Urban Growth Prediction Using Cellular Automata Markov: A Case Study Using Sulaimaniya City in the Kurdistan Region of North Iraq

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Abstract
Many cities in the Kurdistan Region have witnessed a rapid change in land use during the last two decades. Geographic information systems (GIS) and remote sensing have been broadly utilized to monitor and detect urban growth prediction. In this paper, three Landsat TM 5 and one Landsat 8 of Sulaimaniya city were used to identify and develop an urban growth map for 1991, 1998, 2006 and 2014. A supervised classification approach was applied; in order to predict urban growth, the Markov chain and CA-Markov models were used. The result demonstrates that validation of CA-Markov to forecast 2006 land cover map is ineffective in reasonably predicting land coverage for this time period; however this model had significant validation for the year 2014 and also has a good forecast power for 2024.

Keywords
Land Use Change/Cover, Urban Growth Prediction, Supervised Classification, Markov Chain, CA-Markov, Validation.

Introduction

Changes in land use/land cover in most countries are caused by rapid urban growth; it is change resulting from the urbanization process which is common, given the fact that more than half the world's population lives in cities (Shafizadeh and Helbich, 2013). The world is becoming more urbanized every year. It is estimated that the world population living in cities will increase by 14% from 1995 to 2025 (Soffianian et al, 2010). According to a report by the United Nations, the mechanism of increasing population in urban areas applies to Iraq; from 1980 to 2015 the rural population has decreased by 1%, meaning an increase of 1% in urban areas. Sulaimaniya is no different; in 1987 there was a 26% difference between urban and rural areas, 63% of the population living in the city, with 37% living in the countryside (Sulaimaniya Province, 2007). Environment, economy and social issues could be affected by this physical expansion of the cities and the increase of the urban population (Soffianian et al, 2010).

Land use/cover change forecast and analysis of the evaluation of environmental change and ecosystem implications, in terms of numerous temporal and spatial scales (Lopez, 2001). In order to detect and predict this change, satellite imagery and remote sensing are the best techniques. Recent technologies such as the Geographic Information System (GIS) and Remote Sensing (RS) have experienced an efficient and phenomenal growth; the increase of their use in presenting and forming the decision support tools of the spatial modeling method has helped in urban and ecosystem planning (Nouri et al, 2014). The most necessary components for the various complicated ecosystem approaches are urban modeling studies. The anticipation and analysis of predictions of any dynamics of urban growth can be assisted by modeling tools (Kanta Kumar et al, 2011). The study applied the Markov chain and Cellular Automata (CA) theory frameworks combined with the CA-Markov analysis statistical technique; even though it is easier to calculate the Markov chain model by utilizing grid based GIS data and the patterns of land use change (Kim et al, 2011).

Previously, the CA-Markov model has been used in various studies to simulate land use/land cover pattern changes. CA Markov and landscape metrics were used to model and analyze land use change in Portugal by Araya and Cabral (2010). The validation of CA Markov was successful with Klocation 87% and Kquantity of 83%. The model capability for change simulation using a three dimensional approach was not analyzed.

Fan et al, (2008) in the Core Corridor of the Pearl River Delta in China, post-classification method and TM and ETM image satellite were used in order to explore the land use/land cover change in the area during 1998 to 2003. The study concluded that land use/land cover change can be predicted by Markov chain modeling which was selected as the most effective way; therefore they used the CA and Markov chain to predict urban expansion from 2008 and 2013. Prediction of land cover by applying the CA Markov model in Sulaimaniya city is the purpose of this study and also Validation of CA-Markov model to predict the land use/cover changes.

1. Study area

Sulaimaniya city is the capital of the Sulaimaniya Governorate, located in northern Iraq; it borders the Erbil and

Kirkuk governorates from the west and south west, and from the east it borders with Iran. The study area is the most populated of the Iraqi Kurdistan Region and is the cultural capital of Kurdistan. Mountains surround the study area, Baranan and Chwarta mountains are to the south, Tasluja hills are in the west, the Qaiwan range in the north east with the ranges of Azmaer and Goizha also located towards the north. These mountains are often the cause of the variation in weather. Its climate consists of dry hot summers and rainy cold winters due to a semi-arid climate. The demography of this city increases by 3 per cent each year (Sulaimaniya province, 2008). In 1987, only 63% of the population lived in urban areas, and had increased by 15 % in 2008. (Op cit) According to the census carried out in Sulaimaniya in the year 2002 the population was 1,704,740 people (Pakiza, 2013). Sulaimaniya city was chosen as the study area for this research due to the rapid urban growth which has occurred over the last few decades, as well as the prediction of future expansions.

