Research Journal of Environmental and Earth Sciences 6(4): 215-226, 2014
ISSN: 2041-0484; e-ISSN: 2041-0492
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Submitted: January 20, 2014 Accepted: January 30, 2014 Published: April 20, 2014

Predicting the Trend of Land Use Changes Using Artificial Neural Network and Markov Chain Model (Case Study: Kermanshah City)

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Abstract: Nowadays, cities are expanding and developing with a rapid growth, so that the urban development process is currently one of the most important issues facing researchers in urban issues. In addition to the growth of the cities, how land use changes in macro level is also considered. Studying the changes and degradation of the resources in the past few years, as well as feasibility study and predicting these changes in the future years may play a significant role in planning and optimal use of resources and harnessing the non-normative changes in the future. There are diverse approaches for modeling the land use and cover changes among which may point to the Markov chain model. In this study, the changes in land use and land cover in Kermanshah City, Iran during 19 years has been studied using multi-temporal Landsat satellite images in 1987, 2000 and 2006, side information and Markov Chain Model. Results shows the decreasing trend in range land, forest, garden and green space area and in the other hand, an increased in residential land, agriculture and water suggesting the general trend of degradation in the study area through the growth in the residential land and agriculture rather than other land uses. Finally, the state of land use classes of next 19 years (2025) was anticipated using Markov Model. Results obtained from changes prediction matrix based on the maps of years 1987 and 2006 it is likely that 82% of residential land, 58.51% of agriculture, 34.47% of water, 8.94% of green space, 30.78% of gardens, 23.93% of waste land and 16.76% of range lands will remain unchanged from 2006 to 2025, among which residential lands and green space have the most and the least sustainability, respectively.

Keywords: Artificial neural network, forecasting, Kermanshah city, land cover, Markov chain model

INTRODUCTION

Urban growth rate is most important feature of human settlement transformation in developing countries; therefore, the need to better management by people, communities and governments is vital for this growth. In these countries, cities usually attract two-third of increased the total population and more than half of the urban population and thus natural increase and rural to urban migration (McGill, 1988). Cities are complex, open, dynamic and self-organizing systems. Spatial patterns and urban growth trends could be simulated using the modeling of complex urban system, thus, a better understanding of urban system as a whole would be reached. On the one hand, knowledge of the types of land cover and human activities in different parts of land as basic information for various planning is of significant importance. The maps displaying such these activities in different land surfaces are named 'land use maps' (Ahmadzadeh, 2003). Land use maps provide much of the information required by planners to take appropriate measures and principal decision-making. Detecting and forecasting the land cover changes is very effective to present an overview for better managing and policy-making in terms of natural resources in long term. There are diverse approaches for modeling the changes in land use and land cover among which we may refer to Markov Model. Using the Markov Chain Model, it may possible to forecast the different land use transition ratio in the future (Nashat, 2002; Muller and Middleton, 1994). Predicting the land use changes can determine the extent of the resources degradation and guide them to the appropriate routes (Brown *et al*., 2000; Hathout, 2002; Jenerette and Jianguo, 2001). In recent decades, CA models are widely used for simulating different spatial events such as land use and land cover changes, including the studies by Ménard and Marceau (2007), Wu (2002) and Almeida *et al*. (2003). Flahtkar *et al*. (2009) suggested that CA model can applied to display the growth of an urban space. Thereafter, in 1993, the modeling of the urban development and land use change was developed using Cellular Automata Model by White and Engelen and a land use CA model was tested for 4 cities of USA (White and Engelen, 2000). Jenerette and Jianguo (2001) conducted a series of spatial analyses of the land use pattern from 1912-1995 in order to understand how urbanization has transformed the desert landscape in the central Arizona-Phoenix region of the United States. The results of the spatial analysis show that the extent of urban area has increased exponentially for the past 83 years and this urban expansion is correlated with the

increase in population size for the same period of time. The authors developed a Markov-cellular automata model to simulate land-use change (Jenerette and Jianguo, 2001). Ayodeji Opeyemi (2006) detected the changes in land use and land cover of Ilorin, Kwara State using remote sensing data and GIS and data obtained from MSS, TM and ETM$^+$ from 1972 to 2001. Then, he predicted the land use and land cover changes for next 14 years using Markov Model. The results showed the rapid growth in constructed land from 1972 to 1986, while, in a period from 1986 to 2001 a decrease was observed in this class and it is anticipated that this trend will be continued up to 2015 (Ayodeji, 2006). Ali Mohammadi *et al*. (2010) predicted the land use and land cover changes of Tehran suburb using satellite images and Markov Chain Model. Results of their study indicated the uncontrolled expansion of constructed areas and sever degradation of agricultural lands in the study area during this period. Markov Chain Model is primarily considered as a predictor model for knowing the amount of changes that will occur in the future (Ali Mohammadi *et al*., 2010). Chang and Chang (2006) used the SPOT data of 4 representative periods (Mar.1999, Oct.1999, Nov.2002 and Nov.2005) to study the JiouJiou mount vegetation. Finally, the researchers combined the Markov Chain and Cellular Automata for forecasting the temporal and spatial changes. They concluded that CA-Markov model is more suitable for simulating the change trend of vegetation recovery than other models (Chang and Chang, 2006). Mirbagheri (2006) in his master's dissertation applied the CA Model for simulating the expanding mode of urban land use in Eslamshahr City and some parts of Robat-Karim City, Tehran. Flahtkar *et al*. (2009) addressed the ability of the CA Markov model to predict land cover map of city Isfahan. In this study, satellite images MSS (1972) and TM (1990) and ETM$^+$ (2001) were used to provide land cover maps of the area. The calculation of the agreement and disagreement table and goodness of fit test were also implemented to evaluate the CA model capability (Flahtkar *et al*., 2009).

