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Application of CA-Markov Model for the Analysis of Urban Growth in Gumel Town Jigawa State of Nigeria

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Abstract

The land use land cover change and its modelling approach has recently been considered by the scientific community to observe environmental changes. Remote Sensing and Geographical Information System (GIS) give major techniques which can be useful in the analysis at the town locale as well as the city levels. RS data from Thematic Mapper sensor of 1998, 2002, 2010, 2014 and 2018, Operational Land Imager of 2018 were used for the analysis. The study used supervised classification technique for classification, and Cellular Automata Markovian (CA-Markov) Model analysis was used for future projection of 2038. The result shows that the projected the year 2038 with 0.9079 K-standard value of stimulation, the study further uses Maximum likelihood classifier (MLC) a supervised classification method to classify the images. The study reveals a continuous pattern of urban growth from 3.96 km2 in 2018 to 4.73 in 2038 in terms of settlement growth, dense vegetation has decreased from 11.73 in 2018 to 8.55 in 2038 also shrubland has decreased from 44.82 to 36.30, the last bare land has increased more than all the classes from 162.69 to 173.69. The findings of the present study are useful for planners and decision-makers in sustainable natural resource management.

Keywords: CA- markov analysis; GIS; Land use; Remote sensing; Urban; Gumel town; Urbanization.

1. Introduction

In developing wold the pattern of land use dynamic is a manifestation of a random displacement of new settlements, which is considered as dispersed urban sprawl (Arsanjani *et al.*, 2011). This change of urban sprawl is coursed due to conversion of agriculture lands into non-agricultural land uses as a commercial, residential and industrial land uses, i.e. built-up area (Arnous, 2013). Rapid population growth and urbanization are of great concern to the sustainability of cities (Babanyara *et al.*, 2010). Also, the more the population on the earth the more the pressure on the earth resources like land and other necessity of life like food (Musa *et al.*, 2017).

Land use land cover models are grouped as apparatuses to enable find out the cause and results of land use dynamic (Behera *et al.*, 2012). Land use land cover are two different terms, the physical earth features such as rocks, vegetation, water bodies and others similar natural features are referred to as land cover, while land use is referred to those features on the earth surface that are made by man such as settlements, markets, schools among others (Abdulrahman and Ameen, 2020). Land use land cover dynamic is not only caused by socioeconomic activities, but it also involves in loss of fertile land (Rimal *et al.*, 2018). There are insufficient approaches for land use land cover change prediction which include Cellular and Hybrid models, Markov Chain and Cellular Automata Analysis (Ca-Markov) Mode (Katana *et al.*, 2013). The CA-Markov Model is suitable for land use land cover simulations (Hyandye and Martz, 2017; Yu *et al.*, 2019; Yulianto *et al.*, 2019). This is because they consider the spatiotemporal dynamics of land use land cover changes (Ghurah *et al.*, 2018).

CA-Markov chain analysis is a stochastic modelling approach that has been broadly used to study the dynamics of land-use change at different scales (Subiyanto and Amarrohman, 2019; Zhao *et al.*, 2018). Moreover, A Markovian method is one in which the future situation of classification can be modelled merely based on the previous state. This is expert by building up a transition probability matrix of land use land cover from the time one to time two, which frames the reason for the projection of future positions (Gidado *et al.*, 2019).

A Markovian procedure is one in which the future condition of classification can be modelled merely based on earlier state. This is expert by building up a transition probability matrix of land use land cover from the time one to time two, which frames the reason for the projection of future situations (Kamarudin *et al.*, 2018). Moreover, the objective of the present study is to develop land cover projection model using the CA- Markov analysis to predict the year 2038 land -use land cover of Gumel town Jigawa state of Nigeria dependent on the condition of land use land cover image of the year 1998 and 2018.

According to the Markovian statistical system, relative to the previous state, the future condition of an arrangement or classification can be modelled. Hence, it is a skilled way of constructing a transition probability matrix of land use as well as land cover beginning from time one to two. This is essence establish the logic for prediction of the future state of land use land cover.

