MODELING OF FUTURE LAND COVER LAND USE CHANGE IN NORTH CAROLINA USING MARKOV CHAIN AND CELLULAR AUTOMATA MODEL

[1]Mohammad Sayemuzzaman and [2]Manoj K. Jha

[1]Department Energy and Environmental System, USA
[2]Department of Civil, Architectural and Environmental Engineering,
North Carolina A and T State University, 301 Gibbs Hall, 1601 E. Market St., Greensboro, NC, 27411, USA

ABSTRACT

State wide variant topographic features in North Carolina attract the hydro-climatologist. There is none modeling study found that predict future Land Cover Land Use (LCLU) change for whole North Carolina. In this study, satellite-derived land cover maps of year 1992, 2001 and 2006 of North Carolina were integrated within the framework of the Markov-Cellular Automata (Markov-CA) model which combines the Markov chain and Cellular Automata (CA) techniques. A Multi-Criteria Evaluation (MCE) was used to produce suitability future images. The Markov Chain and MCE analyses provided transition probability area and suitable images, respectively which were then dynamically adjusted through the Multi-Objective Land Allocation and CA spatial filter. Two stages of validation procedures were adopted in this study: 1. The Relative Operating Characteristics was used to validate suitability images and 2. The Kappa index of agreement was used to validate the overall LCLU changed simulated map. LCLU prediction of North Carolina for year 2030 shows 20% increase of built up land, 17% decrease of forest land while comparing that with year 1992. About 7% agricultural land was found to decrease in 2030 when compared with 2001 data. No significant changes were found for water body and other land category coverage. Much of the built-up land (urban expansion) was found to be in the southern, mid and mid-eastern portion of North Carolina. Loss of forest area was predicted mostly in western and mid-western part.

Keywords: Land Cover Land Use Change, Markov Chain, Cellular-Automata, Multi-Criteria Evaluation, Multi-Objective Land Allocation

1. INTRODUCTION

An average of 100,000 acres per year of farm and forestland in NC are converted to development, or about 1,000,000 acres per decade-affecting both water quality and quantity (Holman *et al*., 2007). Population expansion, economic development, technological advancement and many forms of migration bring LCLU change, which can cause significant environmental consequences, such as extreme surface runoff, water quality deterioration (Tong *et al*., 2011), eutrophication, ground water depletion, contaminant dissemination in subsurface and loss of wildlife (Sayemuzzaman and Jha, 2014; Chang and Sayemuzzaman, 2014; Schneider and Pontius, 2001). Human activities and future climate related changes are also altering land at an unprecedented rates, magnitudes and spatial scales (Sayemuzzaman and Jha, 2014; Sayemuzzaman *et al*., 2014a; 2014b; Vitousek *et al*., 1997). Thus it's a paramount important to assess the past and current LCLU change trends as well as to simulate future patterns for sustainable development. Various LCLU change models have been developed which are capable of identifying quantitatively the location and pattern of

Corresponding Author: Mohammad Sayemuzzaman, Department Energy and Environmental System, USA

the change, such as: Agent based model, dynamic model, empirical and statistical model. Analysis and prediction of future LCLU change is often complicated because of the dynamic and stochastic nature of change of the natural and socio-economic variables, the most driving forces of change (Parker *et al.*, 2003).

A Markov-CA model is capable of simulating temporal and spatial dynamics of LCLU change by integrating remote sensing and GIS based data with bio-physical and socio-economic data (Myint and Wang, 2006; Courage *et al.*, 2009; Tong *et al.*, 2012). In the Markov-CA model, markov chain analyzes temporal change among the LCLU classes based on transition probabilities matrices (Takada *et al.*, 2010); while the CA geographically evaluates the spatial contiguity and land cover suitability (Houet and Hubert-Moy, 2006). The Markov chain technique in combination with CA is capable of generating a better spatiotemporal pattern of the LCLU change. Although many researchers (Paegelow and Olmedo, 2005; Sun *et al.*, 2007; Courage *et al.*, 2009; Guan *et al.*, 2011; Tong *et al.*, 2012) have used the Markov-CA model in their land use change prediction study, only few studies have combined natural and socio-economic variables into their model. These variables can be efficiently integrated into Markov-CA model as suitability images format by the Weighted Linear Combination (WLC) based MCE method (Wu and Webster, 1998; Eastman, 2006; Yu, 2009; Tong *et al.*, 2012). MCE was first developed in regional economics as a decision support method for structuring and aiding complex decision making processes (Wu and Webster, 1998; Proctor, 2001). In the last two decades, the technique is becoming popular and its application has been greatly expanded. Making decisions based on the criteria about land allocation, alternative actions to achieve a specific objective is very fundamental in land use change modeling. MCE uses a variety of user-defined criteria, either as a factor or a constraint, which can be represented as a map layers in a GIS (Eastman, 2006). Tong *et al.* (2012) used population as only variables with their Markov-CA model to predict LCLU change. Courage *et al.* (2009) combined natural and socio-economic variables into their Markov-CA model to predict future LCLU change, but the integration was not successful due to the lack of consistent information among data sets. The efficient integration of these variables into the Markov-CA model stills a research challenge because of the discrepancy among these different datasets (Veldkamp *et al.*, 2001; Martínez *et al.*, 2011).

The present study was used the Markov-CA model in combination with natural and socio-economic variables to predict the future LCLU changes in 2030 for the entire state of North Carolina. Conditional probability maps and transitional probability area matrix have been generated from the satellite derived LCLU datasets (1992, 2001 and 2006) using the Markov chain analysis. Suitability images were produced using the MCE procedure which combines the natural and socio-economic variables with the conditional probability images of land use categories. Dynamic adjustments and effective land allocation between the Markov model transition probability areas and suitability images have been conducted by the MOLA and CA spatial filters.