Studying the changes and degradation of the resources in the past few years, as well as feasibility study and predicting these changes in the next years can play a significant role in harnessing and controlling the non-normative changes, as well as in planning and optimal use of the resources. This study aimed at mapping land use for years 1987, 2000 and 2006 through the Multilayer Perceptron Neural Network Classification Method and predicting the trend of land use changes using Markov Chain Model in Kermanshah City, Iran.

MATERIALS AND METHODS

Study area: Kermanshah City located on the Silk Road has currently significant importance in relationship between Iran and Iraq. The study area is the same area of Kermanshah City' Master Plan with an area of 9625.55 ha and is located between latitudes 34° 15' 55"and 34° 24' 14" N and longitudes 46° 59' 55"and 47° 10' 56" E. Location of the study area within Iran and Kermanshah Province is showed in Fig. 1.

Materials applied: In this study, the satellite images from Landsat TM (1987), Landsat ETM$^+$ (2000) and Landsat ETM$^+$ (2006) were used. Selecting these images benefits from advantages such as a broad and integrated view, multispectral images and replicated coverage in different time periods. The images of this satellite well meet the objective of the study based on mapping the land cover. For this purpose, satellite data were classified after initial corrections and processing using Multilayer Perceptron Neural Network Classification Method. Following stages has been done to develop land use/cover maps:

After providing satellite data, the geometric correspondence and image coordinating was conducted in order to prepare the data for processing and extracting useful information using vector map of the road network and aerial photo of the study area. Resampling was done through the nearest neighbor interpolation method and all bands used were geometrically matched. Spectral correction of images was conducted to make features manifest, increase the quality of images and to eliminate the adverse effects of light and atmosphere; then, the Perceptron Neural Network Classification was implemented by combining the bands 432 for the years 1987, 2000 and 2007. According to the study objective and different land cover of the area, 7 categories including residential land, agriculture, water, green space, garden, forest and range land were identified and classified. In order to verify the classification, a comparison was done with current land use and field surveys according to the study objective. In this study, the software ENVI 4.5, Idrisi Andes 15 and Arc GIS 9.3 were used.

Methods: In this study, the land use changes matrix and Markov Chain Model has been used for land cover change prediction.

Image classification: After geometric correction, multi-temporal images applied in this study were classified for mapping the land cover. Number of the categories was determined according to the images and maps, the state of the study area and categories required for land cover mapping and 7 classes were considered as follows: residential land, agriculture, water, green space, garden, forest and range land.

Multilayer Perceptron Neural Network Algorithm was used for classification. The concept of Perceptron was first introduced in 1943 by Pitts and McCulloch as an artificial neuron. A Multilayer Perceptron Neural

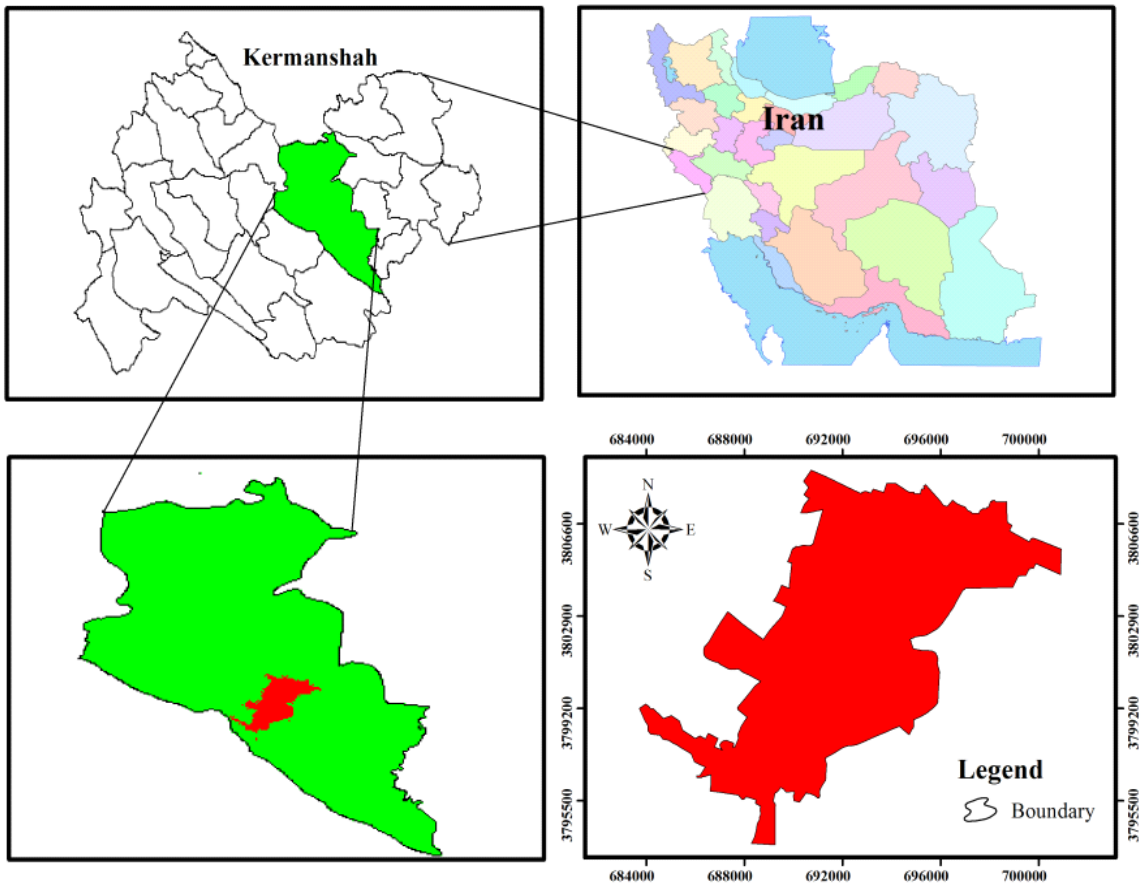


Fig. 1: Country and provincial location of the study area

Network displays a non-linear relation between input and output vectors (Rumelhart *et al*., 1986).

