation capability, high efficiency with data scarcity, simple calibration, ability to simulate multiple land covers and complex patterns. Cellular Automata-Markov has the ability to simulate land use changes among multiple categories and combines the Cellular Automata(CA) and Markov chain procedures. Markov analysis does not account for the causes of land use change and it is insensitive to space. However, Cellular Automata-Markov using the Cellular Automata approach relaxes strict assumptions associated with the Markov approach and explicitly considers both spatial and temporal changes. Cellular Automata-Markov also enables a more comprehensive simulation as compared to other Land use models such as GEOMOD (geometric modeler) and CLUE (Conversion of Land Use and Its Effects). However, Cellular Automata-Markov calibration is operationally based on a single period of time, which renders difficulty in simulating land use dynamics on a temporal scale. In addition, the assumptions underlying Cellular Automata-Markov method tend to be somewhat simplistic when looking at the micro-level changes in land use. Pontius and Malanson (2005) have demonstrated that the predictive power of Cellular Automata-Markov is higher for cases where it concentrates on the major signal of land changes and ignores noises. Pontius and Malanson (2005) compared Cellular Automata-Markov and GEOMOD in terms of simulation power and suitability for different applications in Central Massachusetts, USA. They applied a three stage method to measure simulation power. At first, calibration process was separated from validation process. Secondly, the accuracy was assessed at multiple resolutions. Finally, the calibrated model was compared to a null model that simulates pure persistence. Their investigation showed that the added complexity of spatial contiguity rule in Cellular Automata-Markov was of no benefit. Paegelow and Camacho (2005) studied the potential and limitation of prospective GIS-based Land use modeling. Their approach comprised the Markov chain for temporal simulation.

Study Area

Kano metropolis lies between latitudes 11° 25’ N to 12° 47’ N and longitude 8° 22’ E to 8° 39’ E east. Kano metropolis is bordered by Madobi and Tofa Local Government Areas (LGAs) to the South West, Gezawa LGA to the East, Dawakin Kudu LGA to the South East, and Minjibir LGA on the North East. The study area is made up of eight (8) LGAs. They include Dala, Fagge, Gwale, Municipal, Nassarawa, Tarauni, Kumbotso and parts of Ungogo local governments. Kano Metropolis is the second most populous urban centers in Nigeria after Lagos with nearly three million people. The population density at the city centers and its environs rises to about 10,000 persons per square kilometer (ibid, 2009). and it is referred to as the Center of Commerce in the Country due to long flourished marketing activities. The Climate of the metropolis is classified as tropical wet and dry (*Chen* et al., *2013).*). It is characterized by four distinct seasons, namely; the dry and cool season, which lasts from mid-November to February and marked by occasional dusty harmattan haze**.** Rainfall is a very critical weather element in the metropolitan. This is because of its deficiency during the dry season. The rainfall occurs during summer months which starts mostly from May and ends in October with rain days ranging between 150-200 mm, and an annual rainfall of over 1000mm. The average temperature is a bit hot, even during the cool Harmattan period the minimum temperature hardly falls below 11°C, whilst the monthly average temperature is not less than 20°C, whereas during the hot season usually Mid – March to Mid-May, the maximum temperature reading may be as high as 40°C. The average temperature for these hot months may range between 30ºC and 32°C. Relief ranges from lower plains of about 500 meters to the highlands of over 1000 meters above sea level. Scenery is characterized by picturesque grouped hills, sandy plains alluvial channels and some stand-alone rock formations. It is underlain mainly by quartzite meta- sediments and the Basement

Complex rocks of the Pre-Cambrain age. Action of prolonged denudation resulted in deep clay soil and laterite compositions. Regolithic hills are out crops of the upland plains (Okeagu, et al., 2004).

The Population of metropolitan is predominantly Hausa – Fulani. Nupe and Kanuri tribesmen occupy a distinct part of the old city. Due to high population density (approximately 47 inhabitants per km 2) and the fact that the majority of the people in the study area are dependent on agriculture for their livelihood, there has been a lot of pressure on the available resources, particularly woodlands and agricultural land (Chenje et al., 1998). The major economic activity in the study area is mostly semi-subsistence agriculture, with major crops such as maize, groundnuts, and cotton, as well as vegetables in those areas with irrigation. However, production of the major rain-fed crops is usually affected by the unreliable rainfall patterns, particularly the late onset of the rainy season.