2. MATERIALS AND METHODS

2.1. Study Area

The state of NC is located in the southeastern United States (75° 30'-84° 15' W, 34°- 36° 21' N) (**Fig. 1**). The study area covers approximately 52,664 square miles (136,399 km^2) and is 560 miles (900 km) long by 150 miles (240 km) wide. There are a total of 100 counties and the population was nearly 9.5 million (approx.) in 2010 (USCB, 2010). The population has grown rapidly from 5.5 million (approx.) in 1976 and is projected to be about 11.5 million (approx.) by 2030 (NCOSBM, 2010).

NC has diverse topographic zone from west mountainous region to east coastal region. The eastern 40% of NC is characterized by coastal plains and tidewater. Moving west, the next 40% of NC, about 200 miles wide, consists of the piedmont plateau. Land slopes upward as we move from eastern piedmont plateau to the western part containing southern Appalachian Mountains (Blue Ridge and Great Smokey Mountains).

2.2. Data Sources and Pre-Processing

The state of NC is located in the southeastern United States (75° 30'-84° 15' W, 34°- 36° 21' N) (**Fig. 1**). The study area covers approximately 52,664 square miles (136,399 km^2) and is 560 miles (900 km) long by 150 miles (240 km) wide. There are a total of 100 counties and the population was nearly 9.5 million (approx.) in 2010 (USCB, 2010). The population has grown rapidly from 5.5 million (approx.).

Three sets of historical land use raster image data were collected for years 1992, 2001 and 2006 from the U.S. Geological Survey, multi resolution land cover-National Land Cover Data (NLCD) (USGS-NLCD-MRLC, 2013). Two maps (1992 and 2001) were used to train the markov iteration process for land use pattern identification and the third map (2006) was used for validation of the MC model. The NLCD 2001 and 2006 are based primarily on the unsupervised classification of Land sat Enhanced Thematic Mapper + (ETM+) circa 2006 and 2001 satellite data. Whereas, NLCD 1992 is based primarily on the unsupervised classification of Land sat Thematic Mapper (TM) circa 1990's satellite data (**Fig. 2**).

Since NLCD 1992 and 2001 datasets have 21 classes and 2006 has 26 classes, the land use classes for all three imageries were resampled and reclassified into five broad categories using ArcGIS (**Table 1**). The five categories are: (1) Water body, (2) Built up land, (3) Forestland, (4) Agricultural land and (5) other land. The original datasets were in GRID format; so the maps were converted from GRID to TIFF and then from TIFF to raster (rst) format to be compatible with the interface IDRISI selva17.0. Projected co-ordinate system, maps background values, spatial dimensions and data types of all maps used in this study were resized and reoriented to assure the consistency in prior to the further model application.
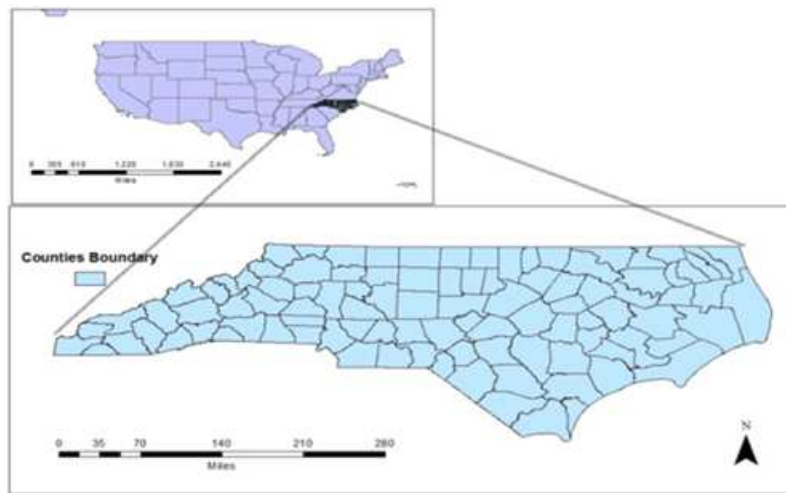

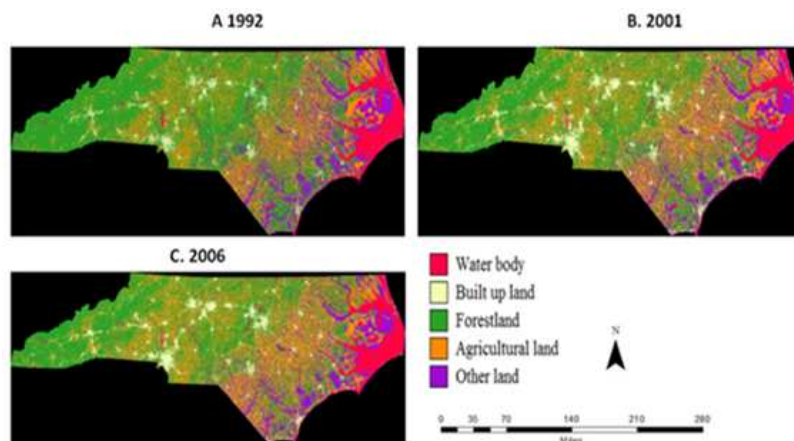**Fig.1.** Study area: North Carolina, USA

Fig. 2. Actual NLCD image data sets of 1992, 2001 and 2006

Table 1. Reclassification of the land use categories

Land use reclassification	Description
Water body	Streams, lakes, reservoirs
Built up land	Industrial, residential, commercial, transportation, urban area
Forestland	Deciduous, mixed, evergreen, shrub/scrub
Agricultural land	cultivated crops, pasture, grassland
Other land	Woody wetland, barren

