Predictive Land Use Modelling as a Tool for Regulating Urban Development in Yola, Nigeria

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Abstract
Analysing land use/cover (LULC) change processes and driving factors of urbanisation can help identify policy measures that can be used to efficiently regulate urban development. CA-Markov principles were adopted to predict urban sprawl to the year 2033 in Yola, Nigeria. The research incorporates socio economic factors in the driving mechanism in Cellular Automata and Markov Chain (CA-Markov) to establish rules for driving forces for urban sprawl specific to Yola Topography using experts' opinion and residents' perception. The results provides scientific basis and opportunity to define and apply tools and strategies for managing urban development by reconciling the imperatives of urban development and conservation of environmental resources.
Keywords: LULC, CA-Markov, Modelling, Landsat Images

Introduction
With the rapid growth in population and economic activities coupled with the increase in erratic weather conditions, Yola and its environs have witnessed land use and land cover changes over the years especially along major roads. Unfortunately due to inappropriate planning and ineffective land resource management, the ever increasing urban growth is associated with loss of farmlands, grazing lands and access roads.

In an assessment of land use growth patterns, Illesanmi (1999) observed that existing Master plans in Yola were prepared for a lower population than we presently have and the growth direction of the communities did not follow the plans, while some of the major assumptions upon which the Master plans were built are no longer tenable. The resultant effect is that unplanned development arose in some areas while sprawl and slums emerged in other areas.

Land use survey constitutes a valuable resource for environmental management planning and urban dynamics research. The FAO (2011) highlights the need for an integrated approach for all land use activities to be considered in policy making in order to bring together competing land uses in a collective way. Just like each country has its own unique set of geographical, economic, social and cultural features, as well as its own political system and patterns of land use and landholding, so are urban settlements within a particular country. A common methodology used in modelling land use change is coupling Cellular automata with Markov Chain. These powerful tools provide for dynamic modelling that can simulate multiple land use types taking spatial interactions into consideration. Using long term land use and land cover trend, the methodology can improve simulations of future states of land use/land cover and contribute to more plausible and realistic scenarios of future changes (Houet and Hubert-Moy, 2006).

Urban growth and the concentration of people in urban areas are creating social and environmental problems worldwide. Yet the temporal and spatial dimensions of the land use changes that shape urbanisation are little known especially in Nigerian cities. Understanding the dynamics of the changing environment require constant measurement of changes. Therefore, modelling and projection of land use change is essential in environmental management practice. Projecting land cover changes and surface processes at regional scale is important in predicting areas that are susceptible to land degradation (Lambin et al., 1993). While, Modelling and simulating future land cover change provides an important means of assessing future land use/cover change and its relationship with driving forces (Lambin et al., 1993; Zhu et al., 2010).

Observations over the years have shown that land cover changes in most Northern Nigerian old city states such as Yola indicated that agricultural and housing expansions are the most dominant trajectory of land cover change which involves loss of savannahs and forests. A deeper understanding of the change processes is necessary and possible through modelling of the system as relationships of driving forces and LULC changes are established.

Several methodologies were employed in the past to analyse LULC dynamics in urban centres. Principal Component Analysis was adopted by Adepoju, Millington and Tansey (2006) to extract land cover changes in Lagos from the Landsat TM and Landsat ETM (2000) images merged with SPOT-PAN. The study revealed that forest, low density residential and agricultural land uses are most threatened: most land allocated for these uses have been legally or illegally converted to other land uses within and outside the metropolis.

However, Adepoju et al. (2006) just like Njike et al. (2011) limited their land use classification scopes and utilised few images. These studies lacked sufficient data for forecasting possible future changes in growth patterns. A reason why both authors were silent on building future scenarios on likely consequences of the identified land use changes if the trend were to continue into the future. Similarly, Ismaila (2013) in Evaluating land use change in Yola (greater), modelled land use change pattern using Geographically Weighted Regression (GWR). The result shows that population of Yola in 2005, political ward area in hectares, population density, and new layouts are the most important variables that explain the changes. Ismaila covered both Jimeta & Yola and did not build scenarios to project into the future.