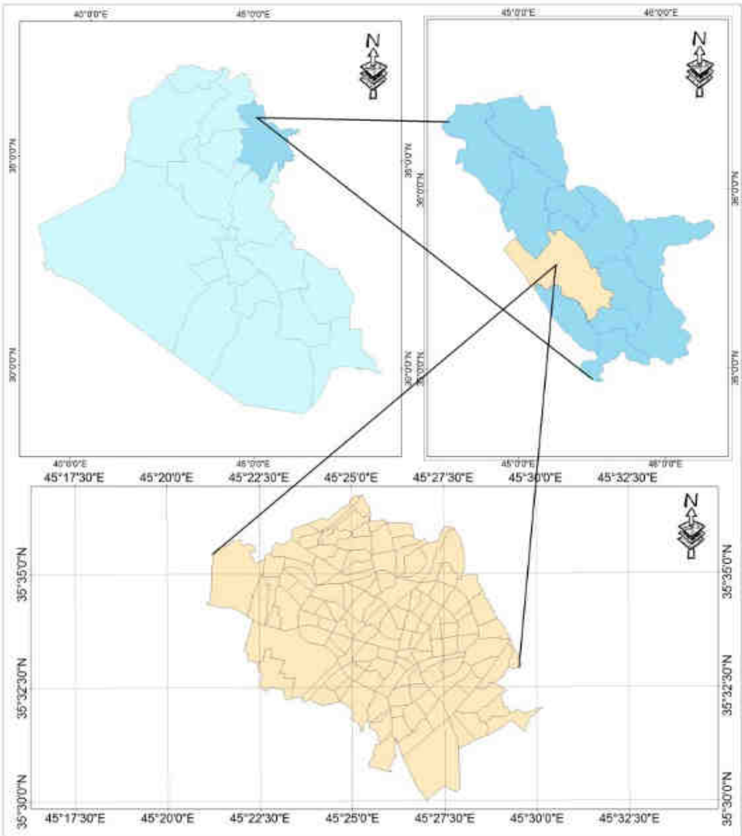

Fig 6. Study area (Sulaimaniya City)

2. Data set

Four Landsat satellites were used in the study three Landsat-5 TM for 1998 and 2006 and one Landsat 8 for 2014, a United States Geologic Survey (USGS) was hired to assess the changes in the land cover maps. According to Shafizadeh et al (2013), despite the fact that Landsat data is cost-effective, it increases the time put into temporal monitoring and the time likely to be spent through their mid-spatial resolution. Alternatively, USGS allows Landsat satellite images to be updated rapidly and keeps them free, which makes them the most suitable for making urban growth models (Yeh, and Xia, 2001). Image satellites with path 169, row 35, covers the Sulaimaniya governorate. A UTM projection system projected all the data used in the study, Zone 38 WGS4 1986 North, the Landsat satellite of 30m spatial resolution is satisfactory to present human development; other categories of land-use from other kinds of land-cover change are identified by the spectral range of the tool.

3. Modelling of Prediction and Validation

In this study the Cellular automata model were applied to predict the land use alterations of the future. The Markovian random process properties with a number of constraints that involves the usual land use structure stable of transfer state, is followed by the dynamically developing land use pattern and, in certain conditions, one land use category may transform into another (Aithal et al, 2011; Kumar et al, 2014). Consequently the Markov chain was used for making the land use map of change probability for the region of study and the Markov module was used to apply it (Araya and Cabral, 2010; Tang et al, 2007). Two land cover images, a transition area matrix, a set of conditional probability images and outputs and a transition probability matrix are analyzed by the Markov chain approach (Razzavi, 2014; Shafizadeh and Helbich, 2013; Mukhopadhyay et al, 2014; Sayemuzzaman and Manojjha, 2014). According to the transition probability matrix, one land-use category will transform into one of the other categories. The number of pixels predicted to alter from one class of land use to another over a stated time is told by the matrix of transition area (Eastman, 2006). Every land usage class provided a set of images of conditional probability by the model. The maps display the probability of a pixel to transform to the chosen class over the next period of time. These maps are called Conditional Probability Maps due to the probabilities being conditional in their current state (El-Hallaq and Habboub, 2015). As mentioned above, the major problem faced with Markov is that the geography provides no sense (Subedi et al, 2013; Eastman, 2006). The probability of the transitions are most likely to be correct on a per class basis, nonetheless there is no information of the incidents' spatial supply within the land uses class (Araya and Cabral, 2010; Nouri et al, 2014; Memarian et al, 2012). Cellular automata are used to provide the model with a spatial dimension by developing CA-Markov in order to solve this problem (Sang et al, 2011; Jalerajabi, and Ahmadian 2013; Thomas and Laurence, 2006; Fan et al, 2008).

In order to access the overall presentation of models for urban growth forecasting, two approaches were used, calculation of agreement and disagreement and error matrices, at the same time real map and predicted map through the validation method (Nadoushan et al, 2012). Model validation is a significant step, even though there is no agreement on the assessment of performance of the models of land use change by the criteria. Comparing the result of the 2006 and 2014 simulation maps to the real maps of 2006 and 2014 using Kappa variations (Kno, Klocation, and Kquantity), was a method used to calculate the predictive power of the model. Kno identifies the amount classified correctly comparative to the correctly classified amount by a simulation, whilst unable to indicate quantity and location accurately (Pontius, 2000; Nadoushan et al, 2012). Klocation calculated the accuracy value of the simulation and its ability to indicate location, divided by the maximum value of simulation accuracy to indicate location perfectly (Pontius, 2000). Kquantity is the measurement of the validation of simulations to perfectly predict quantity (Pontius, 2000; Nadoushan et al, 2012). If the value of prediction power is higher than 80% then its' considered strong so this is a reasonable method to predict future projections (Araya and Cabral 2010).

