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RESEARCH ARTICLE

Evaluation and Forecast of Human Impacts based on Land Use Changes Using Multi-Temporal Satellite Imagery and GIS: A Case Study on Zanjan, Iran

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Abstract Land use and land cover change due to human activities in a time sequence. Detection of such changes may help decision makers and planners to understand the factors in land use and land cover changes in order to take effective and useful measures. Remote sensing and GIS techniques may be used as efficient tools to detect and assess land use changes.

In recent years, a considerable land use changes have occurred in the greater Zanjan area. In order to understand the type and rate of changes in this area, Landsat TM, ETM+ images captured in 1989 and 2008 have been selected for comparison.

First, geometric correction and contrast stretch are applied. In order to detect and evaluate land use changes, image differencing, principal component analyses and Fuzzy ARTMAP classification method are applied. Finally, the results of land cover classification for three different times are compared to reveal land use changes. Then, combined Cellular Automata with Markov Chain analysis is employed to forecast of human impacts on land use change until 2015 in Zanjan area

The results of the present study disclose that about 35 percents of the total area changed their land use, e.g., changing agricultural land, orchard and bare land to settlements, construction of industrial areas and highways. The crop pattern also changes, such as orchard land to agricultural land and vice versa. The mentioned changes have occurred within last 19 years in Zanjan city and its surrounding area.

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In order to evaluate land use changes in this area, the Environmental Impact Index are established into four different categories as: *Very high, High, Medium and Low impacts*. The proposed index shows that the highest impact has been generated due to changing agricultural and bare lands into urban use.

Introduction

The protection of global environment is one of the most critical problems and it is related to several factors, such as population increase, extinction of natural resources, environmental pollution and land use planning. Presently unplanned changes of land use have become a major problem. Most of the land use changes occur without clear and logical planning, paying no attention to their environmental impacts. Floods and air pollution in large cities as well as deforestation, urban growth, soil erosion and desertification are all consequences of mismanaged planning without considering environmental impacts.

Many researchers have employed satellite imagery for land use mapping as well as change detection. Sunarar (1996) has compared the results of five different techniques: band combination, subtraction, band division, principal component analysis and classification, in Ekitally, Turkey. This study revealed that the principal component analysis (PCA) shows better results comparing with classification results. Gupta and Parakash (1998) used a combined method of color composite, band subtraction, band division and supervised classification to prepare a land-use map for change detection in a coal-mining district in India. They concluded that the supervised classification gives better results for detecting changes. Ahanejad (2000) used PCA, image differencing and classification methods for change detection in Maragheh region, Iran. He concluded that a crosstab method and a comparison image classification method are very suitable for land use change assessment. Neshat (2002) employed Markov Chain to detect the change of forest areas to urban use in Golestan province, Iran.

In the present research, supervised classification based on Fuzzy Artmap is employed to detect land use changes occurred in the greater Zanjan area, Iran. For forecasting human impacts on land-use change until 2015, both Cellular Automata and Markov Chain are employed. Furthermore, ecological models are also used to analyze environmental impacts due to land-use changes in the area.

Study area and Methods of study

The study area is located between 36° 33′ 00″ to 36° 44′ 24″ N and 48° 09′ 00″ to 48° 21′ 36″ E. The area covers Zanjan city and its surrounding area with 25,293 hectares. The study area comprises three topographic units, mountain, foothill and plain. The main reason to select this area is that considerable land-use changes have occurred due to urban developments, rural developments, and industrial developments in the east, west and south areas, and that major changes in the crop pattern are ongoing.

In this paper, Landsat TM and ETM+ images captured in 1989 and 2008 are employed for digital image processing. Figure 1 shows the flowchart of this study.

Classification

Various methods have been employed for classification of satellite imagery. Recently, artificial fuzzy methods are used widely because they show very high accuracy in comparison with the conventional ones like Maximum Likelihood Classification (MLC), Minimum Distance Classification, and Parallelepiped Classification.