CA-Markov were integrated by Samat (2009) to evaluate urban spatial growth in Seberang Perai, Malaysia. Validation analysis was performed using Kappa Agreement Index (KIA). In this work, the poor performance of CA-Markov in the development modelling of commercial/public facilities and industrial activities mainly resulted from model development based on physical factors only, model assumption based on the uniform spatio-temporal growth of urbanized area, and inability of the model in recognising new development.

In Toronto, Canada, Vaz, and Arsanjani, (2015) observed the need for coupling a Markov Cellular Automata with Document Meta-Analysis to allow for the creation of a better integration of propensity of future growth indicators. While the transition probabilities were incorporated from the traditional Markov Chain process, the variables for suitability are measured through a text mining approach, by incorporating several planning documents. The result offers a more integrative vision of policymaker's preference of future planning instruments, allowing for the creation of a better integration of propensity of future growth indicators.

Above and several researches especially within the study area support the quest for a methodology that couple socio-economic factors on driving forces generated by residents' and experts' opinions which will provide scientific basis and a broader input for establishing Transition rules than spatio-temporal input relying on physical factors only.

Materials and Methods

The Study Area

Yola Town is centred on Latitude 09.14N and Longitude 12.8E. It is surrounded on its North- west and east by flood plains, and on the South by the Verre hills. Beyond the wide plains, seven kilometres lies Jimeta, on a rocky outcrop directly overlooking the River Benue (Uyanga, 2000). A 15,625.00 hectare parcel enclosing the old city walls of traditional Yola, the surrounding flood plains, Lake Njuwa and a part of the Benue River is selected for this research (See figure 1).

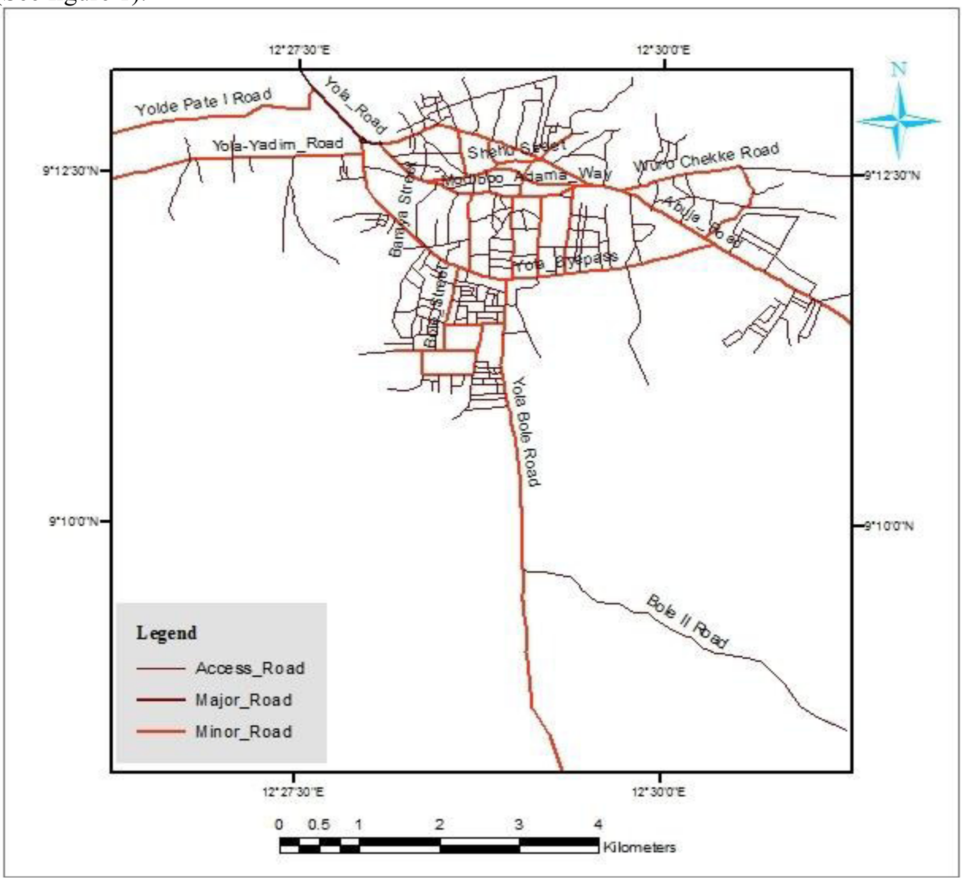

Figure 1: Map of the Study Area

Yola has a population of 196,197 from the 2006 census figures (NPC, 2006). Land use growth pattern in the study area is far away from town planning principles. The resultant effect is that unplanned development arose in Wurochekke and Wuro Hausa while sprawl and slums emerged in Yolde Pate and Unguwan Magaji.