Multilayer Perceptron Neural Network consists of an input layer, a hidden layer at least and an output layer. Learning approach in this algorithm is error back-propagation. In which, network weights are adjusted as gradient, that is, after the comparison between desired output and actual output, network search the maximum gradient descent and error is adjusted in the next replications of network parameters with the guidance of the descending gradient of the error; in this process, parameters adjustment is repeated to the network error reaches an acceptable value. In this study, 7 neurons consist of 7 spectral bands was considered for Multilayer Perceptron Neural Network.

The number of hidden layers and neurons is one of the most important parameters to be determined. In this regard, Sebastian (2002) argued that a network with a single hidden layer can be the most appropriate for classification. He also believed that the number of hidden neurons is appropriate when they are 2 or 3 times the total number of classes. The number of hidden neurons is mostly determined by trial and error, such that the networks with a variable number of hidden neurons (1, 2 or 3 times the number of input neurons) are examined, then, the best network structure will be implemented. In this study, neural network was tested by studying different number of hidden neurons (6, 12 and 18 neurons) in order to determine the hidden neurons for selecting the optimal network for classification. Accuracy of network implementing decreased when the number of hidden neurons reached to 18 or 24 neurons, that is 3 or 4 times the number of input neurons; while, by selecting 7 hidden neurons for the image of study area, the network accuracy increased and error between training data and test data decreased. Therefore, the number of hidden neurons was chosen equal to the number of input neurons. The number of output neurons is equal to the number of training point (number of land uses) which are 7 categories in this study.

One of the parameters affecting neural network is Learning Rate. Very small value of training rate results in increasing the time of the network implementing; while, very large values give poor results. Therefore, studies suggested that the learning rate between 0.01 and 0.02 gives more proper results (Yuan *et al*., 2005). In this study, by introducing various values of the learning rate to the network, the value 0.01 was selected eventually due to implement the classification with higher accuracy.

Table 1: The best optimal values of parameters to create a suitable network for Kermanshah City

Parameters used in artificial perceptron neural network	Optimal values
Number of input neurons	7
Number of hidden neurons	7
Number of outputnodes	7
Learning rate	0.01
Moment rate	0.5
Replications	10000
Acceptable accuracy	91.76
Acceptable error	0.0001

Very small error decreases the results overlapping, so, the value of the error should be defined in an acceptable level to network. In this study, an acceptable value of 0.01 to 0.0001 was considered for the network implementing. Following the parameters selection and implementing the network, results from network training are compared to desired results. If the results are not of appropriate accuracy and acceptable error, the network moves backward and presents new results again which are compared to the desired results. It continues to achieve a high accuracy of the network implementing. In this study, different replications (from 1000 to 11000) were considered for implementing the network, at first. Implementing the network after 1000 replications, the accuracy ranged from 82.19 to 91.76% which is considered an acceptable accuracy. Thus, the network was stopped in this stage. Parameters used for creating an optimal network to classify the study area are presented in Table 1. Classification was applied on the images of the study area and land use map was prepared in 7 categories using this parameters.

Markov chain model: Markov chains have been widely used to model land use/cover changes including both urban and nonurban areas (Wu *et al*., 2006). In most studies, stationary and first-order have usually been assumed except in a few studies where the stationary or the order of Markov chains wastested (Bell, 1974). In Markov Chain Analysis, cover classes have been used as chain states. In such an analysis, two Raster Maps were applied which called model inputs. In addition to these maps, time interval between two images and predicted time interval are considered in the model. Model output includes transition probabilities, transition areas matrix of each class and conditional probabilities images for different land use transition (Gilks *et al*., 1996; Weng, 2002).

Classified images for 1987, 2000 and 2006 were used as land cover maps for state transition. State transition matrix of land cover classes was calculated between any two period using land cover mapping for each period. First state transition matrix was obtained from land cove maps for 1987 and 2000, also, second state transition matrix was calculated from land cover maps for years 1987 and 2000 and finally, a general state transition matrix was calculated from years 1987 to 2006. These matrices contain the data of the percent of each class transition to another one.

Results: In this study, image classification and land use/cover mapping were conducted using Multilayer Perceptron Neural Network Classification Method as a monitored classification technique. In a monitored classification technique, training samples are the basis of classification. In this study, random sampling was used to data classification. Samples were recorded according to land use maps and field surveys of study area using GPS as random polygons from each group of

Table 2: Classification accuracy (%) of images for years 1987, 2000 and 2006

	TM-1987		ETM^+-2000		ETM^+-2006	
Land use category	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy
Residential land	98	96	98	95	99	100
Agriculture	98	70	96	87	97	92
Water	96	79	100	21	97	92
Green space	83	79	64	38	92	70
Garden	81	94	94	96	100	99
Forest	84	100	92	99	93	100
Range land	99	99	99	100	99	100
Overall accuracy	91		92		98	
Kappa coefficient	0.8850		0.9107		0.9644	

Table 3: The area of different land use classes for years 1987, 2000 and 2006

Year	1987		2000		2006	
Class	Area (ha)	%	Area (ha)	%	Area (ha)	%
Residential land	3727.09	38.72	5194.83	53.97	5882.65	61.11
Agriculture	824.92	8.57	939.39	9.76	1208.94	12.56
Water	150.92	1.57	197.51	2.05	263.91	2.74
Green space	1984.33	20.62	927.85	9.64	495.81	5.15
Garden	283.30	2.94	213.89	2.22	141.03	1.47
Forest	724.53	7.53	544.98	5.66	284.21	2.95
Range land	1930.47	20.06	1607.12	16.70	1349.00	14.01
Total	9625.56	100	9625.56	100	9625.56	100

land use/cover. In selecting the training samples, representativeness of samples for target categories and having well dispersion were considered. In order to determine the precision of image classification using trial samples, error matrix was used, as well as statistical parameters such as overall accuracy, Kappa coefficient, producer accuracy and user accuracy were calculated and results are presented in Table 2. Then, the majority filter was applied to obtain uniform image and to remove scattered pixels on images resulted from classification; the results from classification are displayed in Fig. 2 to 4. The statistic related to area and changes occurred are presented in Table 3. The trend of changes is displayed in Fig. 5. In the years from 1987 to 2006, a decreasing trend was observed in range land, forest, garden and green space area; while, residential land, agriculture and water resources area increased. These trends suggest a general degradation trend in the study area through replacing other land uses by residential land and agriculture.