In this paper, the fuzzy adaptive resonance theory (Fuzzy Artmap) is employed for image classification. First, 741 (RGB) color composites of Landsat images

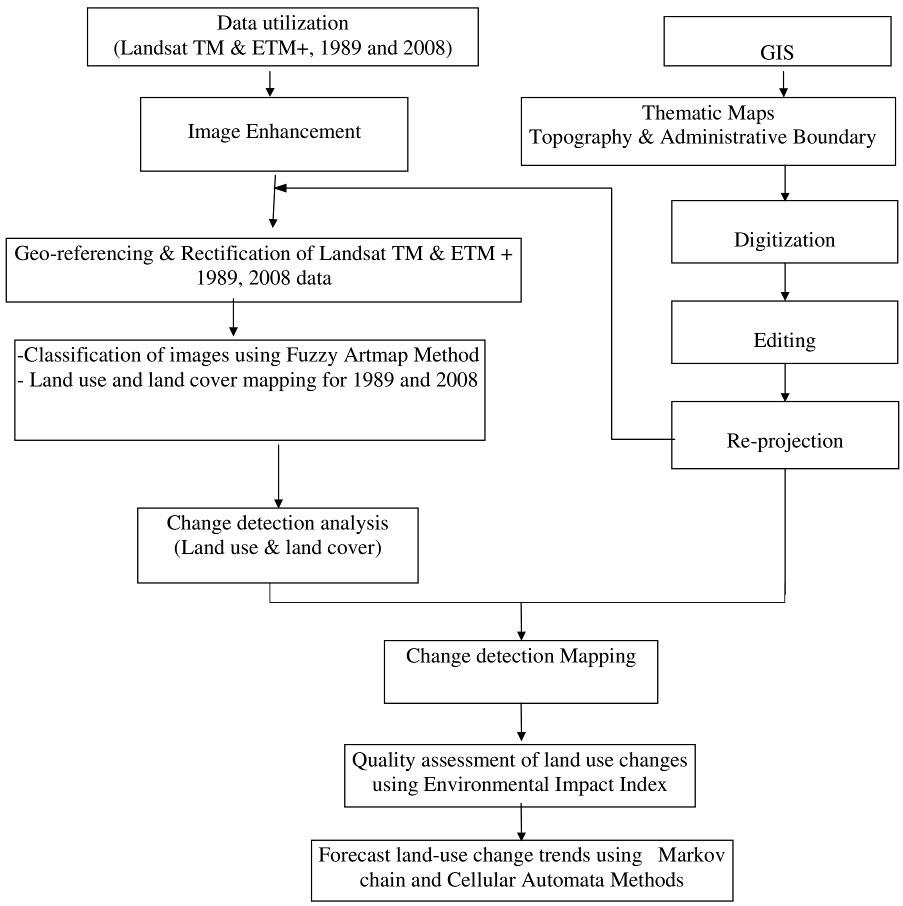

Fig. 1 Flow chart showing the major steps of this research.

were prepared. Then, training areas were selected for 9 land cover classes, which are built-up area, orchards, artificial forest (manmade forest), irrigated agriculture land, dry farming, vegetation cover (ranges), water, waste land, and sandy stone area. These training areas were determined, referring to aerial photographs and GIS thematic maps. To assess the accuracy of classification, topographic maps and aerial photos were employed. Overall accuracy was estimated to be around 95%. Figures 2 and 3 show the results of land use classification and Table 1 shows the summary of the classification.

Comparison of classification results

The classification results for the two different times revealed that the land use of the target area has changed about 35.4 % during the period of 1989-2008. Table 2 shows the estimated land use transitions based on the comparison of the classification results for the 1989 and 2008 images. Figure 4 shows the areas whose land use has changed to built-up ones in these periods. More than 60 % of the area that belongs to built-up and artificial forest changes to dry farming and waste areas. Dry