Maximum temperatures in November could go as high as 33°C daily and the minimum may fall as low as 11°C. The horizon is mostly clear by November providing longer hours of bright sunshine with an average duration ranging from 10.6 to 9.2 hours. The Harmattan period characterised by very strong and cold dusty winds is experienced between December and February. During Hamattan, visibility is generally reduced, Trees shed their leaves and grasses die out entirely.

The vegetation within the study area is basically Savannah woodland with the characteristics of an open biotype. Grass with the combination of more or less densely interspersed shrubs and trees dominates the landscape. Wind speeds range from 115km per day in April/May to 42km per day between August and September. The prevalent winds consist of the north-east and south-east trade winds during the dry and wet seasons, respectively.

Data Used

The study data consisted of field survey, interview schedule and spatial analysis of satellite images. Landsat ETM+ time series image data were acquired for years 1998,2001,2005,2009 & 2013 and used in this study. The Landsat Program consists of a series of land information satellites continuously acquiring imagery about the Earth's surface. Images acquired by the LANDSAT 7 sensor, known as Enhanced Thematic Mapper (ETM+) were processed for this study. Subsets of the raw images were cropped to the 12.5x12.5 km square selected for the study. Field survey was also conducted throughout the study area using Global Positioning System (GPS). This survey was performed in order to obtain accurate location point data for each LULC class included in the classification scheme as well as for the creation of training sites and for signature generation. Ground truth points were collected and used to develop "region of interest" as training data for supervised classification.

Methodology

Land use change models are used to help improve our understanding of the dynamics of urbanisation that arise from human decision-making. The most influential theory associated with this process is the theories of urban development associated with cellular automata (CA).The integration of the Markov chain process and the cellular automaton mechanism offers multi-dimensional modelling advantages. While the Markov Chain process directs temporal dynamics among the land cover classes by means of transition probabilities (Turner, 1987; Silverton et al., 1992; Jennerette and Wu, 2001), the cellular automaton mechanism addresses the local rules relating to neighbourhood configuration. In tandem with the transition probability, it determines the spatial dynamics of land cover types (Silvertown et al., 1992; Wu and Webster, 1998; Houet and Hubert-Moy, 2006).

This study demonstrate that residents' and experts' opinions when coupled in the CA-Markov model can establish socio-economic rules for driving forces of urban sprawl specific to Yola Topography.

Image Processing

Layer Stacking of bands in all images was done using ENVI 4.5 to obtain multi-spectral image data. Band selection to suit research work which lies within environmental studies was selected for optimal distinction between different land covers. Band 4 was selected for red, band 3, green and band 2 for blue. Image rectification/re-registration was also effected using some selected ground control points to remove geometric distortion (Geometric correction). Supervised classification technique was adopted to classify the images into the following feature classes;-

1. Water bodies
2. Irrigated Farmlands
3. Bare Ground
4. Settlement
5. Farmland

Driving Forces

The work also involved survey of residents' perception and experts' opinions needed to establish rules for driving forces for urban sprawl specific to Yola Topography. Rules established were calibrated into CA- Markov module in the Idrissi Taiga software to simulate and model the land use/land cover changes. To predict land use/cover scenario for year 2033 in the study area, LULC maps of the study area for two different time periods were calibrated into CA-MARKOV module in the Idrissi Taiga Software which produced LULC scenario for the year 2033.