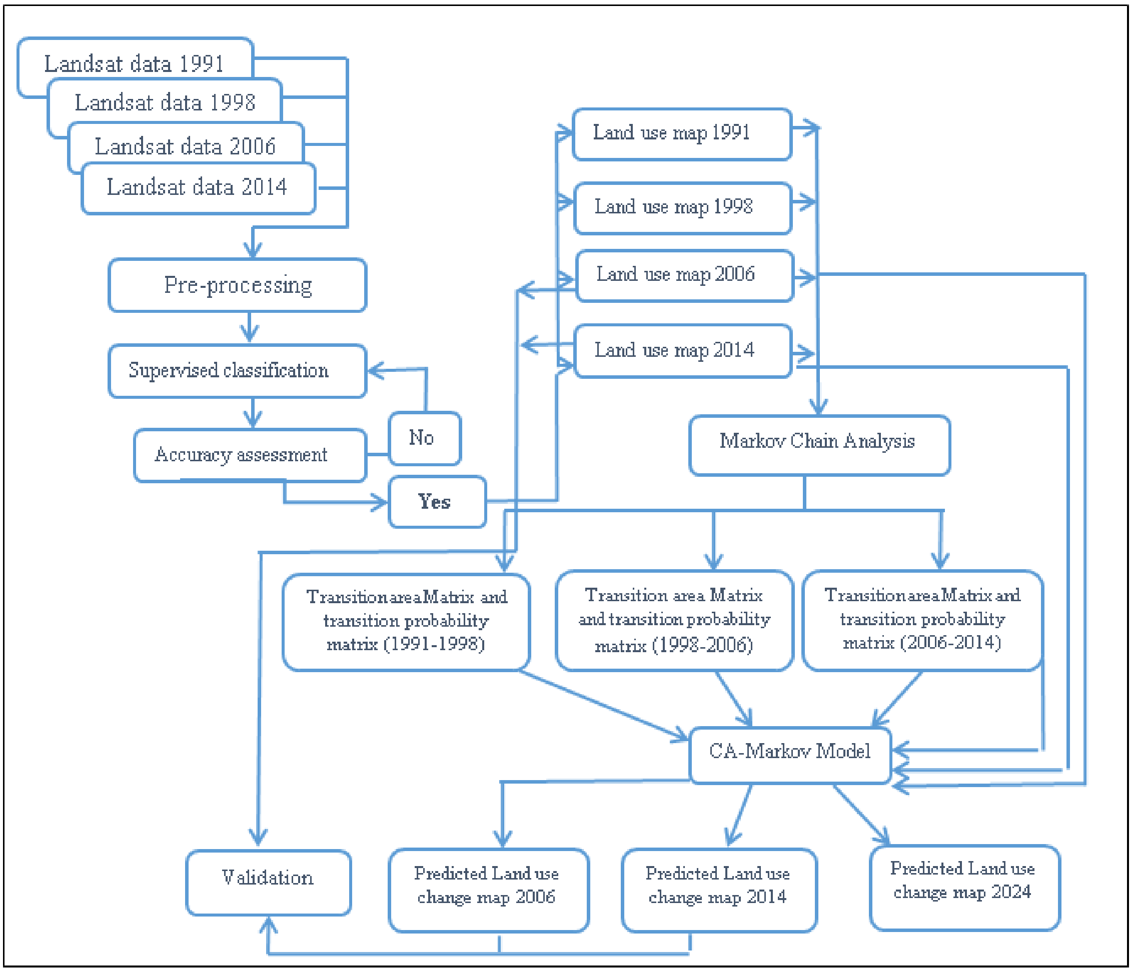

Fig 2. Flowchart illustrate of methodology.

4. Result and discussion

4.1. Land use change analysis

The supervised classification method was applied to the maximum likelihood approach. This is a common approach for supervised classification and the method used to produce the land use maps in 1991, 1998, 2006, 2014) with high precision as shown in figure 2 respectively. Anderson et al, (1976) explains that the minimum standard of overall precision for the urban land use change map, fixed by USGS classification, is more than 85%. In this study, Accuracy assessment and Overall accuracy is calculated and determined by 92%, 86%, 89% and 87% for 1991, 1998, 2006 and 2014 respectively. The Kappa Coefficient Producer for the maps was a point out by 0.90, 0.83, 0.84 and 0.84 for years 1991, 1998, 2006 and 2014 respectively. To confirm the result of user accuracy for LULC map was calculated; Table (1) pointed out that the results are acceptable for assessing LULC changes.