2.3. Markov Chain Land Use Simulation

The LCLU change prediction modeling is more appropriate within the modeling concept of MC model. There is always a certain degree of randomness and uncertainty is inherent in the LCLU change process and that's why stochastic, dynamic model is more appropriate than static, deterministic model (Tong *et al.*, 2012). The MC is a discrete-time stochastic process in which the probability distribution of the current state is conditionally independent of the path of past states. It is a model of the system where the next state is solely depends on the current state not on the previous state (Myint and Wang, 2006; Yu, 2009). The MC model analyzes a pair of historic land cover images and outputs a transition probability matrix, a transition areas matrix and a set of conditional probability images (Eastman, 2006; Takada *et al.*, 2010). The first step in the MC model transition probability analysis is to compare two historic base maps (1992 and 2001 in this study) and produce raster images for the categorical pattern of changes between the maps of two dates. Next, the transition probability matrix (T_{ij}) is calculated based on the projection date. In this research, the prediction was first made for 2006, which was compared with the base map of 2006 for validation. After the successful validation, the future LCLU was projected for 2030. The general assumptions of algorithm are as follows (IDRISI, 2013): If the date is being projected forward an even multiple of the training period, then the new transition probability matrix is calculated through a simple powering of the base matrix. If the projected time period is in between even multiples of the training period, then the power rule is used to generate 3 transition matrices that envelop the projection time period (if the 3 time periods are times A, B and C, the period to be interpolated will be between A and B). The three values at each cell in the transition probability matrix are then fed into a quadratic regression (thus there will be a separate regression for each cell). Given that a quadratic regression ($Y = a+b_1X+b_2X^2$) has 3 unknowns and we have three data points, it yields a perfect fit. This equation is then used to interpolate the unknown transition probability.

2.4. Development of LCLU Suitability Images

The Suitability images for each land cover establish the inherent suitability of each pixel for each land cover type in a specified time period (Eastman, 2006). In this study we computed the suitability images of 2006 and 2030 LCLU by utilizing the MCE method using the natural and socioeconomic variables integrated with the conditional probability images of developed, forest land and agricultural land from the MC model. Water body and other lands were ignored due to the insignificant change within the study time frame. Natural variables in this study include slope, elevation and distance to the nearest water body. Population density and distance to the nearest primary road network are the socioeconomic variables were used in this study. **Table 2** shows detail of the sources of the variables.

For 2030 LCLU projection, all natural and socioeconomic variables were processed utilizing mathematical functions, map algebra and spatial overlay, MCE integrates these criteria by WLC and calculates the suitability of each land cover category, supervises the spatial allocation of the predicted time transition probabilities and displays the results as suitability maps.

2.5. Evaluation of the Markov Chain Model

Two indicators were used in this study to evaluate the validation of MC model prediction: ROC (Pontius and Schneider, 2001) and KIA (Pontius, 2000).

ROC validation was used to evaluate the degree of certainty of the transition suitability images. The ROC can compare and measure the agreement of location a map of actual change in a certain land use category as a Boolean image format with the simulated image of the same category (Tong *et al.*, 2012). ROC provides two by two contingency table of actual change and actual non-change versus simulated change and simulated non-change. According to (Pontius and Schneider, 2001), a ROC value 1 indicates that there is perfect spatial agreement between the Boolean class map and the suitability map of that same class and 0.5 means that there are no statistical significant differences between the two compared objects. The only differences are due to random locations.

Similarities between actual image and simulated image were compared using a KIA which has been widely used to validate LCLU overall change prediction (Pontius, 2000; Courage *et al*., 2009; Tong *et al*., 2012). There are three indicators of KIA are: Kno gives overall accuracy of a simulation run, Klocation and Kquantity indicators validate the location and quantity between the actual and simulated maps (Schneider and Pontius, 2001). The possible values of the statistic range of those 3 indices from 0 to 1, where 1 means perfect agreement and o means no agreement beyond that expected by chance (Pontius, 2000).

2.6. Markov-CA Land Use Simulation

Two Future prediction of LCLU change requires the information relating to causes behind the change. MC ignores the forces and processes that produced the observed patterns and assumes that these forces to stay same in the future. It is also insensitive to space (no sense of geography). Markov-CA model overcomes these limitations by combining MC and CA model. The model depicts the spatial dimension and contiguity as well as includes suitability knowledge by integration of explanatory variables into the MCE method. The Markov-CA model is also called combined Cellular Automata/Markov Chain/Multi-Criteria/Multi-Objective Land Allocation land cover prediction method, which adds an element of spatial contiguity, specific decision from multi-criteria evaluation and also the knowledge of dynamic distribution from MC analysis (Myint and Wang, 2006; Sang *et al*., 2011). The Markov-CA model was executed using algorithms available in IDRISI selva 17.0 and Arc GIS 9.3 Image processing software. The IDRISI Selva is an integrated GIS and image processing software which facilitates not only format conversion between data sets, map composition, map display but also provides statistical analysis, time-series analysis, spatial land use analysis and decision support analysis.

2.7. CA Spatial Filter and MOLA-Dynamic Adjustment Procedure

Since the MC model did not simulate the neighborhood effects and geographical contiguity, CA spatial filter and MOLA dynamic adjustment procedure were introduced to get the final simulation. In this study, 5×5 Gaussian contiguity filter was used as the neighborhood definition. As an input for this operation to simulate 2006 land cover, we used (1) 2006 transition suitability maps derived from analyzing 1992-2001 NLCD base maps by MC and MCE, (2) 2006 transition probability area matrix which was produced by MC and (3) 2001 NLCD base map. The number of iterations selected was10, which established the number of time steps that were used in the simulation. Within each time step, each land cover is considered in turn as a host category. All other land cover classes act as claimant classes (Eastman, 2006). With each CA pass, each LCLU transition suitable map is re-weighted as a result of the 5×5 contiguity filter, which determines the location of the simulated land use/cover class (Pontius and Malanson, 2005). Once re-weighted, the revised transition potential maps are then run through MOLA to allocate 1/10 of the required LCLU in the first run and 2/10 the second run and so forth, until the full allocation of land for each LCLU class is obtained (Myint and Wang, 2006). Based on a minimum distance to ideal point rule using weighted rank, highest weighted transition potential is sorted (Courage *et al*., 2009). MOLA procedure resolves land allocation conflicts with this sorted transition potentials. At the end of each iteration, MOLA procedure generates a new LCLU map by overlaying all results. This procedure was also followed with changed population variables to generate 2030 NC LCLU change map. The above discussed research methodology in section 2 can be well represented in the following flow chart in **Fig. 3**.