Table 1: Driving Forces Weighing Factors

Criteria	factor	%
Road	0.15	15%
River	0.15	15%
Settlement	0.30	30%
Lake	0.40	40%

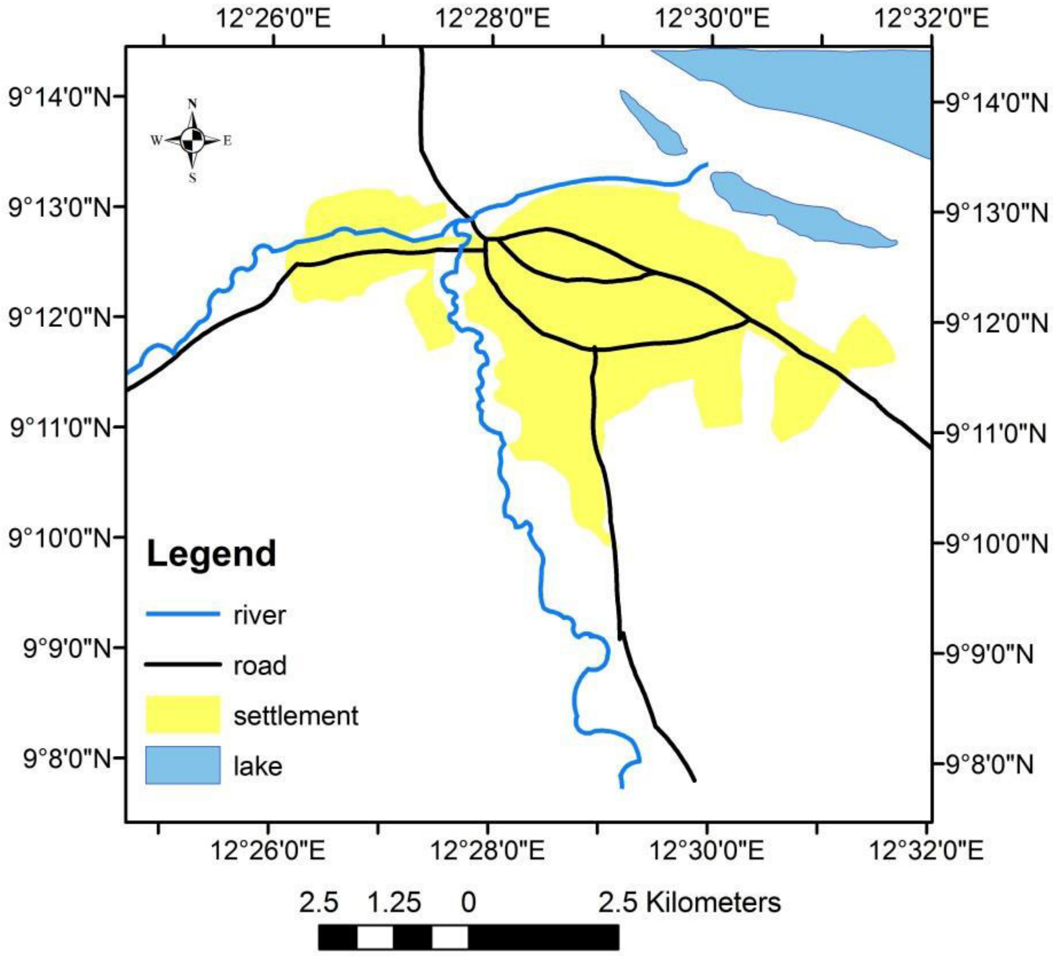

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Figure 2: Map of the Study Area indicating Physical Driving Factors

Markov Chain Analysis

Markovian process involves modeling of future state of a system purely on the basis of the immediately preceding state. Markov Chain Analysis will describe land-use change from one period to another and use this as the basis to project future changes. This is accomplished by developing a transition probability matrix of land-use change from time one to time two, which will be the basis for projecting to a later time period. This procedure did not however take into consideration the spatial distribution of occurrences within each land-use category, i.e., the spatial characteristics of existing land covers and the variability of their level of impact on the future model is neglected.

CA-Markov

CA_MARKOV on the other hand, combines the CA and Markov Chain land-cover prediction procedures. Using the outputs from the Markov Chain Analysis, specifically the Transitions Area file, CA_MARKOV was applied to a contiguity filter to 'grow out' land-use from time two to a later time period

Markovian cellular automaton uses a CA filter to develop a spatially explicit contiguity-weighting factor to change the state of cells based on its neighbors, thus giving geography more importance. Thus changes are based on the rules that relate the new state to its previous state and those of its neighbors. A contingency filter is therefore used.