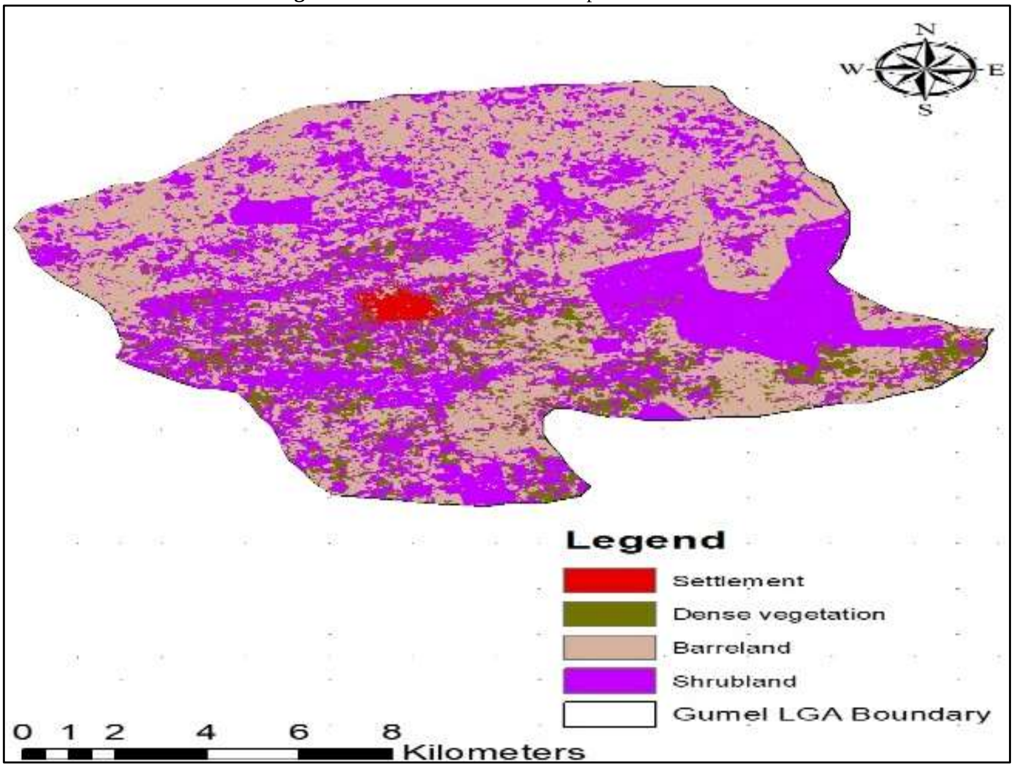
Urban growth, especially the development of residential and business land to provincial zones at the fringe of metropolitan regions, has for some time been viewed as an indication of land use land cover change has been occurring. Moreover, its advantages are progressively adjusted against the ecosystem, comprising degradation of land and loss of fertile land cover, and socioeconomic impacts of financial variations, social discontinuity and infrastructural cost.

2. Study Area and Methodology

Gumel is an urban and a local government headquarter in Jigawa state, Nigeria. It is located 132km North-West from the capital city Dutse and lies about 20km south of Nigerian northern border with Niger republic. Gumel town is bordered north by Maigatari local government. It lies within coordinates 12^0 37' 42" N to 12^0 37' 54" N and 09^0 32' 23" E to 09^0 32' 43" E. The 2006 general census exercise in Nigeria put the population figure of Gumel as 107,161 people. Gumel falls within the chad formation. It is underlain by the sedimentary rock of cretaceous origin and landform sand plain of varying magnitude in common especially around Maigatari town and its surroundings (Olofin *et al.*, 2008).