Table 2. Sources of variables and weight value derived from Analytic Hierarchy Process (AHP)

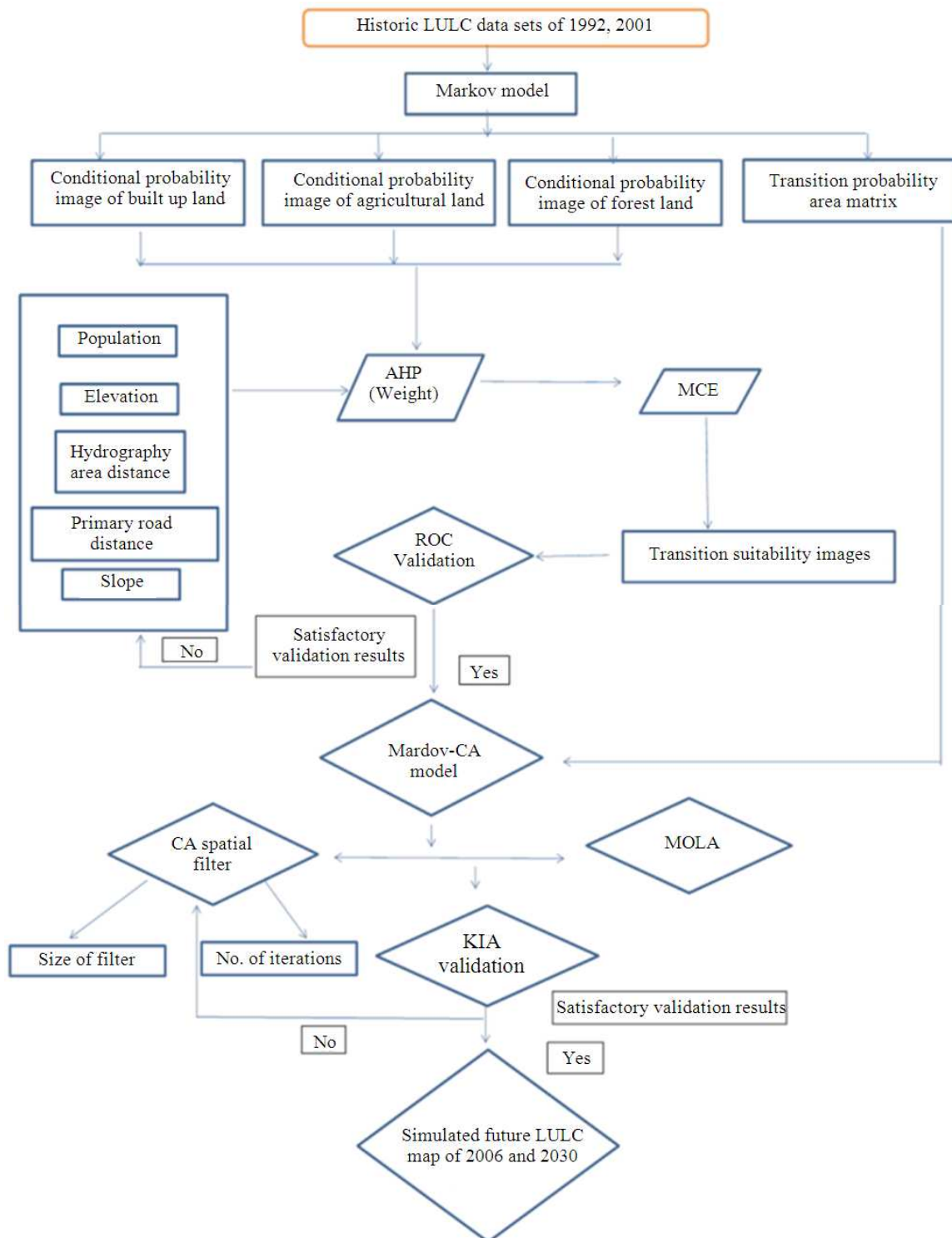| Variables	Sources	Year	Weight (%)
CPI of built up land/ forest land/agricultural land	Markov model	2006 and 2030	60
Population	U.S. census bureau and NCOSBM*	2006 and 2030	20
Elevation	NED*	2006	9
Distance to water body	NHD*	2006	5
Distance to primary roads	NCDOT*	2006	4
Slope	DEM*	2006	2

Fig. 3. Research flow chart

3. RESULTS AND DISCUSSION

3.1. LCLU Suitability Images

Suitability images for each land cover establish the inherent suitability of each pixel for each land cover type in a specified time period. It was computed using the MCE method by integrating natural (slope, elevation, distance to the nearest primary road network and distance to the nearest water body) and socioeconomic (population density) variables. **Table 2** shows detail of the sources and weight values of the variables. The weight values were derived using an Analytic Hierarchy Process (AHP) where each variable is assigned with a value representing its degree of relative importance and also the trial and error process which brings the best validation results. MCE method integrates these weights and criteria using WLC and calculates the suitability of each land cover category. **Figure 4** shows the suitability images for each of the land cover. It ranged from 0 to 255 byte type data in stretched value which is the result after standardize in linear fuzzy method available in IDRISI (Paegelow and Olmedo, 2005); a value 255 indicates the highest suitability and a value 0 indicates the lowest suitability of that particular category.