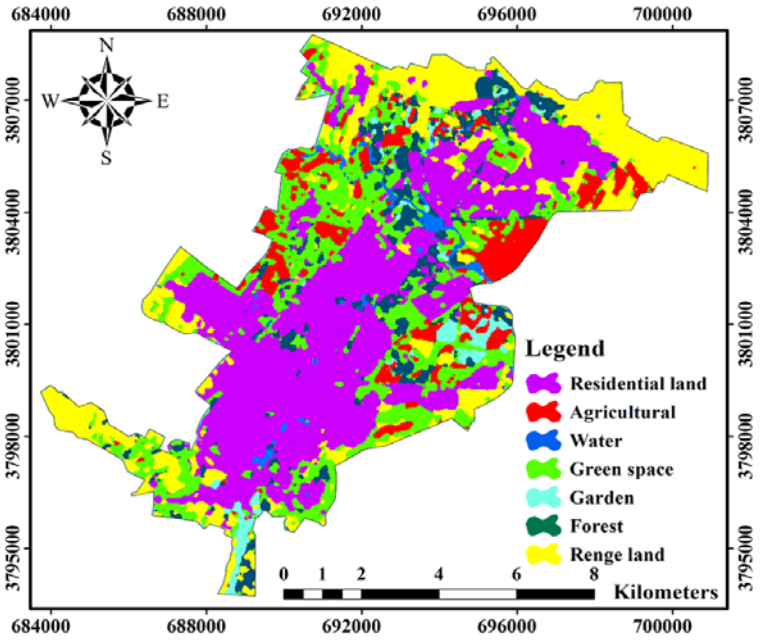


Fig. 2: Map of land use for 1987

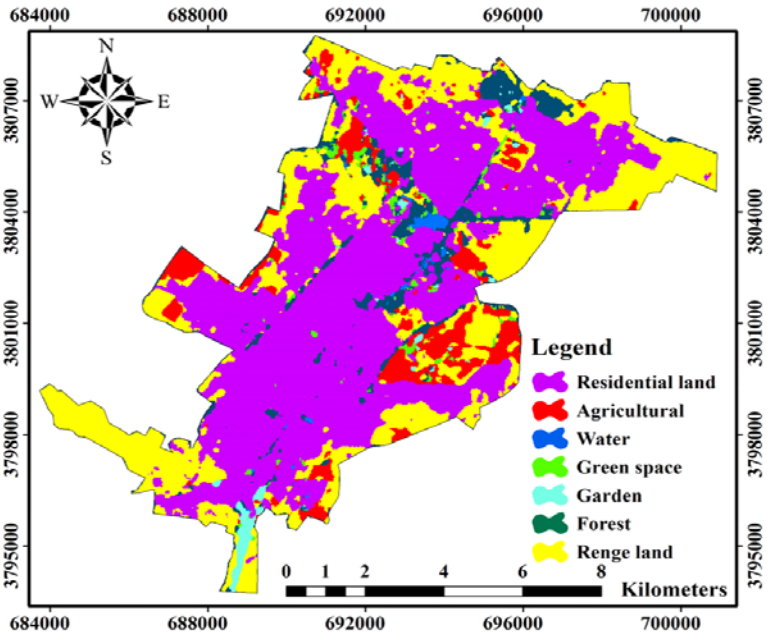


Fig. 3: Map of land use for 2000

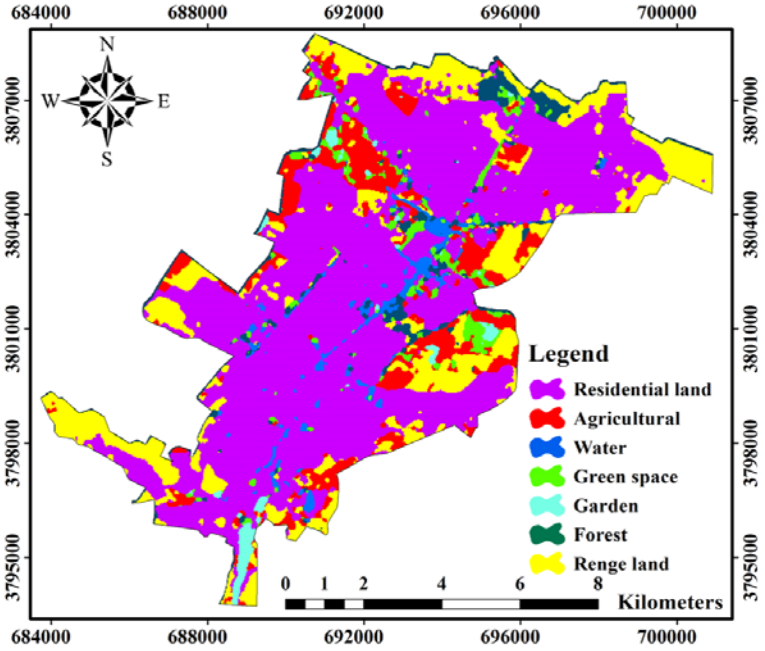
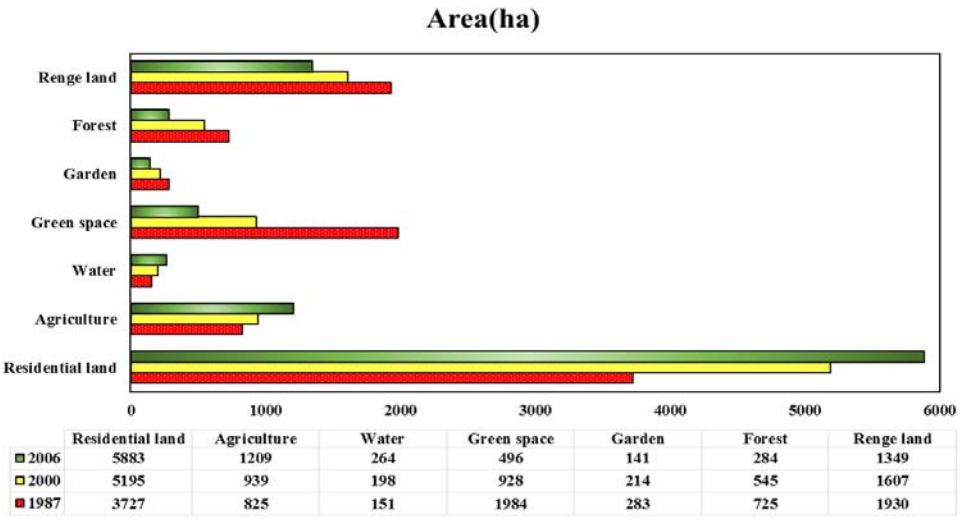