Land use categories	1991		1998		2006		2014	
	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy
Urban area	91.30	93.33	90.69	92.85	91.48	91.48	87.75	93.47
Vegetation	93.61	89.79	88	89.85	87.5	84	88	86.27
Open land	91.22	92.85	85	78.46	84.48	84.48	84.78	81.25
Overall accuracy	92		86		89		87	
Kappa Index	0.90		0.83		0.84		0.84	

Table 10. Classification accuracy (% age) of images for the years 1991, 1998, 2006 and 2014.

According to the outcomes of the study, the land coverage by vegetation in 1991 was 2147.22 hectares as shown in table 2, 6, taking up 9.3% of land; although this percentage lowered to 1554.26 hectares (6.7%) of land in the year 1998, it decreased dramatically in 2006 reaching 2.3% 534.15 hectares but went back up in 2014 to 3.1% vegetation land 728.21 hectares. The study showed that outstanding changes took place in the quantity of vegetation classes between 1998 and 2006, from 6.7% to 2.3%, as confirmed by the data. These changes could be the result of numerous factors including climate change and population growth. Extreme seasons have great effect on this phenomenon. In 1998, 1999, and 2000 the city experienced drought seasons. Rain fall average was 350ml, 500ml and 699.8ml in 1999, 2006 and 2014 respectively. Due to most agriculture in the study area being dependent on rain, the increasing and decreasing of rain consequently caused a change in vegetation land. Environmental researchers and climatologists believe that the few decades of global warming and climate change that causes an increase of temperature, has had a major impact on the change of vegetation. The study area also faced a huge growth in population which was another major impact on the decrease of vegetation land by being replaced with urban areas. Rain percentage went up to 699.8 ml in 2014 therefore the value of vegetation increased to 3.1% (as seen in fig 4 and table 2) due to residents' increasing awareness of environmental issues, planting trees, improving current parks and making new parks and other methods.