3.2. Validation of the Markov Chain Model Prediction

3.2.1. ROC Validation

The ROC validation was used to evaluate the degree of certainty of the transition suitability images. It was performed by comparing the simulated 2006 suitability map for the built up land, agriculture land and forest land with the Boolean image derived from the actual 2006 NLCD map of the three classes. Trial and error of the weighted combination of variables and conditional probability images of MC model provided the best ROC values. Transition suitability images which were generated the best ROC values were used in the Markov-CA model to get the final simulation of 2006. ROC value of 0.83, 0.89 and 0.87 were found for Built up land, Agricultural land and Forest land consecutively (**Table 3**). Ten equal interval thresholds were used for ROC analysis, which aggregates the different no. of threshold into one measure of agreement after analyzing the goodness-of-fit of all numbers in thresholds. Schneider and Pontius (2001) also used the highest ROC value of deforestation suitability images for their further model calculation. Pontius and Schneider (2001) calibrated the suitability maps of forest areas with the combined maps of socio-physical characteristics and forest areas in 1971-1985 for Ipswich watershed. Tong *et al.* (2012) was used 0.1667 and 0.8333 weight values for urban suitability and population ensity images consecutively after several trial and errors.

3.2.2. KIA Validation

Similarities between actual image and simulated image were compared using the KIA approach which has been widely used to validate LCLU overall change prediction. In this research Markov-CA overall simulation yielded three KIA indicators as Kno = 87%, Klocation = 83% and Kquantity = 9 0% when compared between the simulated 2006 map with the actual 2006 map. Visual and statistical analyses revealed that the forest land, agricultural land and water body are relatively well simulated but some portion of buildup land especially north-west part was over predicted. Visual analysis of **Fig. 5** indicates that all the classes of 2006 simulated LCLU maps are relatively close to the corresponding classes in the actual 2006 LCLU map, while the Built up land poorly simulated in some areas specially on the north-west part of NC. There is a big area covered by forest land, 72,499 km^2 in 1992 and 61,242 km^2 in 2006 in NC. The simulated forest land in 2006 was found to be 58,616 km^2 is shown in **Fig. 6** which signifies the better quantitative simulation even though huge areas are involved in simulation process. The best agreement in quantity and location is shown in the Water body 10,253 km^2 and other land class 16,059 km^2 in simulated data sets image, while the corresponding actual data are 10,545 km^2 and 17,100 km^2 respectively (**Figure 6**). Simulated 2006 forest land, Agricultural land and built up land found 58,616, 37,041 and 14,900 km^2 respectively whereas the actual map data are 61,242, 34,270 and 13,242 km^2 (**Fig. 6**).

3.3. Projected 2030 LCLU Scenario

The model verification led to the advantage of integration of natural and population variable in the Markov-CA model in land use change projections. **Table 3** validation results indicated model reliability and predictability. Based on these validation results, the LCLU scenario for the year 2030 in NC was generated (**Fig. 7**). Similar procedure of simulation 2006 map was used to generate 2030 LCLU map. Firstly, 1992 and 2001 NLCD base maps were used to train the map in MC model. MC model produced transitional probability matrix of 2030 and conditional probability images of built up land, agricultural land and forest land of 2030. After that, MCE method produced suitability images of 2030, with the integration of the variables and the conditional probability images of 3 categories of LCLU. Calibrated and validated weight values of each

variable and conditional probability images of respective class from previous section have been adopted. Then Markov-CA model was used to generate 2030 LCLU projected map with the following model inputs: (1) 2001base map; (2) 2030 LCLU quantitative areas transition matrix and (3) 2030 suitability map of built up land, agricultural land and forest land categories.

The simulated 2030 NC LCLU scenario in **Table 4** showed a substantial increase in built up land from 5,865 km^2 in 1992 and 12,161 km^2 in 2001 to 32,717 km^2 in 2030. Built up land was found to increase by 458% when compared with 1992 LCLU map. Forest land and agricultural land were found to decrease 32 and 8% respectively over 40 years of comparison. Very little percentage decreases of water body and other land categories (2 and 5% respectively) were found in 2030 when compared with 1992 data sets. Visual analysis of **Fig. 7** indicates that a more extensive built up land predicted in the southern portion of NC. Generally, the urban built up area is based on the scale of urban population. It seems logical that the southern part of NC projected almost 1.2 million populations in 2030 which is in and around the business city Charlotte in NC. In **Fig. 7**, it's visible that mid portion and mid-eastern part of NC will also be experiencing urban land expansion by 2030. The projected map of 2030 in this portion also provides

logical sense because mid portion is the 3rd largest city of NC and mid-eastern part is the capital of NC. This urban or developed land information will help water resources manager or city planner to thorough assesses water supply and distribution, transport planning and sustainable urban growth. In **Figure 7**, 2030 LCLU projected map also indicates that the 70% agricultural land, rangeland are on the eastern and mid-eastern part of NC and most of the forest land are on the western and mid-western part of NC. Due to the significant amount of agricultural land are situated in the eastern part of NC, further work can be done with the water quality assessment based on the quantitative change of agricultural land.