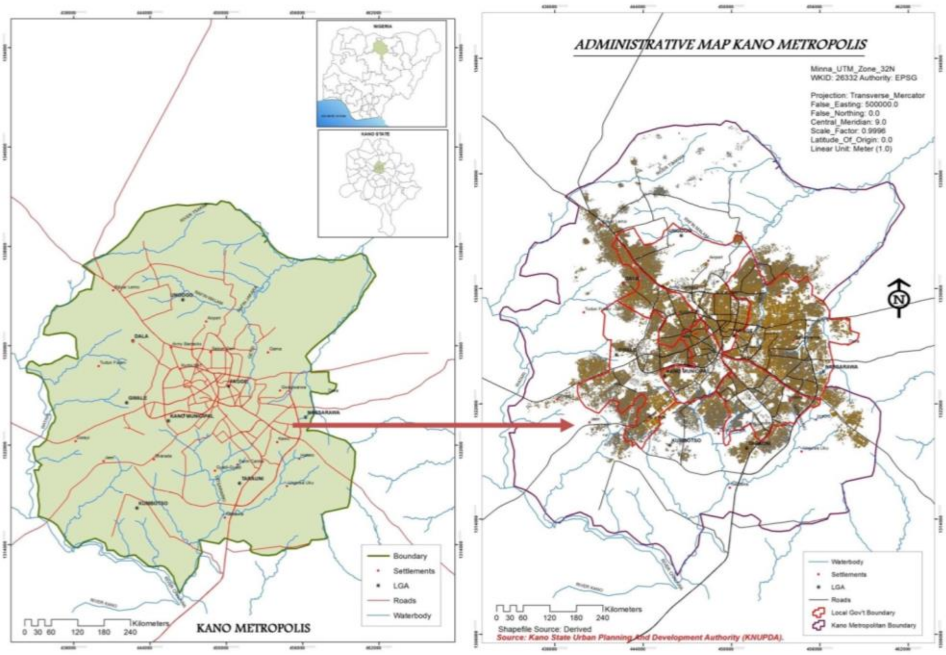


Figure 1. Map of the Study Area (Metropolitan Kano)

Methodology

In this study derived Land use maps dated 1985, 1995, 2005 and 2015 and topographical maps, with the scale of 1: 100,000 were collected from Kano State Urban Planning and Development Authority. Ancillary data such as road and stream networks, contour lines, and population centers were extracted from the topographic maps, with the scale of 1: 50,000. Based on the characteristics of Land use change in the study area, the existing land uses were classified into Six Land use types, Residential, Commercial, Mixed, Industrial, Public/ Semi-Public and Open Spaces. After that, field Survey and Google Earth Imagery were used to check and correct the accuracy of the interpreted images, which allowed obtaining the land use maps for 1985, 1995, 2005 and 2015. Finally, the grid maps, including four periods of land uses and some driving factors, were prepared for the model. Considering the periodic variation of Land use change and the rate of socio-economic development, the time span of the prediction could not be too short, so we selected 1985, 1995, 2005 and 2015 as the time nodes to simulate Metropolitan Kano's Land use pattern in 2025 and 2035. ArcGIS software was used in the preparation of maps and analysis of the relevant primary data in which were stored in the form of thematic layers and attribute table. The data collected was analyzed using simple descriptive statistical techniques and results of the analysis was presented by the use of Maps, table and satellite imageries were also used to illustrate and depict the conditions or characteristics of the entire land uses. Analytical method used are as follows

a. **Trend analysis:** The data collected from the study area was analyzed using attribute tables, satellite imageries in ArcGIS 10.1 software and also using charts and tables in Microsoft excel in classifying the various land uses. Data analysis was carried out in order to observe trends in land use changes. This data was also being used in time series analysis from 1985 to 2015.
b. **Modeling:** This was done using maps from ArcGIS 10.1 to analyze the past and present situation. This is in order to know the extent at which land use changes has taken place over time. This was achieved using the Markov's-Cellular Automata Model of Simulation
c. **Quarries:** This involve the extraction and sieving of information about certain features or attributes on maps, thereby using such information to draw inferences and conclusion.

Markov Model

The Markov model not only explains the quantification of conversion states between the land use types, but can also reveal the transfer rate among different land use types. It is commonly used in the prediction of geographical characteristics with no aftereffect event which has now become an important predicting method in geographic research. Based on the conditional probability formula—Bayes, the prediction of land use changes is calculated by the following equation:

$S(t + 1) = P_{ij} \times S(t)$ (1)

where $S(t)$, $S(t + 1)$ are the system status at the time of t or t + 1; P_{ij} is the transition probability matrix in a state which is calculated as follow

$P_{11}\ P_{12} \cdots P_{1n}$
$P_{21}\ P_{22} \cdots P_{2n} \cdots \quad \cdots \quad \cdots \cdots$
$P_{n1}\ P_{n2} \cdots P_{nn}$

$\{ \quad 0 \le P_{ij} < 1 \text{ and } \sum_{j=1}^{N} P_{ij} = 1, (i, j = 1, 2, \ldots, n)\}$

(adopted from Pontius and Millones, 2011).

Cellular Automata Model

The behavior of CA models is affected by uncertainties arising from the interaction between model elements, structures, and the quality of data sources used as the model input. It focuses mainly on the local interactions of cells with distinct temporal and spatial coupling features and the powerful computing capability of space, which is especially suitable for dynamic simulation and display with self-organizing feature systems. The use of geographic cellular automata for land use change simulations not only takes into account comprehensive consideration soil conditions, climatic conditions, topography and other natural factors, but also considers a comprehensive policy, economy, technology and other human factors, and takes into account the historical trends of land use with strong applicability. The CA model can be expressed as follows

$S(t, t + 1) = f(S(t), N)$ where S is the set of limited and discrete cellular states, N is the Cellular field, t and t + 1 indicate the different times, and f is the transformation rule of cellular states in local space.