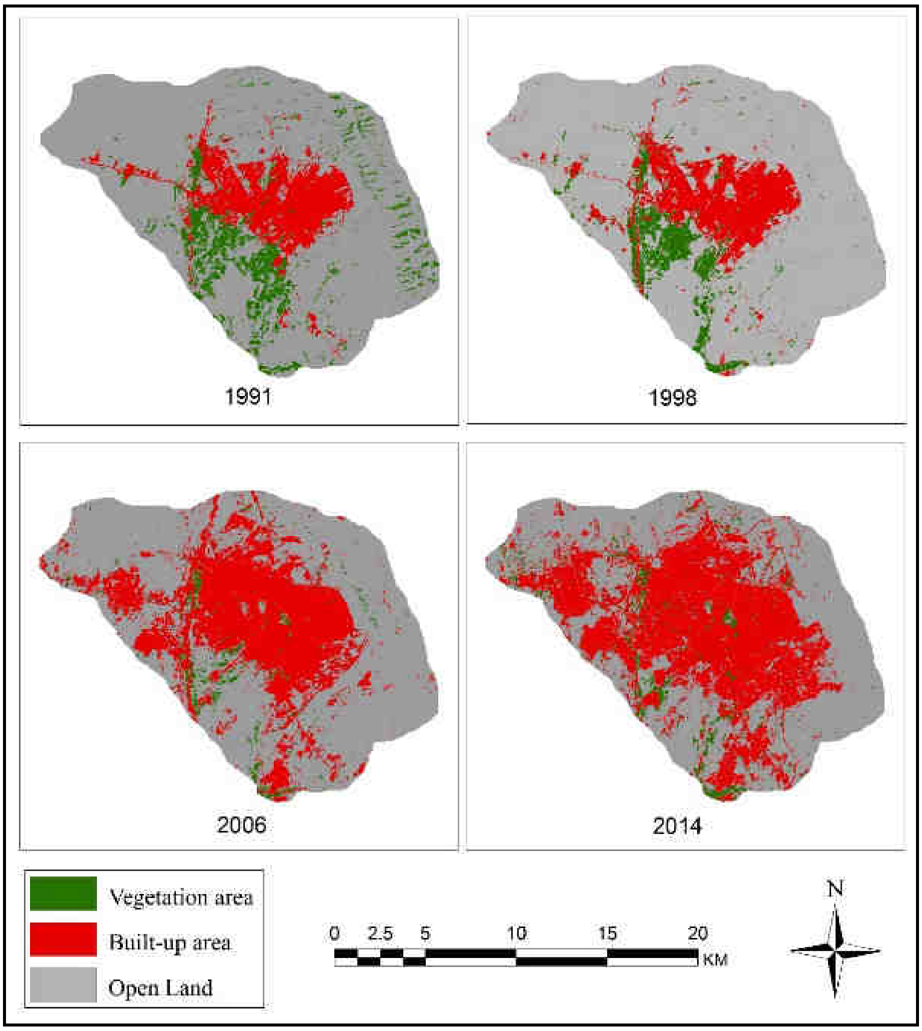

Fig 3. map illustrating the result of land use change

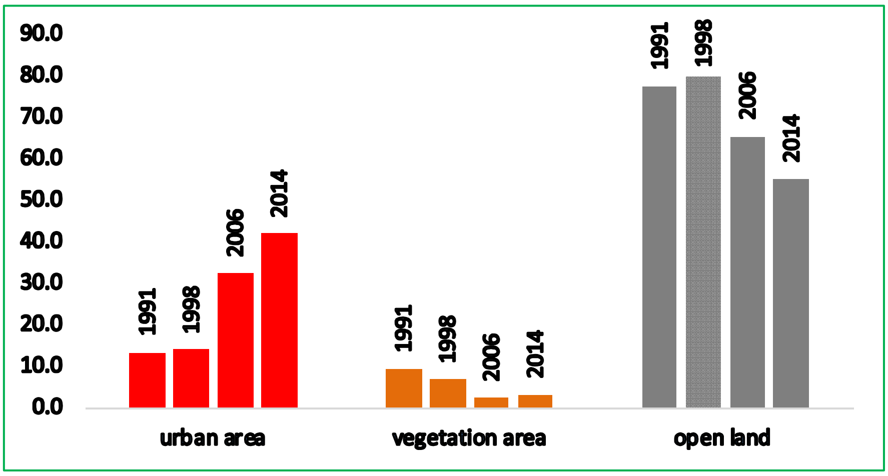

Fig4. Illustrate percentage of land use change during the research study.

Built-up areas experienced outstanding changes; in 1991 built up land was measured to be 13.3% (3063.78 hectares), going up in 1998 to 13.8% and continued to increase in 2006 up to 32.3% (7464.20 hectares) and it experienced major increases until 2014, taking up 41.8% (9654.26 hectares). Table 2, 6 shows the change in built-up areas which took place after 2000 was a result of various factors. Firstly, population growth, during the period of the study there was a large increase of citizens according to the census. Population in 1987 was 175413 and 571507 in 2009. Secondly, the economic and political changes that impacted built up areas, particularly after 2003 when the Iraqi regime fell. The increase of building in the city led improvement in the economic condition of Sulaymaniya city. It experienced development in every sector in the period of the study. For example: residential areas, commerce, schools, tourism and transportation….etc. The construction sector in particular has experienced a great deal of development over the last few years in the entire Kurdistan region as a result of robust economic growth and rising housing demands. This significant change was also noticeable in open land. For example, open land cover 77.4% (17895.51 hectares) in 1991, in 1998 it increased to 79.5% (18370.17 hectares) it decreased in 2006 to 65.4% (15107.16 hectares) and lowered again in 2014 to 55.1% (12724.04hectares). (Table 2, 6) In conclusion, the classification shows the rate of the occurrence of urban development in the study area between 1991 and 2014 was from 13.3% to 41.8%, and also explained the factors that resulted in this change population and economic growth.

4.2. **Transition probabilities matrices**

Markov chain analysis in Idrisi Selva software was used to calculate the transition probability matrices for 3 time periods 1991 to 1998, 1998 to 2006 and 2006 to 2014. The future probable percentages of land use change in these time periods illustrated by transition probability matrices.

It also reflects the probability of transition between different land use classes into other classes. To predict the transition probability matrix of land use change for 2006, land use map dated 1991 and 1998 were used. Also the transition probability matrix was created for predicting land use changes, in 2014; land use maps from 1998 and 2006 were used and in 2024, land use map of 2006 and 2014 were used Figure 2).

Land use categories	1991 %	1998%	2006%	2014%
Urban area	**13.3**	**13.8**	**32.3**	**41.8**
Vegetation area	**9.3**	**6.7**	**2.3**	**3.1**
Open land	**77.4**	**79.5**	**65.4**	**55.1**
Sum	**100**	**100**	**100**	**100**

Table 11: Illustrate the quantity of land use change

The future probability of change from vegetation land to built-up land is 47% and change of vegetation area to open area is 46% from 2014 to 2024. The probability of vegetation area remaining the same is 5.7% (as shown in table 3). This means that the probability of change in vegetation land is 94% from 2014 to 2024.

The possibility of change from vegetation land to urban areas, from the calibration period 1998 and 2006 to the calibration period 2006 and 2014, has experienced a remarkable increase, rising from 22.9% to 47.98%, as shown in tables 3 and 4. The probability of the transition from build-up land (as shown by table 4) was predicted to be 18.34% (to vegetation classes 1.42% and to open land 16.91%). although the probability of build-up areas staying the same rate from 1998 to 2006 was 81.66%, as encouraged by the low change in built up land use from 1991 to 2006, rapid urban growth ceased to occur in this time period.