Consider a given ideal homogeneous land use classes L_t of present time *t,* the land use classes L_{t+1} of a future time t+1 is given by

$$L_{t+1} = P_{ij} L_t \qquad \text{........Equation. 1}$$

Where P_{ij} is the transition probability matrix in the state given by

$$P_{ij} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ . \\ . \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{pmatrix}$$

For $0 \le P_{ij} \le 1$ and $\sum_{j=1}^{m} P_{ij} = 1$ ....Equation. 2

Thus input in in CA Markov includes transition probability matrix, transition area matrix and the land cover suitability map. The transition probability matrix is the measurer of the probability that a pixel in a given land use will change into another class during the time period. It is obtained by cross tabulation of the two images of the different times. The transition area matrix on the other hand gives the number of pixels that are expected to change from a given land-use class to another within the time period. Using the MARKOV module in the Idrisi Taiga software, the transition area files were obtained from a Markov Chain analysis from 2013 to 2033. The weights were assigned to different drivers according to their importance which calibrated the past LULC trends for future prediction.

The weights obtained were based on the degree of attraction or repulsion of the driving factors identified through questionnaire schedules for which suitability maps were generated. Based on the weights allocated to drivers; suitability maps for each LULC was produced using MCE that establishes the inherent suitability of each pixel for each LULC type.

Predictive Modelling

Known land use (LULC map) of the study area for two different time periods, 2005 and 2013 were used as the base maps for estimating future LULC scenario for the year 2033. Land cover change analysis scenario project land use change for the 20 years from 2013 to 2033 using the different time periods, 2005 and 2013. This analysis was used to develop probability statistics for land use change that can be used for future forecasting. Two set of matrices, the transition probability matrix and the transition area matrix were produced together with a set of conditional probability images.

Model Validation

Markovian chain analysis operation was implemented using the Markov module of IDRISI Taiger. The module under change/time series analysis of the GIS was used. The inputs are the transition probability matrix, the transition area matrix and the suitability map. The model was initially validated by projecting 2009 land cover map using 2001 image as earlier image and 2005 as later image. Fig. 4.9 (a) showed the 2009 land cover image predicted by the model in comparison with the reference 2009 land cover (Fig 4.9 (b)).

The two images were analysed statistically using VALID module of the time/series option in GIS analysis. Table 4.9 is the screen snapshot of the results. From the table, it can be observed that there is 83.55% agreement between the projected LULC map and the reference map. This implies that the model can be used to predict future land covers with 83.55% accuracy.