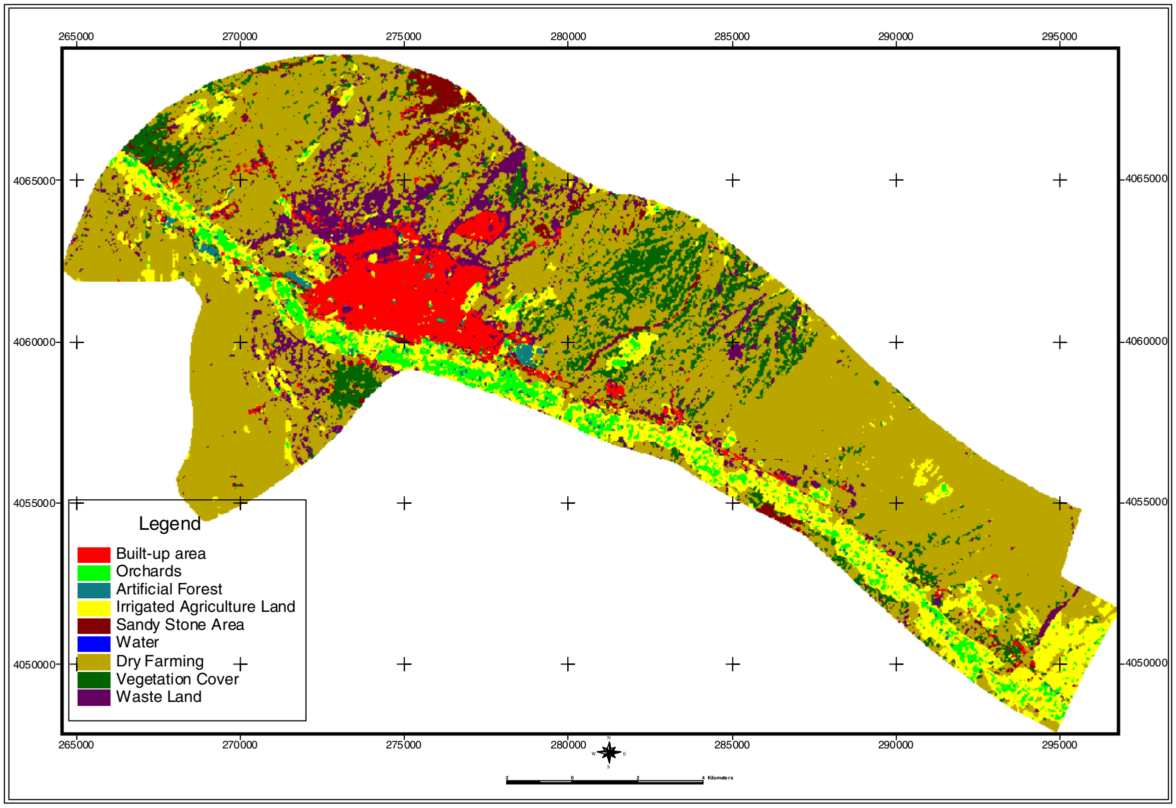

Fig. 2 Result of land use classification for Zanjan, Iran using Landsat TM image captured in 1989.

Table 1 Summary of image classification performed in this study (Hectare)

Class	Land use type	1989	2008
1	Built-Up Area	1473.75	6616.91
2	Orchards	654.27	940.42
3	Artificial Forest	378.02	73.43
4	Irrigated Agriculture Land	2463.80	2122.41
5	Sandy Stone Area	535.27	611.62
6	Water	0.00	3.82
7	Dry Farming	13639.06	10427.75
8	Vegetation Cover	2163.51	1537.67
9	Waste Land	1368.97	342.61
	Total-Hectar	**22676.6**	**22676.6**

land farming attains the least changes (16.3%) in this period.

The increase is mainly due to the needs of settlements in Zanjan City because its population has increased from 291,500 in 1996 to 354,923 in 2008. New suburban areas, such as Sayan, Elahieh, and Kazemieh, have also developed in the period.

Prediction of the trends of land use changes

The other object of this paper is to predict the trend of land use changes in the future. Many methods can be applied to predict the trend. In this paper, two methods are used.