Fig. 4: Map of land use for 2006



	Residential land	Agriculture	Water	Green space	Garden	Forest	Renge land
2006	5883	1209	264	496	141	284	1349
2000	5195	939	198	928	214	545	1607
1987	3727	825	151	1984	283	725	1930

Fig. 5: The trend of changes in class levels during 1987 to 2006

Table 4: Area (ha) predicted for year 2006 using Markov model and transition matrix of 1987-2000

	Residential land	Agriculture	Water	Green space	Garden	Forest	Range land	Total
Residential land	3107	177	31	11	16	3	191	3536
Agriculture	471	549	3	72	21	28	268	1412
Water	314	57	156	30	10	23	133	723
Green space	703	47	6	218	11	102	86	1173
Garden	283	216	44	72	61	53	62	791
Forest	166	118	63	32	12	84	362	837
Range land	752	58	3	62	28	22	228	1153
Total	5796	1222	306	497	159	315	1330	9625

Table 5: Comparison of prediction results and interpolated areas from land use map (ha) for year 2006

Class	Residential land	Agriculture	Water	Green space	Garden	Forest	Range land	Total
Prediction for year 2006 (ha)	5796	1222	306	497	159	315	1330	9625
Area on map for year 2006 (ha)	5882	1209	264	496	141	284	1349	9625
Area difference (ha)	-86	+13	+42	+1	+18	+31	-19	0
Difference percent	-1.46	+1.07	+15.9	+0.2	+12.76	+10.91	-1.40	

Results of Markov chain analysis: Results from the prediction of land use changes using state transition matrix in first period (1987 to 2000) for year 2006 that has been conducted in order to evaluate the Markov Model using existing land use map for this year, are presented in Table 4. In this table, total values of each column show the area of each class for year 2006. Results from prediction accuracy evaluation using Markov Chain Model supported by existing land use map for year 2006 are displayed in Table 4. From this table, it is clear that the differences in different classes are varied and their magnitude is less than 16%, generally. This figure indicates usefulness and applicability of the Markov Model in predicting the land use changes.

Results of detection the changes in Kermanshah City suggest that main land uses in this area are residential land, agriculture, green space and forest. During a 19 years period, the area under green space and forest land use decreased with values of 1488 and 571 ha, respectively; while, the area of residential land and agriculture experienced an increasing trend with values of 2156 and 384 ha, respectively. From these results, it can be found the replacing and transition the land natural cover of this area by residential land and agriculture. Noteworthy in this study is a 22.39% growth in residential land during this 19 years period which is a significant figure. One of the most important influential factors is that Kermanshah City is capital of Kermanshah Province. It results in numerous issues such as physical expansion and degradation of surrounding lands including forests and green spaces. It can be well observed on satellite images used. Another important factor to be noted can be the role of government and political decision makers. Political decision making can make an urban setting attractive or free of attraction and can completely alter the state which is favorable for investment and also for other replacements. Among these decisions, determining the boundaries and its effect on urban growth and development, as well as transmitting the administrative and guidance roles to cities influencing the cities' dynamism.

Table 5 shows probability matrix obtained from the maps of years 1987 and 2006 using Markov Chain for predicting the changes in next 19 years (2025). Given the obtained matrix (Table 6) in years from 2006 to 2025, it is likely that 82.52% of residential lands, 58.51% of agriculture, 34.47% of water, 8.94% of green space, 30.78% of garden, 23.93% of waste land and 16.76% of range land will remain unchanged, such that, residential land and green space have the highest

Table 6: Probability matrix of class transition in years 2006 to 2025 using Markov Model (%)

2005/2006	Residential land	Agriculture	Water	Green space	Garden	Forest	Range land
Residential land	82.52	3.43	4.8	3.15	0.44	2.75	2.92
Agriculture	11.01	58.51	1.46	5.4	3.15	8.8	11.67
Water	16.33	16.49	34.47	11.14	3.27	8.46	9.84
Green space	27.3	20.42	12.33	8.94	3.93	11.39	15.7
Garden	17.06	15.37	1.43	8.47	30.78	10.09	16.8
Forest	22.11	19.53	3.92	9.04	3.24	23.93	18.23
Range land	53.38	13.91	2.3	3.75	1.94	5.96	18.76