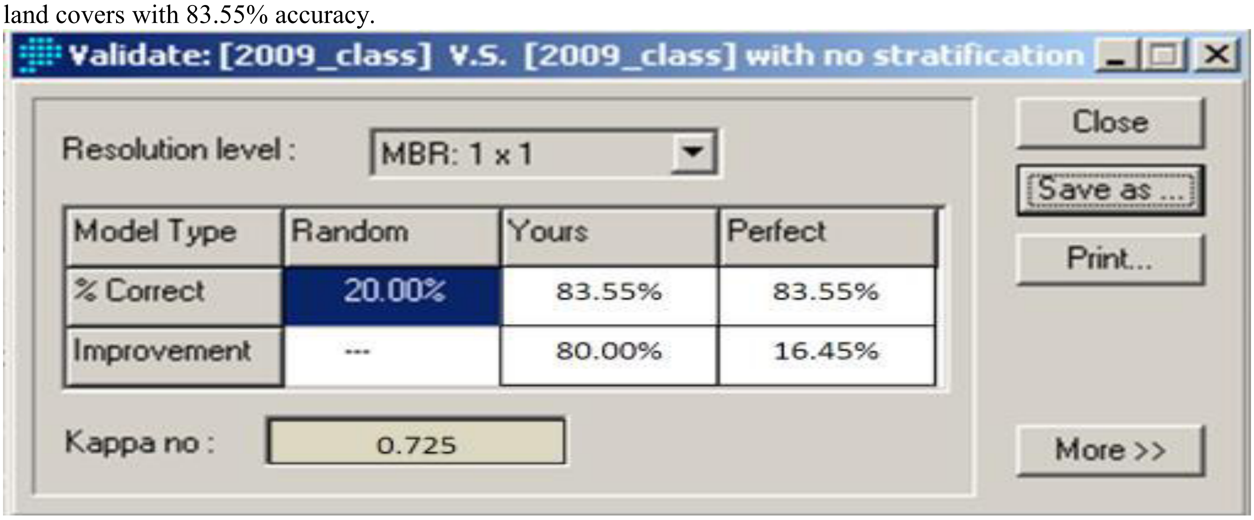

Figure 3: Screen short of computed Kappa Value

A kappa coefficient of 0.725 which is the measure of similarity between the two images has been recorded. Kappa coefficient varies between 0 (no similarity) and 1 (perfect matching). The result of this validity test therefore implies that there is 72.5% similarity between the predicted and the reference images.

Results

Land Use and Cover Change

Changes in the study area are shown in Figure 4 and Table 2 which summarises the trends for each land-use class from 1998. For the class Bare Soil, the growth trend is considerably different from 1998 to 2001 with a sharp drop in coverage from 5478.93 hectares to 181.21 likely owing to the Chouchi irrigation project that was commissioned during the period. This also explains the reason behind an increase in irrigated farmland class from 387.77 in 2001 to 1364.41 hectares in 2005. Bare Soil is expected to increase to 2093.85 hectares by 2033 following the decrease of farmlands in the study area.

Water Body remains surprisingly consistent on average with a little rise from 212.49 to 488.81 from 1998 to 2001 and a slight drop to 407.7 in 2005. This confusing phenomenon might not be unconnected with the difficulty in differentiating farmlands with irrigated farmlands from available satellite images. The Chouchi irrigation project at the bank of the river Benue which started in 2001 has also altered the geographical features of the area.

The class of the Irrigated farmland had a slight drop from 1998 to 2001 but rose to 1364.41 in 2005. This could be due to the construction of spillways and canals to aid dry season farming in Chouchi. This however continues to fall due to the conversion of areas close to the wetted areas of Njuwa, Damare and Angwan Magaji to residential areas.

Table 2: Land-Use Trends

	1998	2001	2005	2009	2013	2033
Bare Soil	5478.93	181.21	299.52	128.79	951.30	2093.85
Water Body	212.49	488.81	407.79	260.82	43.56	295.03
Irrigated Farmland	505.62	387.77	1364.41	222.30	336.78	27.18
Settlement	2618.73	2767.09	2939.78	5184.86	7769.05	11962.79
Farmland	6791.67	11398.71	9782.28	8997.03	6239.76	1966.13