	Vegetation area	**built-up**	**open land**
Vegetation area	**0.3027**	**0.0475**	**0.6498**
built-up	**0.0142**	**0.8166**	**0.1691**
open land	**0.0423**	**0.0334**	**0.9243**

Table 3- Transition probability matrix for land use change modeling under the 1991-1998 calibration period.

	Vegetation area	**built-up**	**open land**
Vegetation area	**0.204**	**0.229**	**0.567**
built-up	**0.0085**	**0.9685**	**0.023**
open land	**0.0103**	**0.219**	**0.7707**

Table 4- Transition probability matrix for land use change modeling under the 1998-2006 calibration period.

	Vegetation area	built-up	open land
Vegetation area	**0.0576**	**0.4798**	**0.4626**
built-up	**0.0329**	**0.6786**	**0.2885**
open land	**0.0349**	**0.4537**	**0.5114**

Table 5-Transition probability matrix for land use change modeling under the 2006-2014 calibration period

Reading the transition probability matrix for land use change modeling and the analysis of results indicated that Sulaymaniya city will face rapid urban growth to 2024 and, therefore further analysis and urban planning will be needed.

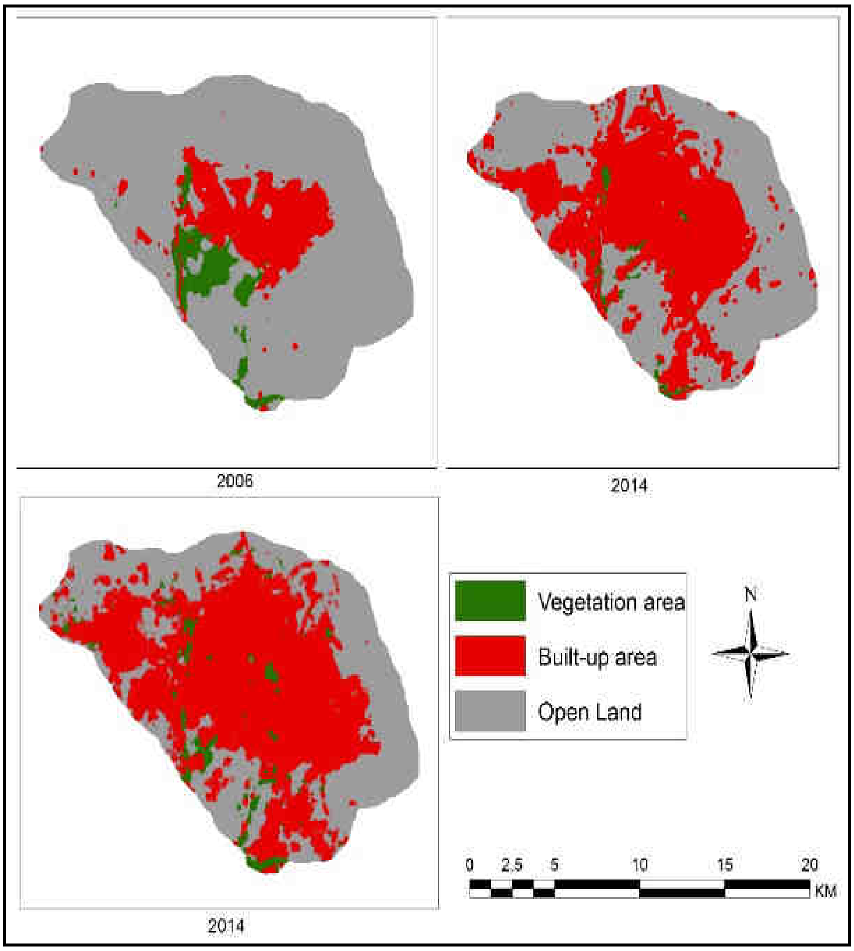

Fig 5. Illustrates the result of CA-Markov prediction of land usage change.