Cellular Automata –Markov Model

Cellular Automata–Markov is a combined Cellular Automata/Markov Chain/Multi-Criteria/Multi-Objective Land Allocation (MOLA) land cover prediction method that adds an element of spatial contiguity as well as knowledge of the likely spatial distribution of transitions to Markov chain analysis. The Markov model focuses on the quantity in predictions for land use changes. For this model, the spatial parameters are weak and do not know the various types of land use changes in the spatial extents [Moreno et al. 2009]. The Cellular Automata model has a strong space conception, which is a strong capability of space-time dynamic evolution with complex space systems. The Cellular Automata–

Markov model, which incorporates the theories of Markov and Cellular Automata, is about the time series and space for the advantages of forecasting. It can achieve better simulation for temporal and spatial patterns of land use changes in quantity and space. The Cellular Automata–Markov module in IDRISI 32 integrates the functions of cellular automaton filter and Markov processes, using conversion tables and conditional probability of the conversion map to predict the states of land use changes, and it may be better to carry out land use change simulations.

The Cellular Automata- Markov model to simulate land use changes has been put into use in this paper. Firstly, converting the vector data into raster data and describe land use change from one period to another and use this as the basis to project future changes. This is achieved by developing a transition probability matrix of land use change which shows the nature of change while still serving as the basis for projecting to a later time period. The specific process is as follows:

(1) Determining the transition rules.

With Markov chain analysis, future land use changes can be modeled on the basis of the preceding state; that is, a matrix of observed transition probabilities between maps in 2001 and 2008 can be used to project future changes from current patterns. Through spatial overlay analysis, the transition probability matrix and the transfer area of the matrix are achieved. Among them, the transition probability matrix reflects the various land use types in to other types of probability; the transfer area of the matrix reflects the land use conversion to other land use types in the expected area in the next period. Note that the baseline is the land use map of 2005, which is superimposed on the map of 2015. The calculated transition probability matrix will serve as the transformation rules to put Cellular Automata–Markov model simulations into practice.

(2) Determining Cellular Automata filters.

Cellular Automata filters can produce a clear sense of the space weighting factor, which can be changed according to the current adjacent cellular state. The standard 5 × 5 contiguity filter is used as the neighborhood definition in this study. That is, each cellular center is surrounded by a matrix space which is composed by 5 × 5 cellular to impact the cellular changes significantly.

(3) Determining the starting point and the Cellular Automata number of iterations. The study takes the year 1985 as a starting point. The number of Cellular Automata iterations is selected at 15 in order to simulate the landscape spatial pattern for the study area in 2015, using CA–Markov modules in IDRISI.

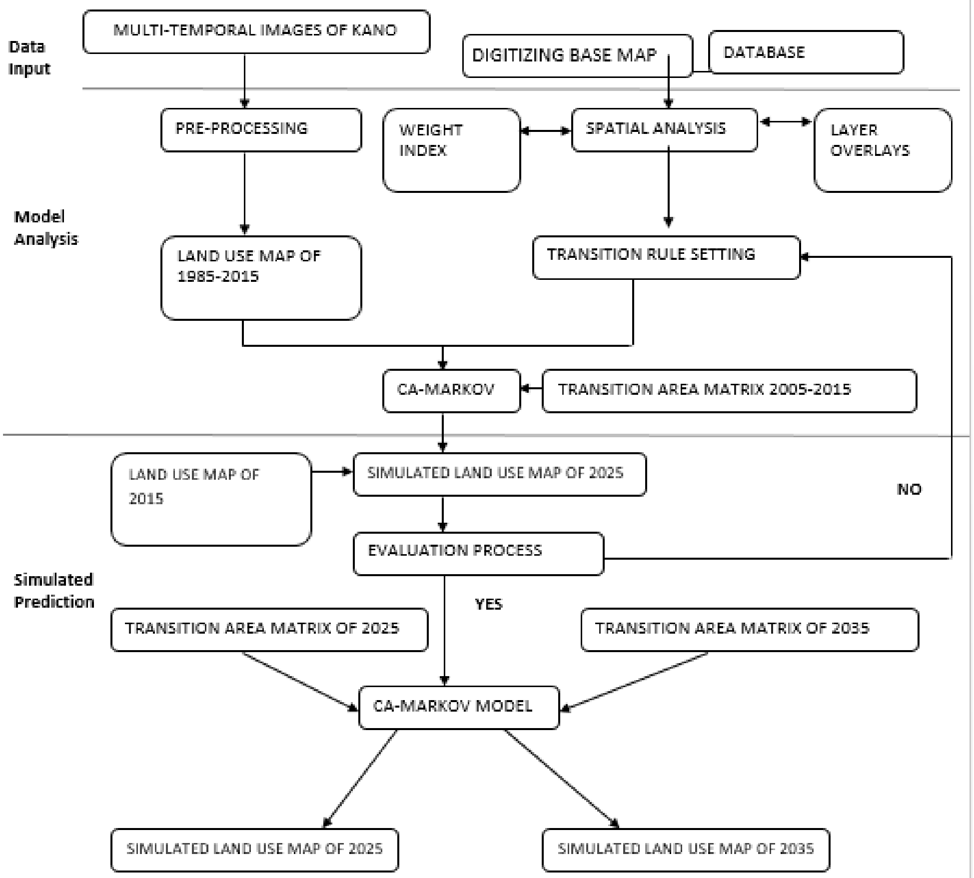


Figure 2: Technological routine of land use Simulation based on GIS and Cellular Automata -Markov Models

Results and Discussion

Implementation of the Markov-Cellular Automata Model

The following procedures were performed using algorithms available in IDRISI Selva v. 17.0 an Image Processing software in order to implement the Markov-cellular automata model in the study area;

(1) Computation of land use transition potential maps based on Multi Criteria Evaluation (MCE) procedure,