Figure 8 shows the percentages of land allocation of 1992, 2001 and 2006 base maps and projected 2030 LCLU of 5 categories. In 2030, 36, 24 and 20.1% land are allocated in forest land, built up land and agricultural land consecutively (**Fig. 8**). 8.3% of forest land was decreased from 1992 to2006 periods and 8.9% is going to be decreased from 2006 to 2030. There are increasing-decreasing percentages of agricultural land allocation found over 40 years. About 7% agricultural land was found to decrease in 2030 when compared with 2001 data. No significant changes were found for water body and other land category coverage over 40 years of analysis (**Fig. 8**).
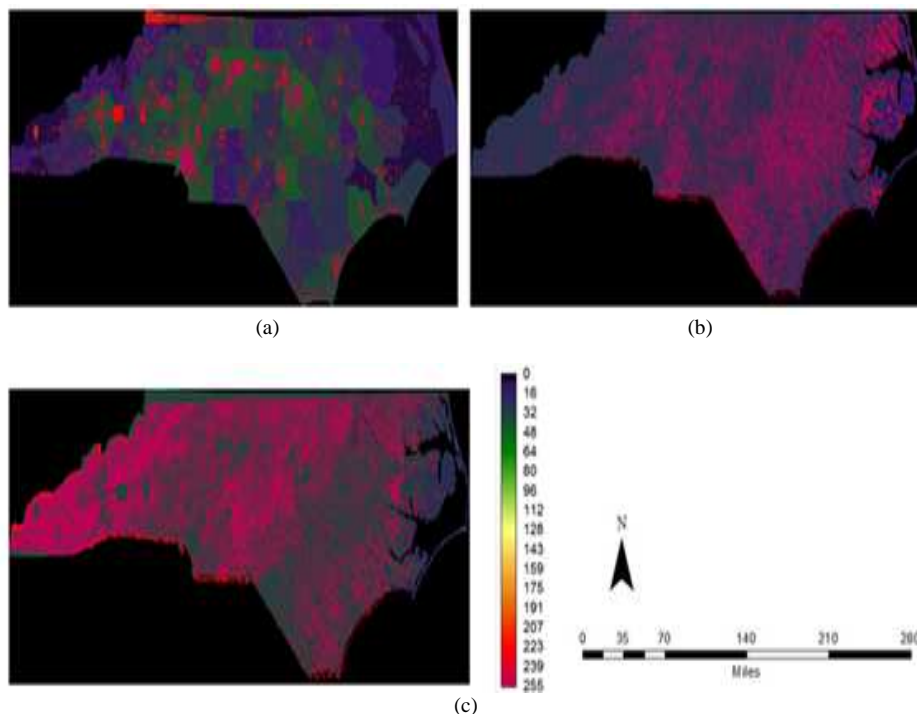

(a)

(b)

(c)

Fig. 4. Suitability images of A. Built up land, B. Agricultural land and C. Forest land
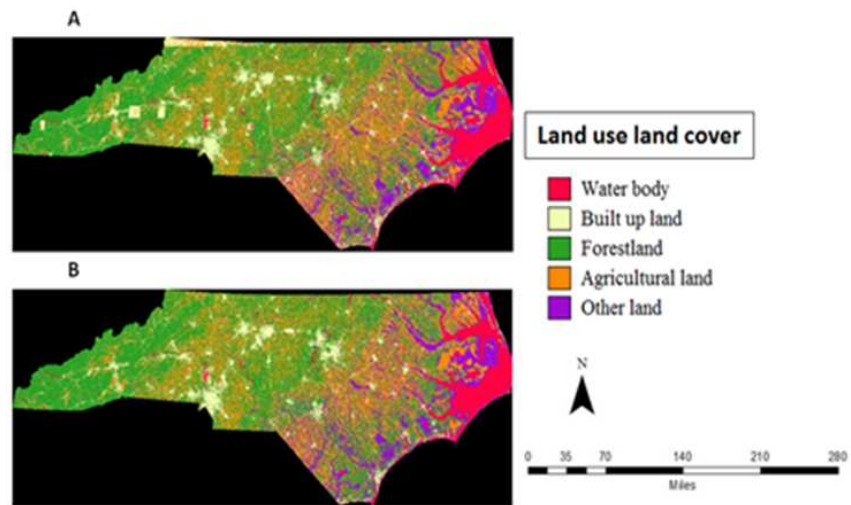
Fig. 5. LCLU maps of 2006 A. simulated by Markov CA model versus B. actual datasets
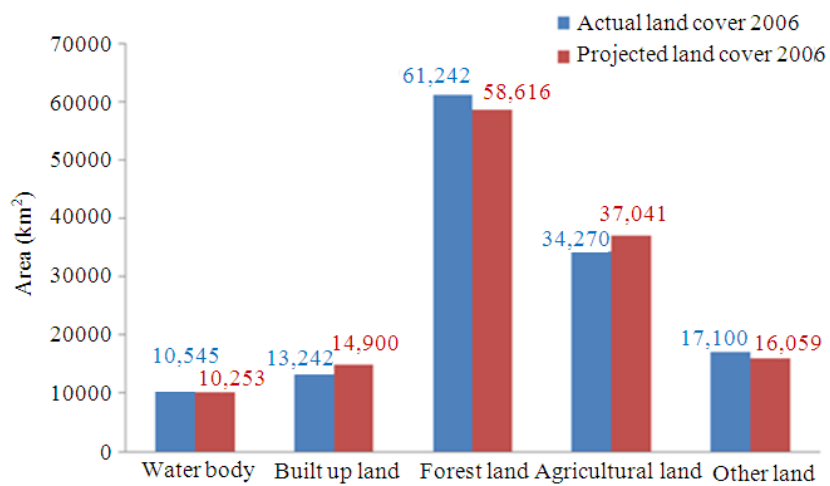
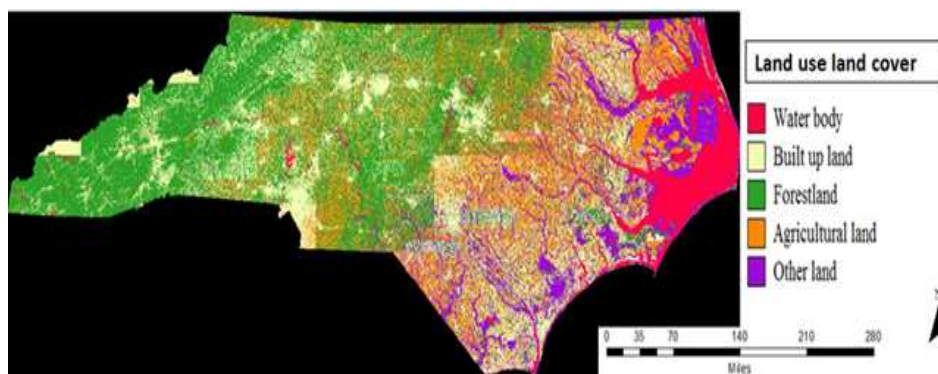