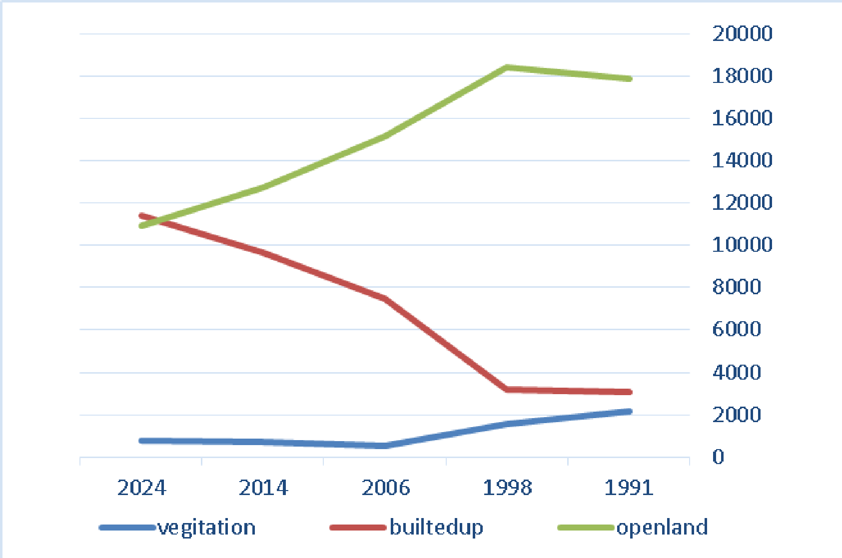

Fig 6. Illustrate the variation in land use change duration 1991 to 2024

	1991	1998	2006	2014	2024
vegetation	**2147.22**	**1558.26**	**534.42**	**728.49**	**797.78**
Build-up	**3063.78**	**3182.94**	**7465.59**	**9652.96**	**11388.72**
Open land	**17895.51**	**18382.5**	**15123.69**	**12723.97**	**10918.92**

Table 6: the quantity of land use change between 1991 and 2024

To conclude the study, urban land cover change in study area was forecasted for 2024 by utilized CA-Markov model. The study detected that the urban area of Sulaimaniya city was a growing trend in the resident areas (figure 5, 6) thus, based on forecasting, built-up areas will show a remarkable increase from 3063.78 to11388.72 h between 1991and 2024 (table 6). Figure (5) illustrates that the key growth in urban areas re forecasted to happen in the adjacent and suburban parts of the study area. Table (6) shows that the vegetation area will rise from 2147.22 to 797.78 between 1991 to 2024 whereas the open land will decrease from 17895.51 to 10918.92 in the 1991 to 2024 (table 6).

5.3. CA-Markov model and validation model

The CA Markov model was applied by using Idrisi Selva software for three time periods in this study. The Markov transition area file that was achieved from the model for time periods 1991 to 1998 and land use map dated 1998 were combined to predict the 2006 land use map. the real 2006 land use map and the achieved Markov transition area file from the Markov model for time period 1998to 2006 were used to predict the land use map for 2014. In the final stage, land use map of 2014 and Markov transition area file was achieved from the Markov model for the time period 2006 to 2014 and were used to predict land use map for the year 2024.

The point of this validation is to compare the model output with the actual data; this assesses the efficiency of the model. Validation tools in the Idrisi software were used to perform the CA Markov validation in two different time periods. The first stage of validation model was by comparing the 2006 land cover map as a reference image alongside the predicted 2006 map generated by the CA Markov model. The result is driven this validation the result of the agreement between the real and predicted map [M (m)] for 2006 was 66.86% and disagreement [1-M (m)] was 33.13% (as shown in figure 7).

The agreement due to the chance [N (n)] achieved without any location and quantity information was 25%. Agreement due to quantity (number of pixels for each class in both maps) that was calculated using the ([N (m)]-[N (n)]) relation was 25%. Disagreement due to the quantity ([P(p)] - [P(m)]) is 17.44 % and also agreement due to location and disagreement due to location equal 16 % and 5% (Figure 7).

The Klocation index, that represented Kappa index, embodied CA Markov models' ability to predict pixels in location, which was 74%. Kquantity, represents the model's ability to predict pixel quantity and it is achieved by putting data into this formula:

Kquantity = $\frac{M(m)-M(n)}{M(p)-M(n)} = \frac{.6686-.4455}{.6867-.4455} = 0.92$

The result of the validation of the CA-Markov model to predict the 2006 land cover map and image, compared to the real land cover image, demonstrated that CA Markov was unsuccessful to acceptably predict land cover image for this time period efficiently as shown above. Low rates of change took place in land cover images, particularly in the built up land class, from 1991 to 1998, the rates increased dramatically in the time period from 1998 to 2006; this was caused mainly by the spatial and temporal local condition of the study area. The following validation model for the year 2014 did not face these problems because of the relative similarity from the previous validation models for both the time periods 1998-2006 and 2006-2014.

Agreement between the actual and predicted map [M (m)] from 2014 was 89.15%, and the disagreement was calculated to be 10.85%. Agreement due to chance [N (n)] was 25%. Agreement concerning quantity which was calculated using the [N (m)]-[N (n)] relation) equals 8%, (figure 8) disagreement due to the quantity ([P (p)] - [P (m)]) is 8.22 %. And also agreement due to location and disagreement due to location equal 56.94 % and 2.63%. Klocation index is 95.58 % and Kquantity equals 1. (Figure 8) All of the indexes demonstrated that the CA-Markov model was able predict land cover change for the 2006-2014 time periods successfully. This discovery agrees with the finding of Araya and Cabral (2010)) detected that validation of CA Markov was successful with Klocation 87% and Kquantity of 83%.