(2) Computation of transition probabilities using Markov chain analysis, and

(3) Spatial allocation of simulated land use/cover probabilities based on Multi Objective Land Allocation (MOLA) and a cellular automata spatial filter, using the 5x5 contiguity filter

Computation of Land Use Transition Potential Maps

Firstly, we transformed the different range and measurement units of the driving factors into comparable transition potential values using the IDRISI standardization algorithm in order to compute transition potential maps that represent the likelihood or the probability that land would change from one land use class to another (Eastman, 2003). Then, an Analytic Hierarchy Process (Saaty, 1977) weight derivation tool was used to compute factor weights based on preference factor information, derived during the 2015 field survey. Subsequently, Consistency Ratio (CR) that shows the probability to which the preference factor ratings were randomly assigned was calculated. In this study, we also obtained a satisfactory CR of 0.87 (Saaty & Vargas, 2001).

Computation of Transition Probabilities Using Markov Chain Analysis

The Markov chain analysis was used to compute transition probabilities based on the digitized land use maps for 1985, 1995, 2005 and 2015. Three transition matrices were constructed from the cross-tabulation of the land use maps (that is, the 1985–1995, 1995-2005 and 2005–2015 land use maps). The time intervals used for calibration were 10 years for the 1985–1995 transition, 1995-2005 and the 2005–2015 transition matrices, respectively.

Table 1: Probability value of 2015 based on transition area matrix of 1985-2005

	Residential	Commercial	Public	Industrial	Mixed	Open Spaces
Residential	0.8835	0.0487	0.0615	0.0062	0.0001	0.5035
Commercial	0.0007	0.9907	0.0054	0.0031	0.0001	0.0037
Public	0.0133	0.0689	0.9124	0.0052	0.0001	0.0219
Industrial	0	0.0335	0.0232	0.9428	0.0005	0
Mixed	0.0105	0	0	0	0.9895	0.0097
Open spaces	0.4712	0.0372	0.0500	0.0260	0.0041	0.2057

Source: Derived

Table 2: Probability value of 2025 based on transition area matrix of 1985-2015

	Residential	Commercial	Public	Industrial	Mixed	Open Spaces
Residential	0.9361	0.0402	0.0218	0.0017	0.0002	0.0061
Commercial	0.0036	0.9873	0.0055	0.0035	0	0.0096
Public	0.0144	0.0576	0.9223	0.0055	0.0003	0.0444
Industrial	0.0018	0.0088	0.0064	0.9816	0.0013	0.0066
Mixed	0.0211	0.0102	0	0.0066	0.9621	0.0460
Open spaces	0.3916	0.0602	0.0180	0.0611	0.0022	0.0036

Source: Derived

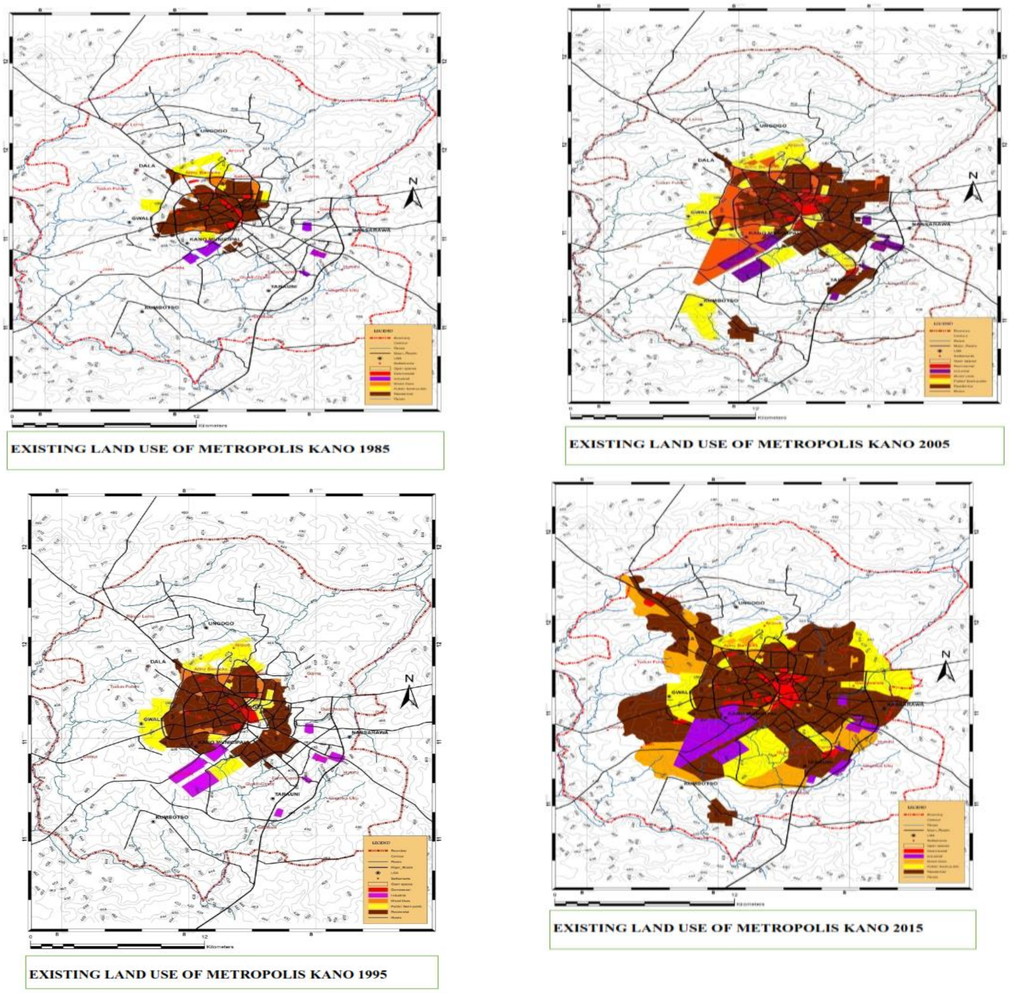
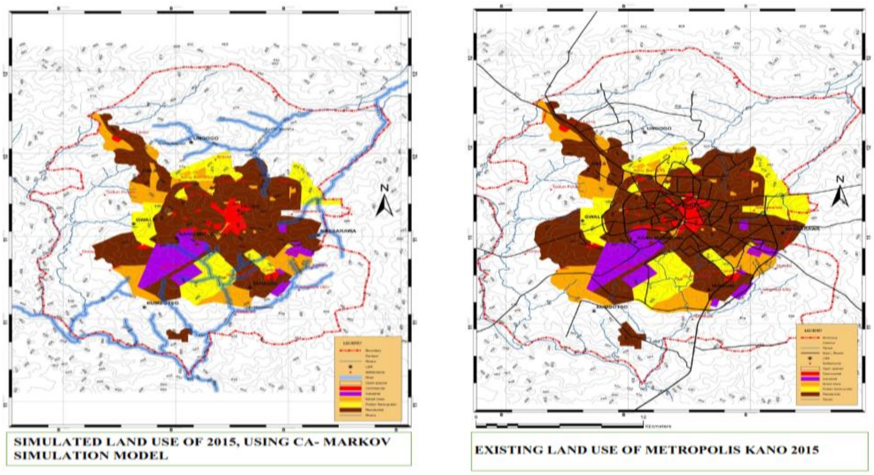