Fig. 6. Simulated versus actual LCLU classes area (km^2) in 2006

Fig. 7. Simulated future LCLU map in 2030

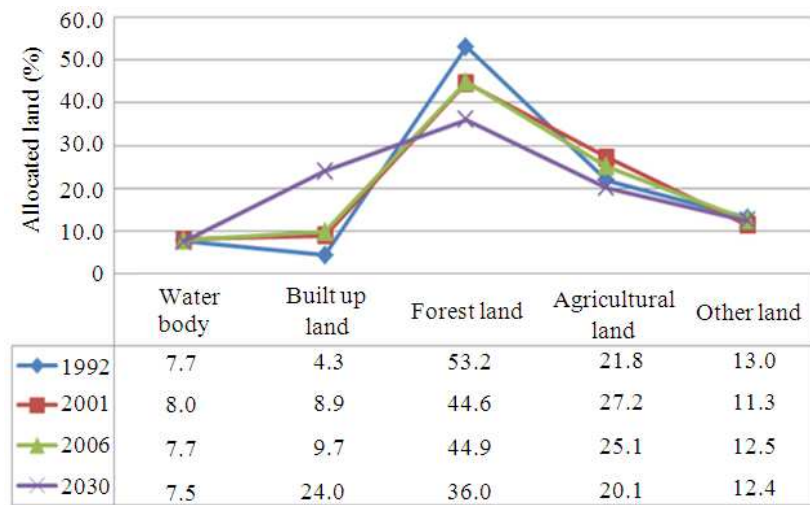|	Water body	Built up land	Forest land	Agricultural land	Other land
1992	7.7	4.3	53.2	21.8	13.0
2001	8.0	8.9	44.6	27.2	11.3
2006	7.7	9.7	44.9	25.1	12.5
2030	7.5	24.0	36.0	20.1	12.4

Fig. 8. Percentage of land allocation in each year of 1992, 2001, 2006 and 2030

Table 3. Kappa statistics and ROC values for model validation

Image comparison criteria	Validation	Values
Simulated suitable built up land VS Boolean actual built up land	ROC	0.83
Simulated suitable agricultural land VS Boolean actual agricultural land	ROC	0.89
Simulated suitable forest land VS Boolean actual forest land	ROC	0.87
Simulated 2006 LULC VS actual LULC image	KIA	0.86

Table 4. Actual (1992, 2001) and simulated (2030) LCLU area (km^2) and % change in 2001 and 2030 in North Carolina when compared with 1992 in different categories

Land class, year	1992	2001	Change (%)	2030	Change (%)
Water body	10455	10869	4	10286	-2
Built up land	5865	12161	107	32717	458
Forest land	72499	60879	-16	49121	-32
Agricultural land	29785	37044	24	27398	-8
Other land	17795	15446	-13	16861	-5

4. CONCLUSION

The Markov-CA model in combination with natural and socio-economic variables was used to predict the future LCLU changes in 2030 for the entire state of NC. Conditional probability maps and transitional probability area matrix have been generated from the satellite derived LCLU NLCD datasets (1992, 2001 and 2006) using the MC analysis. Suitability images were produced using the MCE procedure which combines the natural and socio-economic variables with the conditional probability images of land use categories. Dynamic adjustments and effective land allocation between the Markov model transition probability areas and suitability images have been conducted by MOLA and CA spatial filters. Two stage validation procedures were adopted in this study. ROC was used to validate suitability images created by MCE. KIA was used to validate overall LCLU simulated map of 2006. Based on the reliable ROC and KIA validation, the Markov-CA model is used to simulate 2030 LCLU change in NC.

LCLU prediction of NC for year 2030 shows 20% increase of built up land, 17% decrease of forest land while comparing that with year 1992 (~40 years period). Much of the built-up land (urban expansion) is projected to be in the southern, mid and mid-eastern portion of NC within 2030. About 7% agricultural land was found to be decreased in 2030 when compared with 2001 NLCD data. 8.3% of forest land were decreased from 1992 to 2006 periods and 8.9% is projected to decrease from 2006 to 2030. Loss of forest area is projected mostly in western and mid-

western part of NC. No significant changes were found for water body and other land cover category.

Paegelow and Olmedo (2005; Sun *et al*., 2007) did not consider socio-economic variables in their LCLU change analysis, although they used the same Markov-CA model. On the other hand, (Tong *et al*., 2012) did not consider natural variables (slope, elevation, hydrography) but considered population as a socioeconomic variable in LCLU change analysis using the same model. This study provided an important contribution to LCLU change analysis by integrating both natural and population variable into the Markov-CA model. In addition, a large scale application in an urban-rural mixed landscape (136,399 km^2) may be considered a novel attempt.

The outcome of the LCLU study presented here will provide basic information for the integrated assessment and management of the future water resources in the state. The simulation results can also be considered as a strategic proactive guide for reduction of deforestation, ecological conservation and sustainable city development planning. While the model has successfully simulated LCLU changes based on natural and population variables, it did not consider future climate change, fluctuation of development strategy, government incentives/discouragement influence to local farmer's behavior in agricultural land. Future study plans to address these factors in LCLU analysis.

5. REFERENCES

Chang, S.Y. and M. Sayemuzzaman, 2014. Using unscented kalman filter in subsurface contaminant transport models. J. Environ. Inform., 23: 14-22. DOI: 10.3808/jei.201400253

Courage, K., A. Masamu, A. Bongo and M. Munyaradzi, 2009. Rural sustainability under threat in Zimbabwe-simulation of future land use/cover changes in the Bindura district based on the Markov-cellular automata model. Applied Geography, 29: 435-447. DOI: 10.1016/j.apgeog.2008.10.002

Eastman, J.R., 2006. IDRISI Andes tutorial. Clark Labs, Worcester, MA.