The climate of Gumel falls within AW climate as classified by Koppen. The climate of the area is characterized by its dryness and extreme temperature and scanty of rainfall. The mean daily maximum temperature between May and June, which is the hottest period, varies from $38^0{}_C$ to $42^0{}_C$. The average annual rainfall varies from 400 to 600mm (Alvares *et al.*, 2013; Eludoyin *et al.*, 2014). The area is bare land during dry season, characterized by sparsely scatted trees without much densely grasses and shrubs (Ibrahim *et al.*, 2014).

Figure-1. Land Use Land Cover Map of Gumel Town



3. Data Sets and Methodology

In this study secondary data is used in the form of Landsat images, these Landsat images are downloaded from the United State Geological Survey (USGS). Landsat images for the year 1998, 2002, 2006, 2010, 2014 and 2018 are used for the study. The supervised classification method of maximum likelihood algorithm was applied for the land use land cover classification to generate the classified images of 1998, 2002, 2010, 2014 and 2018. Landsat image for 1998, 2002, 2006, 2010, 2014 and 2018 are used in the study to analyse the historic land use land cover changes, the evolution of new land-use class and finally to predict the land use land cover of Gumel town Jigawa state of Nigeria for the year 2038.

Markov analysis is a statistical tool in remote sensing software which uses the transition probability matrix based on neighbourhood effects in a spatial influence algorithm (Hyandye and Martz, 2017). Markov is a tool for modelling land-use changes for setting "current trends" scenario; because it uses evolution from (t−1) to (t=0) to project probabilities of land use changes for a future date (t +) (Pontius and Neeti, 2010).

Starting Markov process, using the classified land use land cover image for the year 1998 as (t -1) or the earlier and the classified land use land cover image of 2018 as (t = 1) or the later, this stage, generates transition probabilities matrix and transition areas matrix. moreover, the transition areas matrix expresses the total area (in cells) likely to change in the next period while transition probabilities matrix shows the likelihood of a pixel from one class changing to another class or within the same class in the coming period (Khawaldah, 2016). For validation, which is an essential stage in the development of any land use land cover change prediction model (Khawaldah, 2016). The validation involves the use of a real map of 2018 (classified) to predict land use land cover map of 2018 to generate Markov analysis result. The strength and weakness of the CA Markov model of the future were examine using IDRISI 16.0.

4. Results and Discussion

The validity of the Cellular Automata Markovian (CA-Markov) model was valued using multiple of base resolution statistical algorithms to measure the agreement and disagreement between two land use land cover maps (Aburas *et al.*, 2015). The agreements and disagreement between a set of two maps are measured regarding location and quantity of cells in each land use land cover class by computing the Kappa Indices of Agreement and disagreement statistics. For the CA-Markov model validation in the study, is the ability of the model to simulate correctly the land use land cover of Gumel town Jigawa state of Nigeria to the year 2038. The validation involved using the real map (classified) of 2018 and projected land use land cover map 2038 generated from the Markov analysis result in the time series modification module in IDRISI 16.0 to examine the strength/weakness of the CA-Markov model in upcoming model. Figure 2 shows the images Gumel town to the analysis of the CA-Markov model (A and B), where A is the projected image and B the classified land use land cover map of 2018 (reference image).

Table-1. Validation Summary of Agreements and Kappa Indices

Agreement due to chance	0.333
Agreement due to quantity	0.1785
Agreement due to location at the stratified level	0
Agreement due to location at the grid cell level	0.4434
Disagreement due to location at the grid cell level	0.0128
Disagreement due to location at the stratified level	0
Disagreement due to quantity	0.0322
Kappa for no information	0.9325
Kappa for grid-cell level location	0.9719
Kappa for stratum-level location	0.9719
Kappa Index of Agreement (Kappa Standard)	0.9079