Figure 3. Land use pattern by year in Metropolitan Kano (1985, 1995, 2005 and 2015)

Table 3: Probability value of 2035 based on transition area matrix of 1985-2025

	Residential	Commercial	Public	Industrial	Mixed	Open Spaces
Residential	0.8469	0.0936	0.0493	0.0096	0.0005	0.0007
Commercial	0.0003	0.9885	0.0059	0.0052	0.0001	0.0061
Public	0.0188	0.1131	0.8579	0.0099	0.0003	0.0023
Industrial	0	0.0434	0.0198	0.9362	0.0005	0.0005
Mixed	0.0105	0.0009	0	0	0.9886	0.7886
Open spaces	0.1269	0.0422	0.0130	0.0047	0.0025	0.5000

Source: Derived



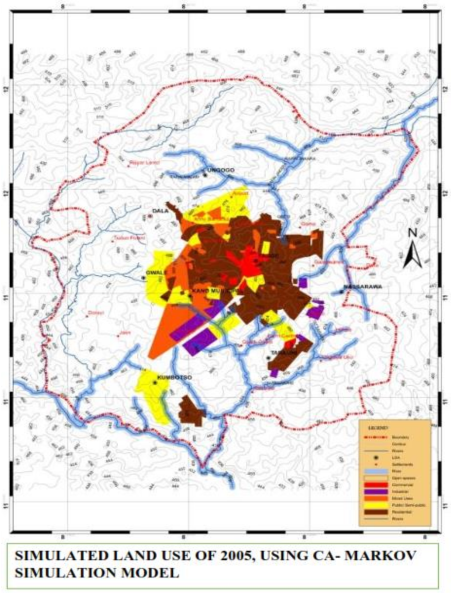
(A) SIMULATED LANDUSES,2015 (B) OBSERVED LANDUSES,2015

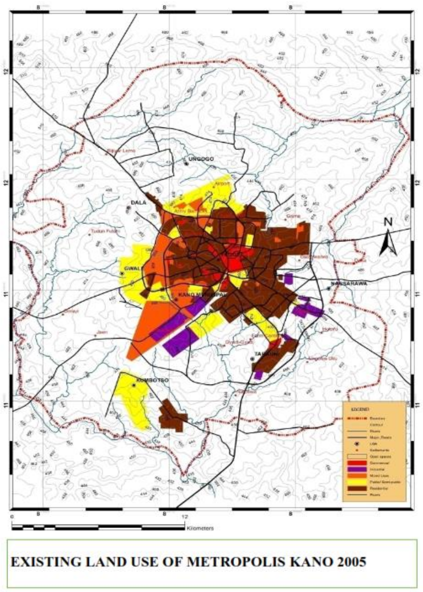
Figure 4: Simulated versus actual land use maps in 2015.

Consequently, transition probabilities were normalized to annual time steps as demonstrated by (Bonde, etal., 1993) in order to take account of differences in the lengths and even changes between the two time periods (t_1-t_2).