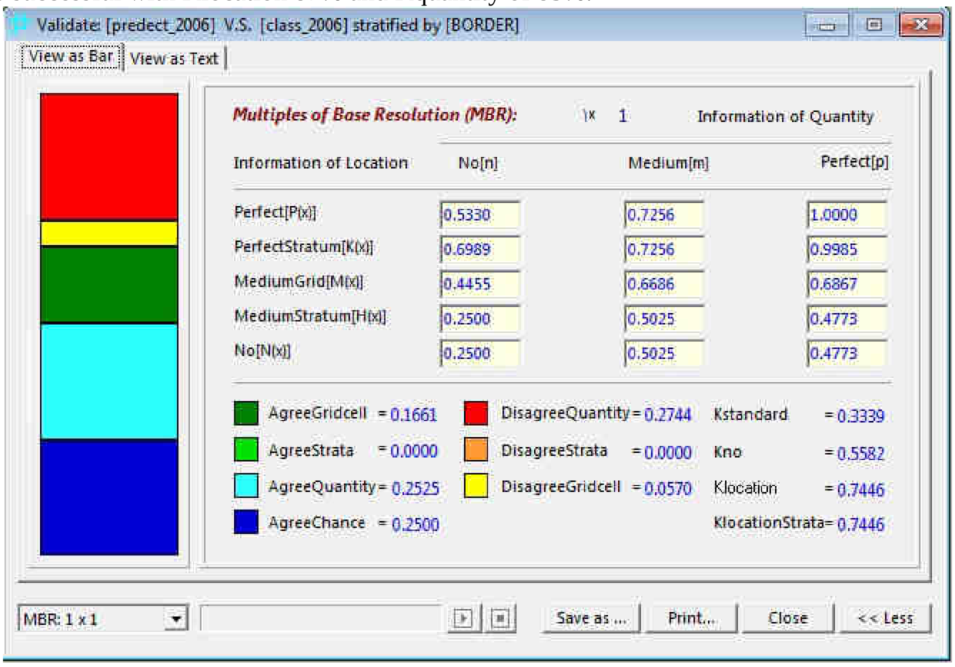

Fig7. The validation of simulating the CA-Markov and classified image of year 2006.

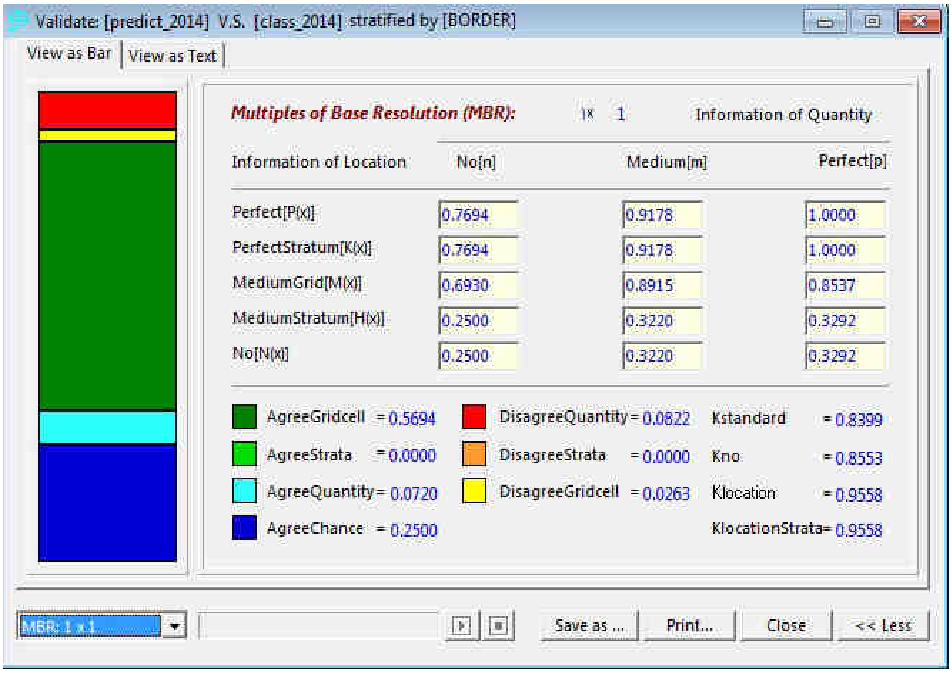

Fig 8. The validation of simulating CA-Markov and classified image of year 2014

5. Conclusions

Modelling of urbanization is a significant technique to forecast the built-up dynamics to comprehend the possible effects of future growth. GIS and remote sensing have significant roles, applying the spatial and temporal data is also an important step to help understand how the land use alterations in the earlier periods to predict land use in the future which assists managers, planners and decision makers and the planning of sustainable advance policies. This study noticed that the decreasing occurrence of vegetation and open land areas, particularly the vegetation area, at the same time as built–up areas remarkably increased in the period between 1991 and 2014 (Figure 6). The result showed that CA-Markov is not appropriate to accurately simulate land cover modification since actions of land use alteration was anomalous and not fixed and stable as predicted. The city of Sulaimaniya saw moderate changes in the period of 1991-1998 due to the socioeconomic and political factors; consequently the CA-Markov model was incapable of offering an accurate prediction for 2006. Nonetheless, CA-Markov offered a true prediction for 2014 because the study area had remarkable changes occurring in the period from 1998 to 2006.

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