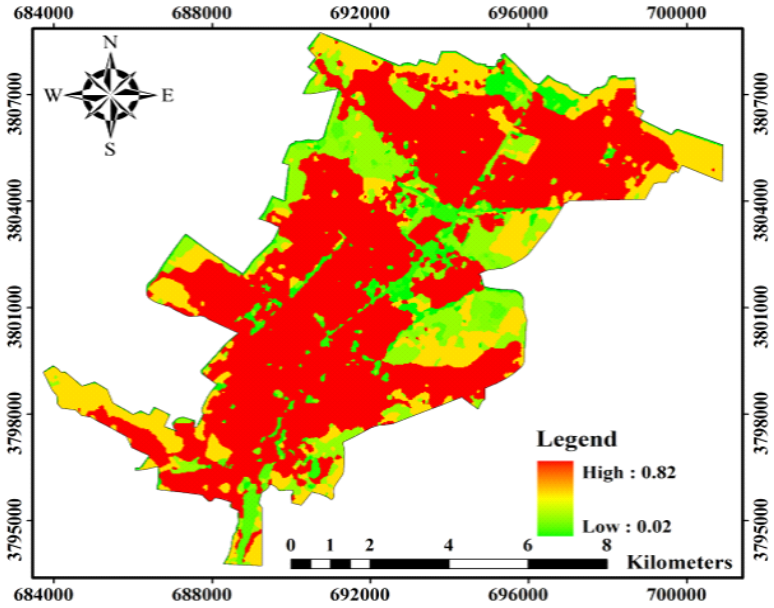


Fig. 6: Map of residential land use prediction for year 2025

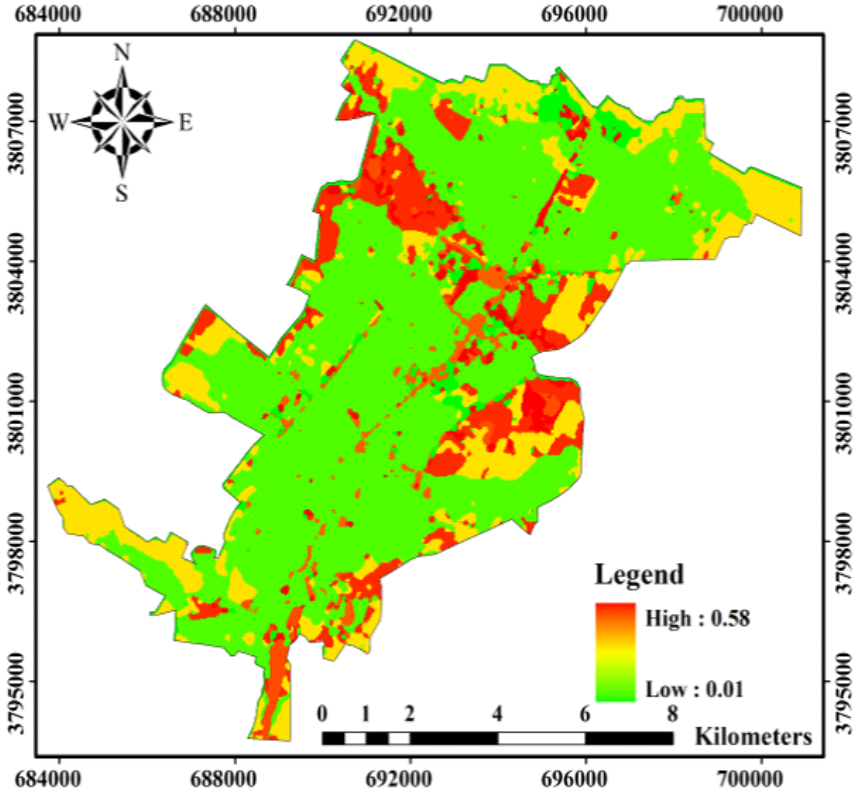


Fig. 7: Map of agriculture land use prediction for year 2025

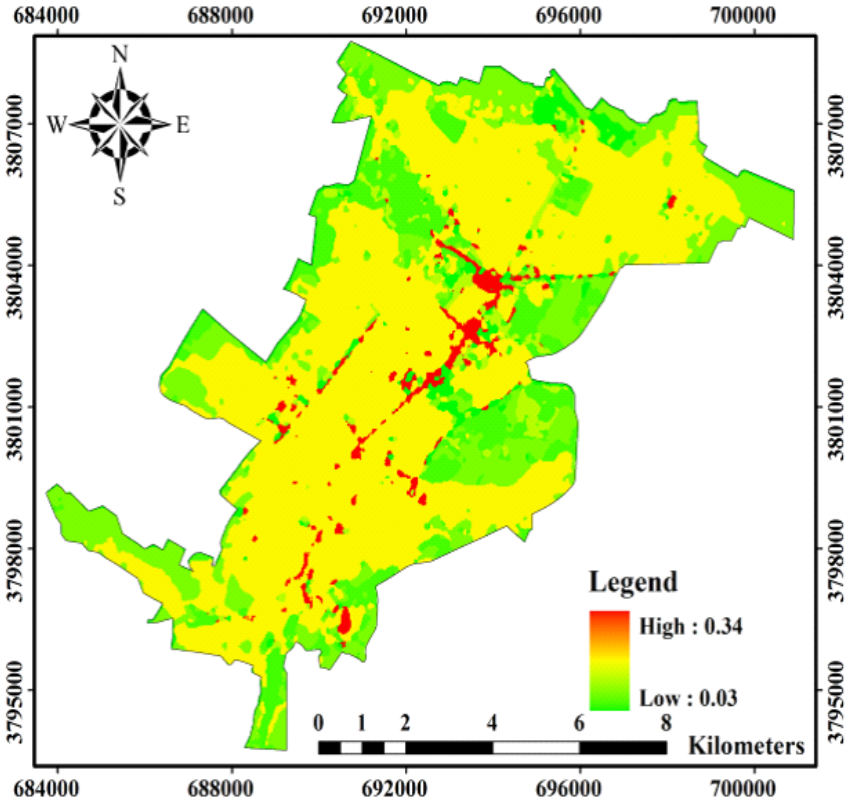


Fig. 8: Map of water land use prediction for year 2025

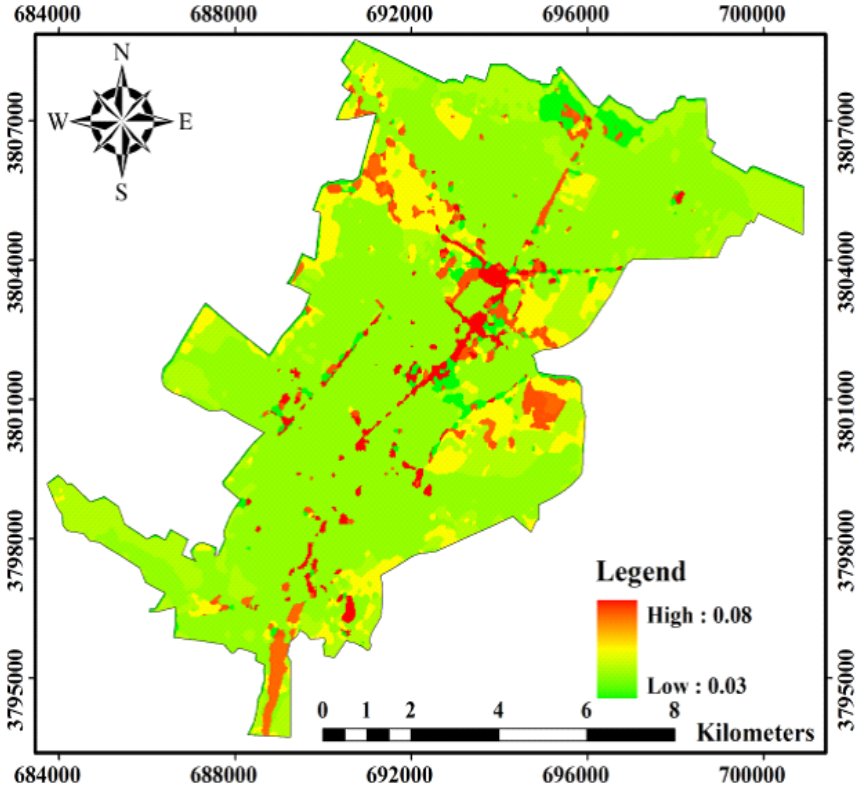


Fig. 9: Map of green space land use prediction for year 2025

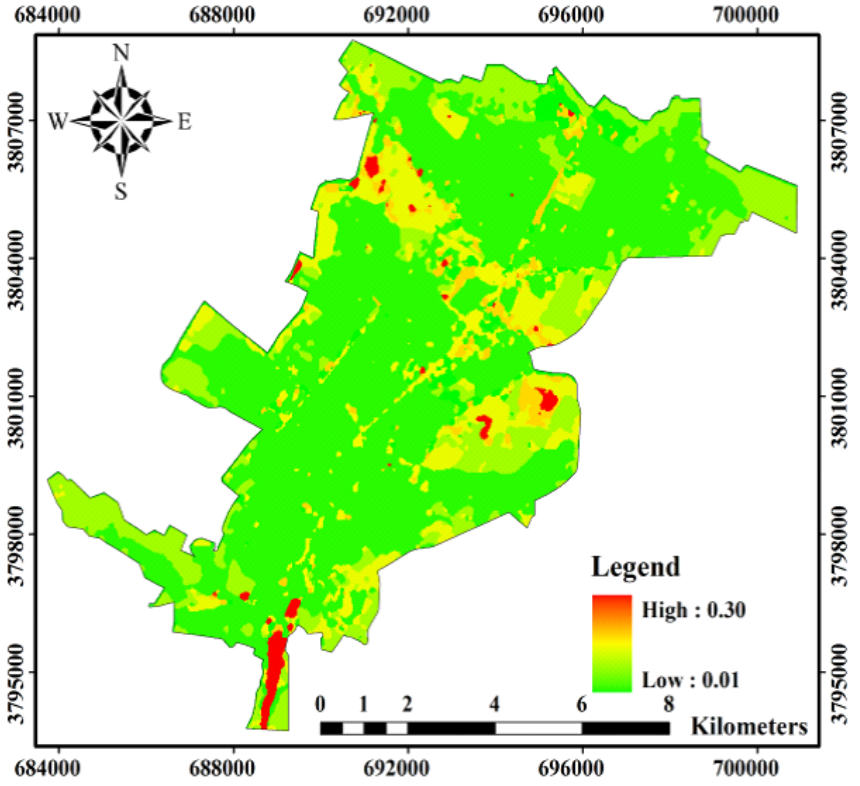


Fig. 10: Map of garden land use prediction for year 2025

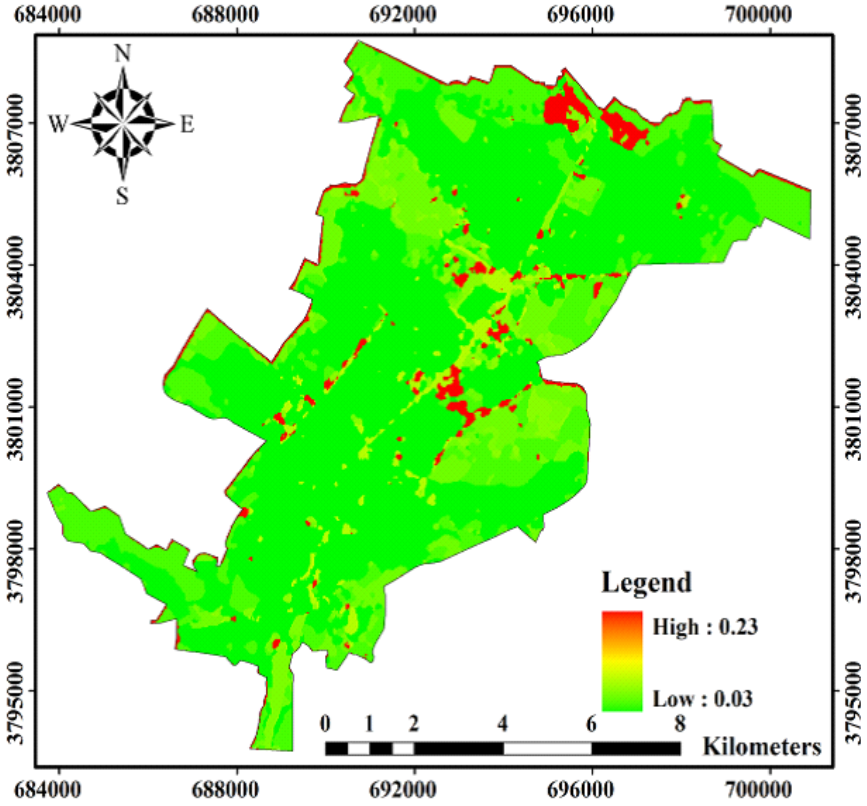


Fig. 11: Map of forest land use prediction for year 2025

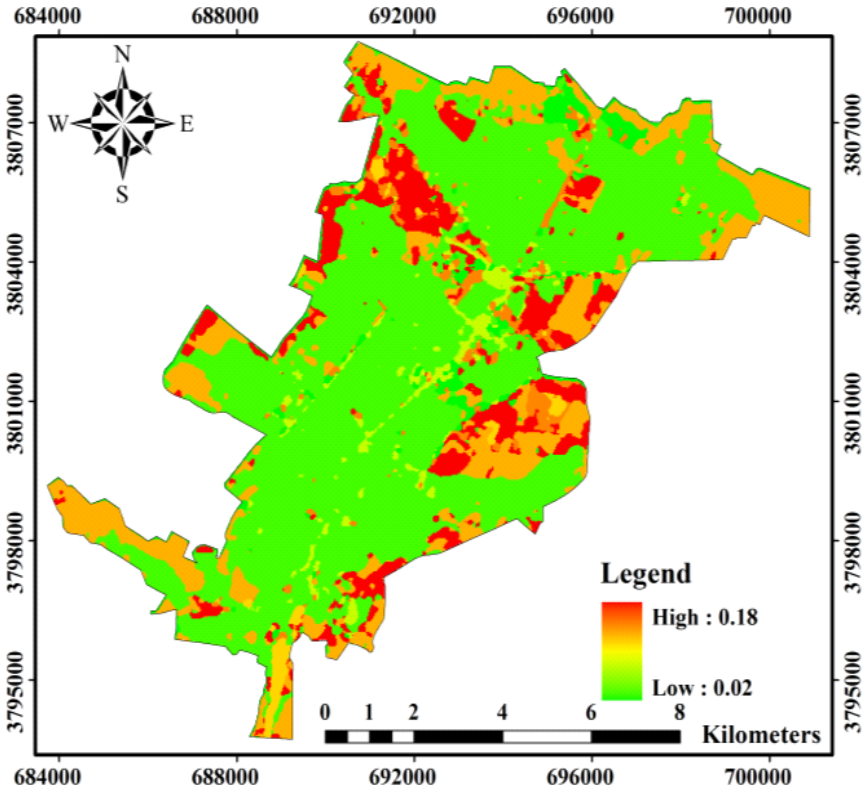


Fig. 12: Map of range land use prediction for year 2025

and the lowest sustainability, respectively. Furthermore, during the period between 2006 and 2025, converting the range land to residential land (53.38%) and the green space to residential land (27.3%) is the highest probability; conversely, converting the green space to water (1.43%), agriculture to water (1.46%) and range land to garden (1.94%) is the lowest probability. Maps resulted from prediction using Markov Chain for each land uses are given in Fig. 6 to 12.

DISCUSSION AND CONCLUSION

Land is the most important element in urban development. Hence, controlling the land use and calculating the actual need for land in order to maintain different land uses in past and present, as well as generalizing