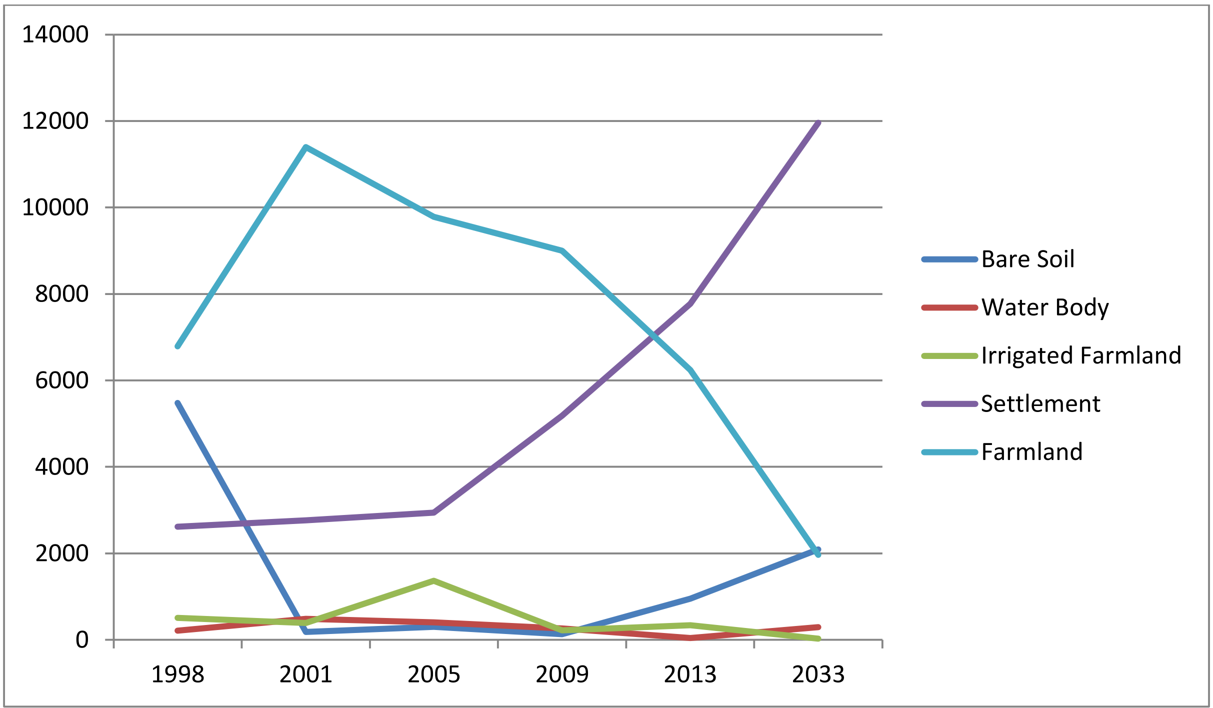

Figure 4: Land Use Trends for Various Classes

This research has shown that land use and cover change happens in an unpredicted, haphazard and unplanned manner within the study area. While other feature classes increase spatially with time others are compromised

Predicting LU/LC Change Scenario for Year 2033

The statistics of land use/land cover projection for 2033 in Table 3 shows a tremendous gain in settlement from about 7769 hectares in 2013 representing 50.6% to about 11962.79 hectares in 2033, representing 73.19%. This is associated with decrease in farmland from 6239.762398 hectares representing 40.6% to about 1966.13 hectares representing 12.02% within the same period.

Although this showed an increase in water body from 0.28% in 2013 to 1.8% in 2033, there is nearly total absence of irrigated farmland at the projected period, with a record of just 0.17%. Thus the results show an increase in built up areas, but on the other hand, a decline in agricultural land use.

Table 3: Statistics of Land Use/Land Cover Projection for 2033

Class	Area (hectares)	Area (%)
Bare soil	2093.85	12.81036
water bodies	295.03	1.805019
irrigated farmland	27.18	0.16629
settlement	11962.79	73.18938
farmland	1966.13	12.02895

Settlement kept expanding in a steady rate in protective growth pattern from 1998 to 2005 (an average of 0.87 km^2 every year), the growth rises astronomically from 2009 to 2013. This might not be unconnected to the in-migration at the wake of the Boko Haram crises which became heightened in the neighbouring Borno State from 2009. New road network and the establishment of new schools such as the American University have also influenced settlements in Mbamba, Yolde Pate and Lelewarji.

Farmland class area drops from 11398.71 in 2001 to 6239.7624 in 2013. This is in response to the growth of settlement within the study area. When asked to suggest likelihood of land-use/cover changes from one class to another, 60% of experts interviewed opined that farmland is the most significant class likely to change to settlement.

Conclusion

The study demonstrates that the developed methodological approach where residents' and experts' opinions are coupled in the CA-Markov model, possesses potential as a technique to support urban land-use planning and policy for sustainable development. Yola will experience settlement growth along the arterial roads leading to Fufore, western Bye-pass (Greater Yola Ring road) in Bole/Yolde pate and in Lelewalji along the road leading to Bantaje. This is owing to the identification of nearness to major road as a significant driving factor in land use change in the area. Middle class housing growth experienced in Mbamba after the establishment of the American University will continue and put more pressure on farmlands and grazing area.

This project has revealed that the coupling of land use change detection and Cellular Automata modelling allows for integrated simulation of the physical and socio-economic nature of land use/cover changes. However, the 30m resolution of the Landsat Images created limitations in land use classification.

Challenges associated with the application of CA-Markov based models consist mainly on the problems existing in the research on the driving mechanism of land use change and the resolution of satellite images used. This is an area that require further improvements. This may involve a different kind of science for which the methodology and standards have not yet been fully established theoretically.

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