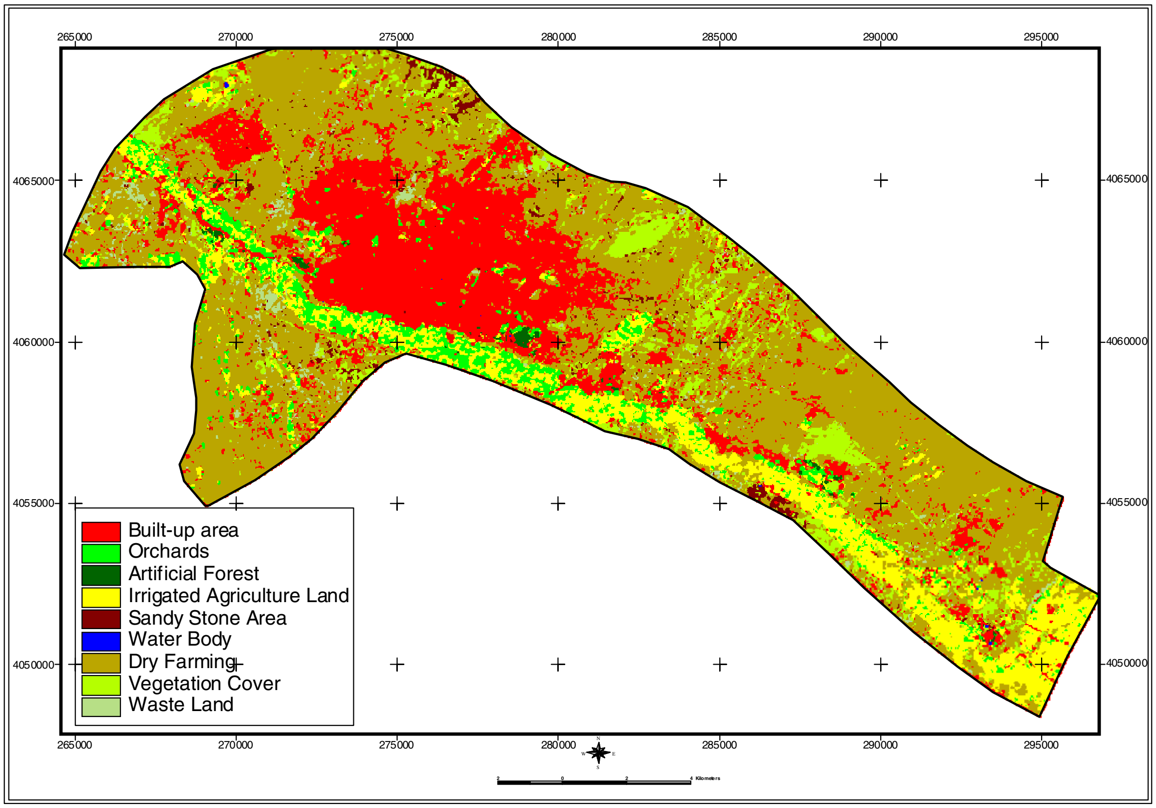

Fig. 3 Result of land use classification using Landsat ETM+ image captured in 2008.

Markov chain

The Markov chain method analyzes a pair of land cover images and outputs a transition probability matrix, a transition area matrix, and a set of conditional probability images. The transition probability matrix shows the probability that one land-use class will change to the others. The transition area matrix tells the number of pixels that are expected to change from one class to the others over the specified period.

The conditional probability images illustrate the probability that each land cover type would be found after a specific time passes. These images are calculated as projections from the two input land cover images. The output conditional probability images can be used as direct input for specification of the prior probabilities in Maximum Likelihood Classification of remotely sensed imagery (such as with the MAXLIKE and BAYCLASS modules). A raster group file is also created listing all the conditional probability images.

In this study, a series of image processing was performed to predict the trend of land use change in 2015 (Table 3). The result shows that the probability to change to Built-up area is highest. Figure 5 shows the probability that the area will be converted to Build-up one in 2015.

Table 2 Estimated land use transitions in Zanjan city, Iran between 1989 and 2008 (hectare)

	Built-up area	Orchards	Artificial forest	Irrigated agriculturea	Stone Area	Water	Dry farming	Vegetation cover	Waste land	Total	Change %
Built-Up Area	1460.3	0.0	0.1	0.0	0.2	0.0	0.0	0.0	0.0	1460.6	2.3
Orchards	83.1	201.3	3.7	282.2	3.8	0.2	65.9	15.9	3.7	659.8	1.02
Artificial Forest	99.4	59.0	22.3	125.8	5.6	0.2	46.5	16.2	2.9	378.0	0.59
Irrigated Agriculture Land	341.3	233.3	13.1	1146.4	85.2	1.1	479.1	135.2	29.2	2463.8	3.84
Sandy Stone Area	147.8	24.4	2.5	33.3	121.6	0.0	136.1	62.9	6.6	535.3	0.83
Dry Farming	3070.7	345.3	24.1	448.0	301.3	1.2	8332.1	899.1	224.7	13646.7	21.26
Vegetation Cover	605.9	44.6	5.7	56.3	73.7	0.9	986.3	354.0	36.2	2163.5	3.37
Waste Land	808.4	32.6	2.0	30.4	20.2	0.1	381.7	54.4	39.2	1369.0	2.13
Total	6616.9	940.4	73.4	2122.4	611.6	3.8	10427.7	1537.7	342.6	22676.6	
Change %	10.32	1.47	0.11	3.31	0.95	0.01	16.26	2.4	0.53		35.36