and adjusting the figures and quantities obtained to the future are affecting on appropriate urban growth. Increasingly development of technologies such as GIS and RS, as well as applying the spatial-temporal data in order to study how the land uses change in the past and to simulate land cover in the future may help managers and consumers to manage, plan and use the sustainable development policies. In this study, Kermanshah City is one of the most important cities in Iran which has undergone significant changes due to human interventions in one hand and trend of increasing the population, on the other hand. These changes were studied through aerial photos and satellite images. In this research, Multilayer Perceptron Neural Network Classification Method was used for Kermanshah City' land use mapping. Studying the change trends of land use by comparing satellite images for three periods of 1987, 2000 and 2006 suggests high changes in land use around Kermanshah City. Results of the study are in agreement to researches by Hopkins *et al*. (1988) and Riahi Bakhtiari (2000) but in different circumstances. The results suggest that highest changes are associated to transition of green space and range land use to other land uses such as residential land and agriculture, such that the area under residential land and agriculture is reached to 2156 and 384 ha in 2007, with an increasing trend, respectively. It indicates the role of demographic developments and consequently need for housing and other urban required land uses in changes of other urban constructed land uses. In this study, Markov Chain Model was applied to study the prediction of land use change trends in 2025. Results of this study are in accordance with Ayodeji Opeyemi (2006), Chang and Chang (2006), Sheikh Goudarzi *et al*. (2009) and Flahtkar *et al*. (2009) in terms of using Markov Chain Model to predict the land cover changes. Moreover, from the results obtained from changes prediction matrix based on the maps of years 1987 and 2006, it is likely that in the period from 2006 to 2025, 82.52% of residential land, 58.51% of agriculture, 34.47% of water, 8.94% of green space, 30.78% of garden, 23.93% of waste land and 16.76% of range land will remain unchanged, among which residential land and green space will have the highest and the least sustainability, respectively.

According to the prediction made in this area and due to existing the suitable lands for physical expansion around Kermanshah City, if there is no proper planning for this city we will witness the disappearing the green space and range land around the city and converting them to the urban area in the near future. Therefore, results of the study can be a warning for urban planner to avoid unplanned urban expansion by appropriate planning.

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