Spatial Allocation of Simulated Land Use Probabilities

Three datasets, (1) the 1985 land use map, (2) the 1995 transition potential maps, and (3) the 2005–2015 transition area matrix, were integrated using MOLA and cellular automata spatial filter in order to simulate the 2015 land use map. Cellular automata iterations were specified as 10 because of the 10-year difference between 1985 and 1995. With each cellular automata pass, each land use transition potential map is re-weighted as a result of the 3x3 contiguity filter, which determines the location of the simulated land use class (Pontius & Malanson, 2005). Once re-weighted, the revised transition potential maps are then run through MOLA to allocate 1/10 of the required land use/cover in the first run, and 2/10 the second run, and so forth, until the full allocation of land for each land use class is obtained (Myint & Wang, 2006). MOLA procedure resolves land allocation conflicts by allocating the cell to the objective for which its weighted transition potential is highest based on a minimum distance to ideal point rule using the weighted ranks (Houet & Hubert- Moy, 2006). At the end of each iteration, a new land use map is generated by overlaying all results of the MOLA procedure. For the simulation of the 2005 land use map, a similar procedure described for the 2015 simulated map was carried out, specifying 15 cellular automata iterations based on the (1) 1985 land use map, (2) the 1985 transition potential maps, and (3) the 1985–2015 transition area matrix.





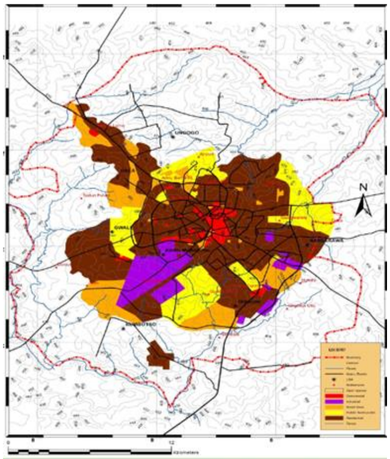
(A) SIMULATED MAP,2005 (B) OBSERVED LANDUSES, 2005

Figure 5: Simulated versus actual land use maps in 2005.

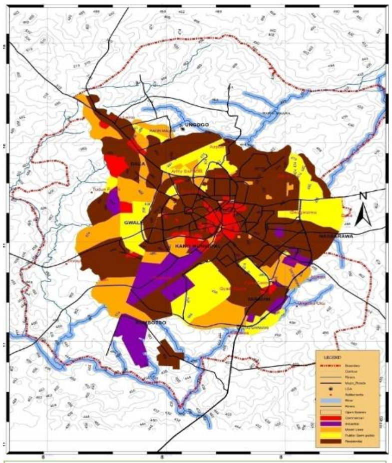
Analysis of land use changes and transition probabilities

Figures 4 and 5 Indicated that Residential, Public and mixed land uses were the dominant land use classes in the study area. From 1995 to 2005, Residential land use occupied 1499.13 ha (12.24 %) in 1995 as against 5511.37 ha (30.99 %) in 2005. This indicates an increase of 4012.24 ha. Commercial use takes 107.66 ha (0.88 %), which further increased to 554.35 ha (3.12 %) in 2005. Public land use accounted for 314.79 ha (2.57 %) as at 1995 and increased drastically to 3218.05 ha (18.09 %) in 2005.Industrial land use accounted for 139.93 ha (2.42 %) in 1995 and experienced another increase to 925.20 ha (5.20%) in 2005 mixed land use accounted for 110.52 ha in the 1995 land use and increased drastically to 2249.82 ha (12.65 %) and Finally Open spaces occupied 7054.95 Ha (47.39 %) of land and decreased to 5327.93Ha (29.95%) in 2005.

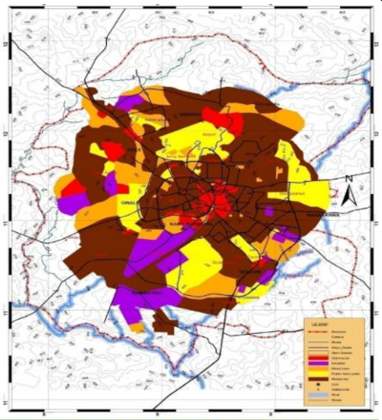
The land use transition probabilities and transition area matrix for the 1985–1995 and 1995–2005 and 2005-2015 periods, calculated on the basis of the frequency distribution of the observations, are shown in Tables 1, 2 and 3. The diagonal of the transition probability represents the self-replacement probabilities, that is the probability of a land use class remaining the same (shown in bold in Tables 1,2 and 3), whereas the off-diagonal values indicate the probability of a change occurring from one land use class to another. While there is a 10-year time lag for the 1985–1995 matrix and 30-year time lag for the 1985–2015 matrix, Table 3 shows that there are no substantial differences in the normalized transition probabilities for the two time periods. Therefore, transition probabilities in Tables 1, 2 and 3 can be used as an input in the Markov-cellular automata model.



EXISTING LAND USE OF METROPOLIS KANO 2015 (a)



SIMULATED LAND USE MAP BY 2025, USING MARKOV SIMULATION MODEL (b)



SIMULATED LAND USE MAP BY 2035, USING CA-MARKOV SIMULATION MODEL (c)

Figure 6: Simulation of land use demand under different scenarios in Metropolitan Kano, 2025 and 2035.
(a) Natural development scenario
(b) Rapid development scenario
(c) No planning intervention scenario.