Guan, D., H. Li, T. Inohae, W. Su and K. Hokao *et al*., 2011. Modeling urban land use change by the integration of cellular automaton and Markov model. Ecological Modell., 222: 3761-3772. DOI: 10.1016/j.ecolmodel.2011.09.009

Holman, B., L. Kleczek and E. Polk, 2007. The future of water in North Carolina: Strategies for sustaining abundant and clean water. Conference report. Nicholas institute for environmental policy solutions. Duke University, Durham, North Carolina.

Houet, T. and L. Hubert-Moy, 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. EARSele Proceed., 5: 63-76.

IDRISI, 2013. IDRISI Clark Lab. Clark University.

Martínez, Á. J., S.S. Seoane and E.D.L. Calabuig, 2011. Modelling the risk of land cover change from environmental and socio-economic drivers in heterogeneous and changing landscapes: The role of uncertainty. Landscape Urban Plann., 101: 108-119. DOI: 10.1016/j.landurbplan.2011.01.009

Myint, S.W. and L. Wang, 2006. Multicriteria decision approach for land use land cover change using Markov chain analysis and a cellular automata approach. Canad. J. Remote Sens., 32: 390-404. DOI: 10.5589/m06-032

NCOSBM, 2010. County/state population projections. North Carolina Office of State Budget and Management, State Demographics Branch, Charlotte, NC.

Paegelow, M. and M.T.C.Olmedo, 2005. Possibilities and limits of prospective GIS land cover modeling-a compared case study: Garrotxes (France) and Alta Alpujarra Granadina (Spain). Int. J. Geographical Inform. Sci., 19: 697-722. DOI: 10.1080/13658810500076443

Parker, D.C., S.M. Manson, M.A. Janssen, M.J. Hoffmann and P. Deadman, 2003. Multi-agent systems for the simulation of land-use and land-cover change: A Review. Ann. Associat. Am. Geographers, 93: 314-337. DOI: 10.1111/1467-8306.9302004

Pontius, R.G. and J. Malanson, 2005. Comparison of the structure and accuracy of two land change models. Int. J. Geographical Inform. Sci., 19: 243-265. DOI: 10.1080/13658810410001713434

Pontius, R.G., 2000. Quantification error versus location error in comparison of categorical maps. Photogrammetric Eng. Remote Sens., 66: 1011-1016.

Pontius, R.G.J. and L.C. Schneider, 2001. Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. Agric. Ecosystems Environ., 85: 239-248. DOI: 10.1016/S0167-8809(01)00187-6

Proctor, W., 2001. Multi-criteria analysis and environmental decision-making: A case study of australia's forests. Ph.D Thesis, Australian National University and Canberra, Australia.

Sun, Y.L., Q. Zhang, J.L. Jimenez, M.R. Canagaratna and J.D. Allan *et al*., 2007. Ubiquity and dominance of oxygenated species in organic aerosols in anthropogenically-influenced Northern Hemisphere midlatitudes. Geophysical Res. Lett., 34: 13801-13801. DOI: 10.1029/2007GL029979.

Sang, L., C. Zhang, J. Yang, D. Zhu and W. Yun, 2011. Simulation of land use spatial pattern of towns and villages based on CA-Markov model. Math. Comput. Modell., 54: 938-943. DOI: 10.1016/j.mcm.2010.11.019

Sayemuzzaman, M. and M.K. Jha, 2014. Seasonal and annual precipitation time series trend analysis in North Carolina, United States. Atmospheric Res., 137: 183-194. DOI: 10.1016/j.atmosres.2013.10.012

Sayemuzzaman, M., M.K. Jha, A. Mekonnen and K.A. Schimmel, 2014a. Subseasonal climate variability for North Carolina, United States. Atmospheric Res., 145: 69-79. DOI: 10.1016/j.atmosres.2014.03.032

Sayemuzzaman, M., M.K. Jha and A. Mekonnen, 2014b. Spatio-temporal long-term (1950-2009) temperature trend analysis in North Carolina, United States. Theoretical Applied Climatol., 116: 3-4. DOI: 10.1007/s00704-014-1147-6

Schneider, L.C. and R.G. Pontius, 2001. Modeling land-use change in the Ipswich watershed, Massachusetts, USA. Agric. Ecosystems Environ., 85: 83-94. DOI: 10.1016/S0167-8809(01)00189-X

Takada, T., A. Miyamoto and S.F. Hasegawa, 2010. Derivation of a yearly transition probability matrix for land-use dynamics and its applications. Landscape Ecol., 25: 561-572. DOI: 10.1007/s10980-009-9433-x

Tong, S.T.Y., Y. Sun, T. Ranatunga, J. Heand and Y.J. Yang, 2011. Predicting plausible impacts of sets of climate and land use change scenarios on water resources Applied Geography, 32:477-489.

Tong, S.T.Y., Y. Sun and Y.J. Yang, 2012. Generating a future land use change scenario with a modified population-coupled Markov cellular automata model. J. Environ. Inform., 19: 108-119.

USCB, 2010. Bureau of the Census. Census Bureau.

USGS-NLCD-MRLC, 2013. United States Geological Survey-National Land Cover Data-Multi Resolution Land Cover.

Veldkamp, A., P.H. Verburg, K. Kok, G.H.J. Priess and A.R. Bergsma *et al*., 2001. The need for scale sensitive approaches in spatially explicit land use change modeling. Environ. Model. Assess., 6: 111-121. DOI: 10.1023/A:1011572301150

Vitousek, P.M., H.A. Mooney, J. Lubchenco and J.M. Melillo, 1997. Human domination of earth's ecosystems. Science, 277: 494-500. DOI: 10.1126/science.277.5325.494

Wu, F. and C.J. Webster, 1998. Simulation of land development through the integration of cellular automata and multicriteria evaluation. Environ. Plann. B: Plann. Design, 25: 103-126. DOI: 10.1068/b250103

Yu, F., 2009. Study on forecast of land use change based on Markov-CA. Land Resources Inform., 4: 38-46.