(Row related to 1989 land use and column related to 2008 land use)

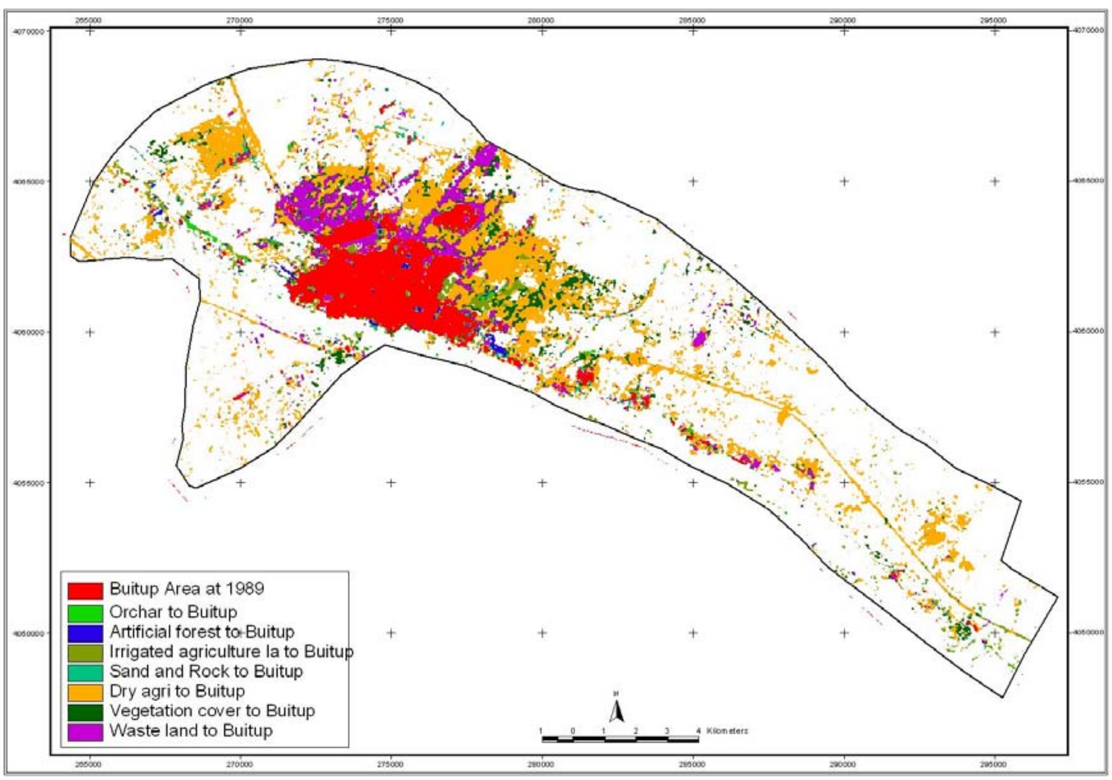

Fig. 4 The areas that have changed to built-up ones in the period of 1989-2008.

Table 3 The probability of land use changes based on Markov Chain in the period of 2008-2015

	Built-up area	Orchards	Artificial forest	Irrigated agriculture	Stone area	Water	Dry farming	Vegetation cover	Waste land
Built-Up Area	0.9963	0	0	0	0	0	0	0	0
Orchards	0.039	0.459	0.0048	0.4945	0	0.0003	0.0003	0.0022	0
Artificial Forest	0.1691	0.2107	0.1095	0.4026	0.0049	0.001	0.0528	0.0426	0.0067
Irrigated Agriculture Land	0.0321	0.0974	0.0056	0.6285	0.0341	0.0005	0.1353	0.0534	0.013
Sandy Stone Area	0.1126	0.038	0.0052	0.0361	0.4595	0	0.1582	0.1804	0.0101
Water	0.1971	0.1005	0.0048	0.0986	0.1236	0.0005	0.3608	0.0861	0.0279
Dry Farming	0.0829	0.0191	0.0014	0.0148	0.0185	0.0001	0.7723	0.0714	0.0196
Vegetation Cover	0.1363	0.0119	0.0031	0.0082	0.044	0.0007	0.4907	0.2824	0.0228
Waste Land	0.4997	0.0268	0.0018	0.0119	0.0166	0.0001	0.3396	0.0514	0.0521