Model Validation

For model validation, we compared the simulated land use maps for 2005 and 2015 with the actual derived land use maps based on the Kappa statistic. The Markov-cellular automata's overall simulation success is 69% and 83% for 2005 and 2015, respectively. Based on Data from 2005, Residential land use occupied 1499.13 ha (12.24 %) in 1995 as against 5511.37 ha (30.99 %) in 2005. This indicates an increase of 4012.24 ha. Commercial use takes 107.66 ha (0.88 %), which further increased to 554.35 ha (3.12 %) in 2005. Public land use accounted for 314.79 ha (2.57 %) as at 1995 and increased drastically to 3218.05 ha (18.09 %) in 2005.Industrial accounted for 139.93 ha (2.42 %) in 1995 and experience another increase to 925.20 ha (5.20%), mixed land use accounted for 110.52 h in the 1995 land use and increased drastically to 2249.82 ha (12.65 %) and Finally Open spaces occupied 7054.95 Ha (47.39 %) of land and decreased to 5327.93Ha (29.95%) in 2005.

Visual analysis of the 2005 results indicate that Residential, Public and mixed classes in the simulated land use map are relatively close to the corresponding classes in the actual land use map, while the bare land class is poorly simulated. The best agreement is shown in the Residential class, where the actual class is 12970.49 ha and the corresponding simulated class is 1878.57 ha

Analysis of the simulated land use maps in 2005 and 2015 reveals that the Markov-cellular automata model generally over predicted the location of the commercial class.

Table 4: Land use transition area matrix (in Hectares) 1985–2015.

	Residential	Commercial	Public	Industrial	Mixed	Open Spaces
Residential	3685	13	34	0	0	38
Commercial	55	20905	923	110	12	106
Public	23	514	11177	247	15	64
Industrial	0	0	114	4330	0	58
Mixed	0	0	0	0	6385	7569
Open spaces	24	1323	1900	133	7	604

This is partly explained by the poor calibration of commercial land transition potential maps due to the unavailability of spatial data such as the area of extended spatial development. Furthermore, the Markov-cellular automata model employs the contiguity rule, with which It simulates the growth of a land use class near the existing similar land use class (Pontius & Malanson, 2005). In this study, the Markov-cellular automata's contiguity rules apply a 5x5 spatial filter to the transition potential maps with strong weighting towards predicting new Residential areas near mixed and Commercial land use edges. Because many of the nearby pixels belong to the land use class such as Residential or mixed land uses, high transition potential is maintained, resulting in moderate to good simulation of the Residential, mixed and Commercial classes. This suggests that the model's simulation accuracy increases with the proportion of a given land class relative to others. Conversely, if few of the nearby pixels belong to a land use class such as commercial, then the transition potential is down-weighted, which could possibly result in the poor simulation of that class. It is also important to consider the influence of the time step on the location of the simulated land use class when the contiguity rule is applied because the definition of edge is updated at every iteration of the time step (Pontius & Malanson, 2005). For example, if the

extrapolation has small time steps, then the Markov-cellular automata model can simulate incremental growth at the locations with high transition potential values, because smaller time steps lead to more iterations and hence more frequent updates of the spatial dependency.

Future Land Use Changes

Combined with the land demand under different scenarios, land transfer rules, related driving factors and constraints, we conduct the simulation and prediction of the spatial distribution of Metropolitan Kano's land use in 2025 and 2035.

Under the natural development scenario (map of 2015) and rapid development scenario (map of 2025), the trend of Commercial land expansion is clearly along the direction of main traffic arteries, such as the Kwari and Sabon Gari Market. Comparing the simulated scenarios for 2025 with the actual map for 2015, this conversion to urban land occurs primarily in the northeast, northwest, southwest and east of the Metropolis, in wards, such as Gaida, Jaba and in Dorayi . Affected by the development policy of the new town, the functions in the inner city gradually transfer to the new towns, which attracts population concentrated in Sabon Gari and Rijiyar Lemo, and leads to the expansion of residential land, with the area of cultivated land and waters greatly reduced. The results of the simulation in the rapid development scenario are similar to those in the natural development scenario, but the changes in land use types are more fundamental. The dramatic change in land use types, including water area reductions of 20.7% by 2025, will lead to water-resource shortages, most seriously in Kano Metropolis. In addition, Residential land increases 31.4% and primarily comes from Open spaces, waters and unused land; the change trend of mixed and commercial is subtler. Based on the success of the models for 2005 and 2015, we simulated future land use maps for, 2025 and 2035, using the 2015 land use base map, the 1985–2015 transition area matrix and the 2015 transition potential maps. The Markov-cellular automata model simulations predicted that Residential would increase from 12970.49 ha to 13287.31 ha in the study area, while mixed would increase slightly from 3527.55 ha to 4696.85 ha, Commercial land areas could also increase from 809.47 ha to 1450.76 ha. Conversely, Open Spaces could slightly decrease from 3763.16 ha to 3357.29 ha.

The simulated future land use changes have significant environmental and socioeconomic implications for sustainable urban land use planning in Metropolitan Kano. Taking into consideration the high population density and overcrowding in the City Centre, the simulated future land use changes indicates increasing pressure on land within the Metropolis. For instance, the continuing decline in Open Spaces on one hand and the increase in Residential and Mixed uses on the other hand imply severe land fragmentation in the future, which potentially threatens Urban sustainability, which can thus be prioritized for immediate policy interventions.