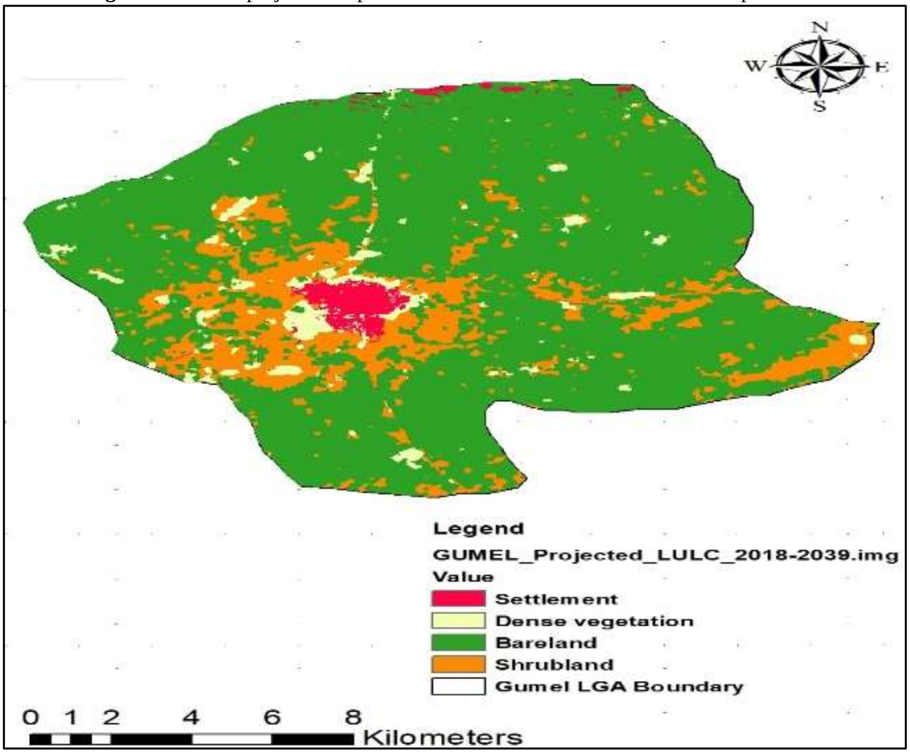
Nevertheless, the results from generated from the validation module shows the kappa coefficient (K) values for the validation in the study as Kstandard = 0.9079 as seen in Table 1. The Kappa coefficient values give the acceptable K-standard value of stimulation for a perfect prediction, moreover, the results are shown in Tables 2 the transnational probability matrix derived from the land use land cover map of 1998 and 2018 indicating the probability of land use land cover changing in 2038 within same category of land use land cover or to another class of land use land cover, and the area expected to change.

Table-2. Transition probability matrix derived from Land Use Land Cover Map 1998 and 2018 Probability of changing to 2038

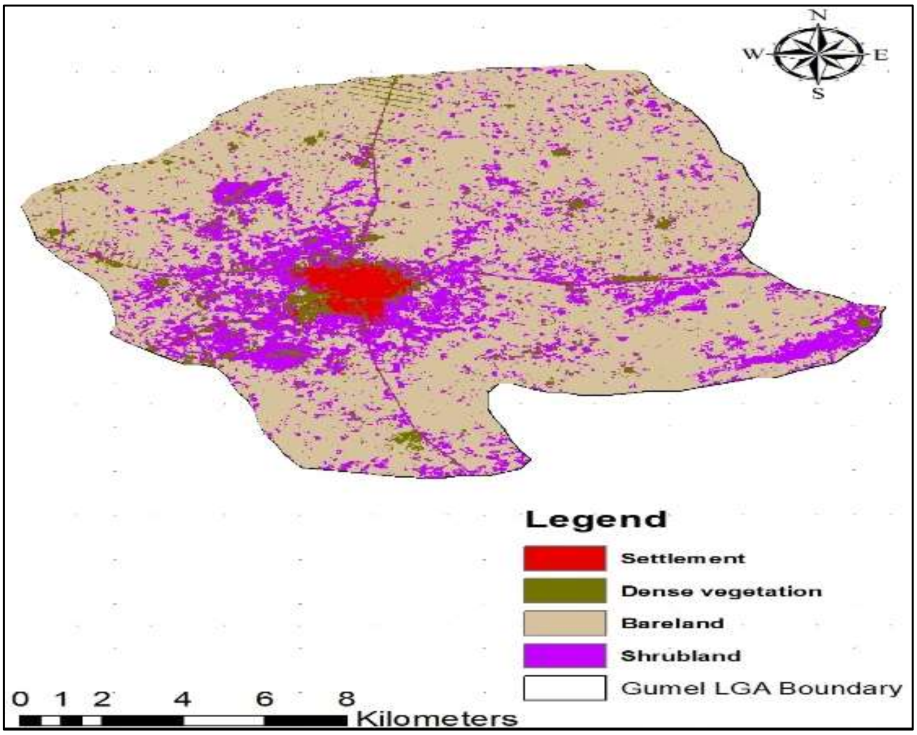
Class	Settlement	Dense vegetation	Bareland	Shrubland
Settlement	0.7519	0.1082	0.0203	0.12
Dense vegetation	0.0243	0.972	0.56	0.32
Bareland	0.0054	0.0212	0.85	0.12
Shrubland	0.0132	0.0789	0.64	0.27