(Row related to 2008 and column related to 2015)

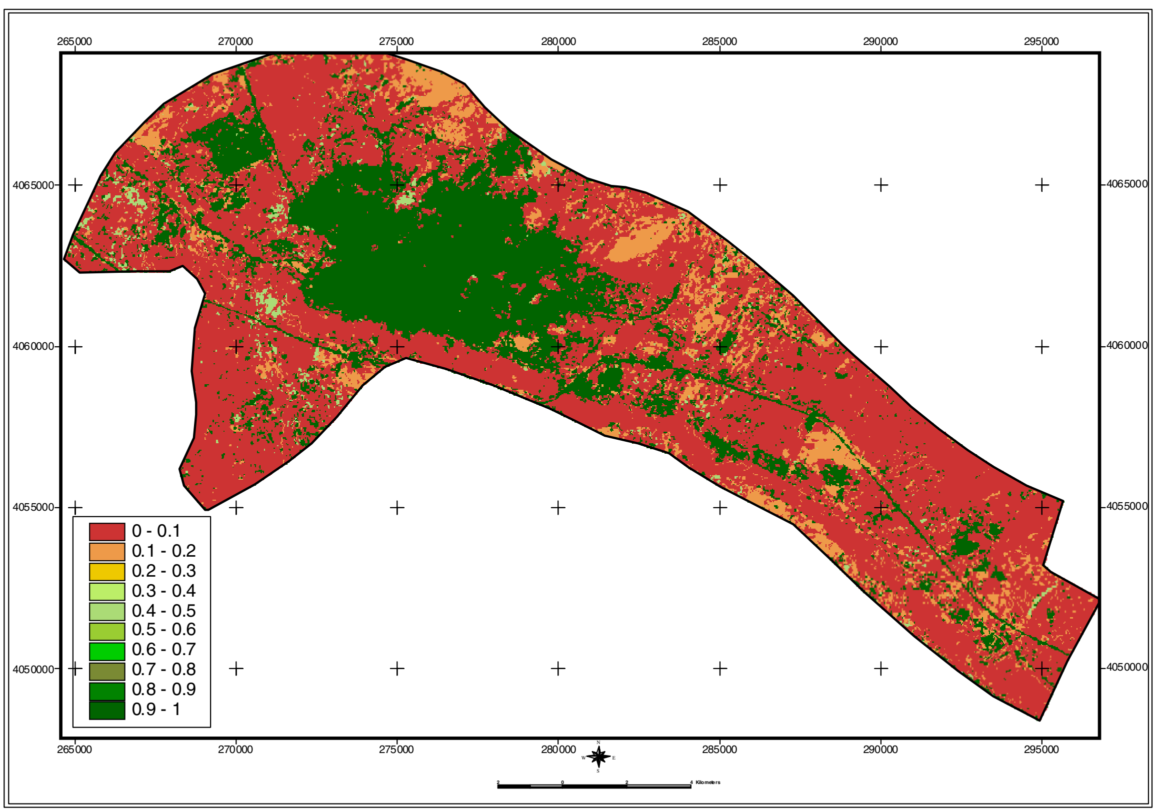

Fig. 5 The probability to be/change to built-up areas by 2015 obtained by Markov Chain.

Combination of Cellular Automata and Markov Chain

To know the changes that have occurred in the past may help to predict future changes. Combination of Cellular Automata and Markov Chain is often employed to predict land cover change estimation.

In order to predict the trends of land use changes, first 1989 and 2008 land use map were analyzed with Markov Chain. Then, combined method of Cellular Automata and Markov Chain was used for forecasting land use change in 2015. According to the results (Figure 6 and Table 4), built-up areas increase from 6616.9 hectare in 2008 to 8453.8 hectare in 2015 and the probability that the areas will change to built-up one is highest.