Conclusions

Using derived land use maps (1985, 1995, 2005 and 2015), and biophysical and socioeconomic data, the Markov-cellular automata model that combines the Markov chain analysis and cellular automata models simulated successfully land use changes in Metropolitan Kano in Nigeria. The model's overall simulation success was 69% for the 2005 simulated land use map and 83% for the 2015 simulated land use map. Based on the 2005 calibration scenario, the Markov-cellular automata model simulated future land use/cover changes up to 2035, projecting the decrease in Open spaces and an increase in Residential areas in the study area. Future land use simulations up to 2035 indicated that if the current land use/cover trends continue without holistic sustainable development policies involving the participation of all the stakeholders in the study area, severe land degradation will occur, with potential threats to urban sustainability. This study represents an important contribution to land use modeling as shown by the integration of biophysical into a spatially explicit Markov-cellular automata land use simulation model in an urban landscape, which to our knowledge has not been attempted before. Equally important, the Markov-cellular automata model applied in this study area incorporated local knowledge in the simulation of land use changes through a GIS-based multi-criteria decision support system. In light of land degradation problems, the simulated future land use maps produced in this study provide a strategic guide to urban land use planning, especially efforts to reduce abuse of urban land. Furthermore, the simulated future land use maps can serve as an early warning system of the future effects of land use changes, particularly in other cities around the world, which are experiencing similar land use changes. While the model has successfully simulated future land use changes based on biophysical and socioeconomic factors, policies that influence the behavior of locals in Kano Metropolis have not been considered. Thus, future study should attempt to Include policy related factors in the simulation of future land use changes.

References

Chen, D.; Chen, H. W. (2013). *"Using the Köppen classification to quantify climate variation and change: An example for 1901–2010". Environmental Development.* ***6****: 69–79.*

Chenje, M., Sola, L., & Palecny, D. (Eds.). (1998). The state of Zimbabwe's environment 1998. Harare, Zimbabwe: Ministry of Mines, Environment and Tourism.509 pp.Directory Vol. 2.

Eastman, J. R. (2003). Idrisi Kilimanjaro, guide to GIS and image processing. Clark University Edition. 328 pp.

Houet, T., & Hubert-Moy, L. (2006). Modelling and projecting land-use and land-cover changes with a cellular automaton in considering landscape trajectories: an improvement for simulation of plausible future states. EARSel eProceedings, 5(1), 63–76.

Ibid (2009). Population of *metropolitan Kano* is predominantly Hausa – Fulani. Ibrahim *Ado-Kurawa (2003). "Brief History of Kano 999 to 2003". kanostate.net. Kano State Government Nigeria. Archived from the original on 2009-12-10.* Retrieved 2009-12-07.

Kasperson, R.E., Dow, K.E.; Archer, D. Caceres, T.; Downing, T.; Elmqvist, S.; Eriksen, C.; Folke, G., Han, K., Iyengar, C., Vogel, K., Wilson, G., & Ziervogel, L. (2005). Vulnerable People and Places, pp. 143-164 in R. Hassan, R. Scholes, and N Ash, eds. Ecosystems and Human Wellbeing: Current State and Trends. Vol. 1, Washington, D.C.: Island Press.

Meyer W.B & Turner B.L. (1994). Changes in land use and land cover. A global perspective. Cambridge. Cambridge university press.

Moreno J., Asner G.P., & Bach H. (2009). Fluorescence Explorer (FLEX): an optimized payload to map vegetation photosynthesis from space in*: AIAA 57th International Astronautical Congress Vol, 3Valencia*: IAC, 2065–2074

Myint, S. W., & Wang, L. (2006). Multicriteria decision approach for land use land cover change using Markov chain analysis and a cellular automata approach. Canadian Journal of Remote Sensing, 32(6), 390–404.

Okeagu, O; Leonard, N.O. and Phillip, E. (2004) Nigeria Cultural Festivals and Tourism Sites

Paegelow, M., & Olmedo, M. T. C. (2005). Possibilities and limits of prospective GIS land cover modelling a compared case study: Garrotxes (France) and Alta Alpujarra Granadina (Spain). International Journal of Geographic Information Science, 19(6), 697–722

Pastor, J., Bonde, J., Johnston, C., & Naiman, R. J. (1993). Markovian analysis of the spatially dependent dynamics of beaver ponds. In R. H. Gardner (Ed.), Predicting spatial effects in ecological systems. Lectures on mathematics in the life sciences, 23 (pp. 5–27). Providence, RI: American Mathematical Society.

Pontius, R. G., Jr., & Malanson, J. (2005). Comparison of the structure and accuracy of two land change models. International Journal of Geographical Information Science, 19(2), 243–265

Pontius Jr. and M. Millones.(2011) "Death to Kappa: Birth of Quantity Disagreement and Allocation Disagreement for Accuracy Assessment," *International Journal of Remote Sensing*, Vol. 32, No. 15, 2011, pp. 4407-4429. doi:10.1080/01431161.2011.552923.

Saaty, T. L. (1977). A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology, 15, 234–281.

Saaty, T. L., & Vargas, L. G. (2001). Models, methods, concepts and application of analytic hierarchy process. Boston, USA: Kluwer Academic Publishers. 333 pp.
Silverton, J., Holtier, S., Johnson, J., & Dale, P. (1992). Cellular automaton models of interspecific competition for space-the effect of pattern on process. Journal of Ecology, 80, 527–534.

Turner II, B.L., Skole, D., Sanderson, S., Fischer, G., Fresco, L., Leemans, R. (1995). Land-use and land-cover changes science/ research. IGBP Report No. 35/HDP Report No. 7. Stockholm and Geneva. International Geosphere-Biosphere Programme and Human Dimensions Programme.