The agreements and disagreement between a set of two maps are measured regarding location and quantity of cells in each land use land cover class by computing the Kappa Indices of agreement and disagreement statistics. For the CA-Markov model validation in the study, is the ability of the model to simulate correctly the land use land cover of Gumel town to the year 2038. The validation involved using the real map (classified) of 2018 and projected land use land cover map 2018 generated from the Markov analysis result in the time series change module in the Remote Sensing (RS) IDRISI 16.0 to examine the strength/weakness of the CA-Markov model in future simulation. Figure 2 shows the images of Gumel town to the analysis of the CA-Markov model (A and B), where A is the projected image and B the real or the classified image.

Figure-2. A is the projected map while B is classified land use and cover map of 2018



A



B

5. Projected Land Use for 2038

The simulation results also indicate a significant change of land use land cover in Gumel through the narrowing of settlement cover to 3.96 km^2 in 2018 compared to the area it will cover 2038. The area covered by the settlement is expected to increase slightly by 0.35 per cent in the year 2038. This increase could be an increase in population as shown in Table 3. Also, However, the result indicates an expected decrease in dense vegetation and shrublands areas from the 11.73 km^2 in 2018 to 8.55 km^2 in the year 2038, while for shrublands also decrease from 44.82km^2 in 2018 to 36.30km^2 in the year 2038 (as shown in Table 3), this could be cost by natural and artificial factors. The natural factor can be attributed to global climate change like decrease in rainfall and increase in temperature, while the artificial can be a result of afforestation (cutting down of trees for fuel) and over overgrazing, which could affect or worst the climatic condition of the study area. Providing the effect of climate change and other climatic events such as decrease rain and rise temperature, government and political interventions has not been considered in the current study, these factors have likely to affect the predicted situations.

Table-3. Amount of Changes in Land Use Land Cover Base on CA-Markov Model During 2018 – 2038

Year	2018		2038		Change 1998-2038	
LULC Class	**Area (km²)**	**Area (%)**	**Area (km²)**	**Area (%)**	**Area (km²)**	**Area (%)**
Settlement	3.96	1.77	4.73	2.12	0.77	0.35
Dense vegetation	11.73	5.26	8.55	3.83	-3.18	-1.43
Bareland	162.69	72.89	173.69	77.79	11.00	4.90
Shrubland	44.82	20.08	36.30	16.26	-8.52	-3.82

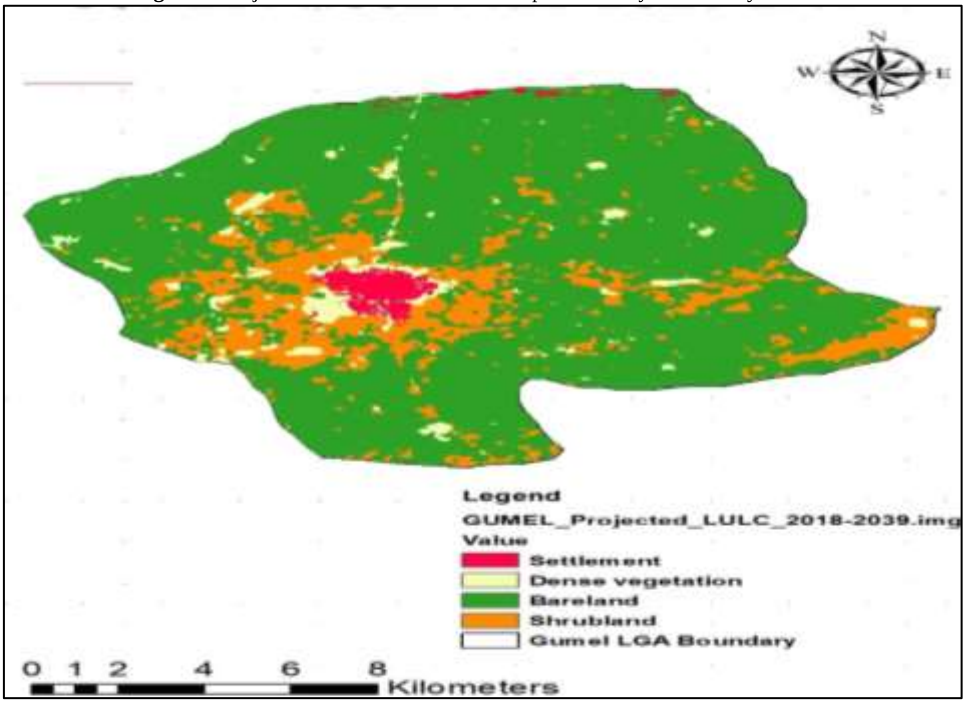
Table-4. Predicted Areas of Land Use Land Cover Base on the CA-Markov Model For 2038 in the Study Area

LULC Class	Settlement	Dense vegetation	Bareland	Shrubland
Area in (km²)	4.73	8.55	173.69	36.30
Area in Percentage (%)	2.12	3.83	77.79	16.26

The conversion of settlement to dense vegetation has a low probability as seen in table 4. Besides the probability of vegetation converting into the settlement is 0.0243, while the probability of settlement cover to remain in its existing form is 0.7519. Moreover, the probability of dense vegetation remaining in its original state is 0.972, both of the land use land cover probability to remain in their original state is quite high. The one with the highest chance of remaining in its original state is bare land with a probability of 0.85. It may be caused by desert encroachment caused by man to have fuel while overgrazing is caused animals mainly cows, sheep and goats.

The year 2038 simulated land use land cover maps reveal a significant increase of settlement area by 0.35 per cent while table 4 that is predicted area of land use land cover reveals that settlement will cover a landmass of 4.73km^2 which is 2.12 per cent of the total area of Gumel town. Also, dense vegetation will cover 8.22km^2 which is 3.82 per cent, shrubland will occupy 36.30 km^2 that is equivalent to 16.26 per cent than the last land use land cover, bare land is the most dominate of all the classes with a value of 173.69km^2 which is 77.76 per cent of the total area of Gumel town in the year 2038. The main cause of land use land cover change in the study are is caused by population growth, overgrazing, afforestation and desert encroachment.

Figure-3. Projected Land Use Land Cover Map of the study are for the year 2038



6. Conclusion

The CA-Markov chain analysis reveals the difference in one land use land cover to one another and further use this to predict the future of Gumel town. Modelling of land use land cover plays an important part in understanding the concepts of land use land cover dynamic. The analysis states how remote sensing and GIS technology is a compelling methodology using the CA- Markov analysis of land use land cover dynamic projected for the year 2038. The study is important for researchers, planners and decision-makers.

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