Table 4 The result of prediction of land use in 2015 by the combination of Cellular Automata and Markov Chain

Class	Land use type	2015
1	Built-Up Area	8453.8
2	Orchards	1036.0
3	Artificial Forest	183.4
4	Irrigated Agriculture Land	2291.6
5	Sandy Stone Area	727.28
6	Water	3.81
7	Dry Farming	10637.9
8	Vegetation Cover	1629.9
9	Waste Land	329.9

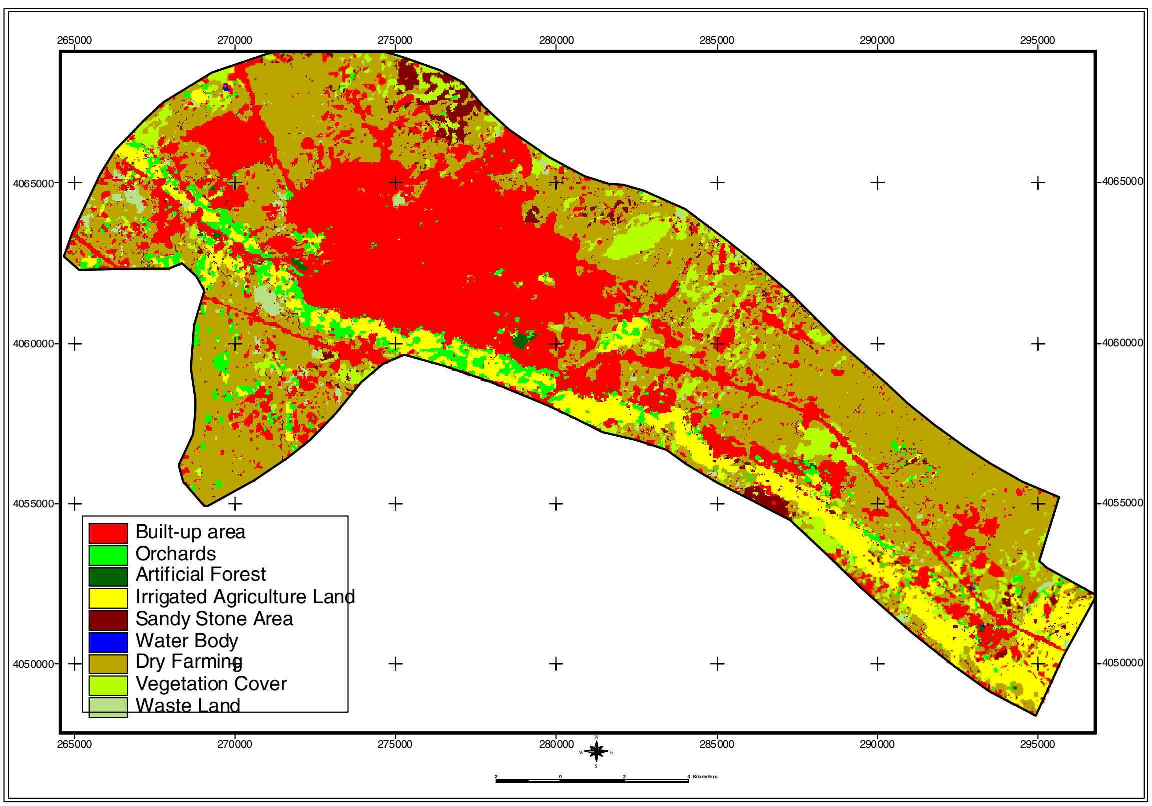

Fig. 6 Predicted result of land-use change in 2015 by the combination of Cellular Automata and Markov Chain.

Qualitative evaluation of land use changes by Environmental Impact Index

Qualitative evaluation as well as the rate of land use changes carried out through the visual inspection of the pollution rate caused by every land use. In case of change from agricultural land and orchards to construction and settlements, a high rate of environmental impact is assigned. To show the environmental impacts quantitatively, the weighting factor was assigned to each land use class (Table 5). Then, the effects of land use change to the environmental impact were evaluated.

According to the obtained results, the rates of impacts due to land use changes are classified into 4 levels, very high, high, medium and low impacts. The results of this study revealed that the total area of about 8300 hectares caused environmental impact during the years of 1989-2008 (Table 6).

Considering Table 7, the land use changes with the area of more than 5000 hectares due to development of settlements which occurred mostly in the urban fringe of Zanjan city, are recognized as very high impacted areas. About 158 hectares recognized as high impacted areas are mostly related to the changes due to construction and settlements built on agricultural land around Zanjan city. The areas, which are related to the natural resources (range) and vegetation cover in the area, are classified as moderate impact (about 1458 hectare). Figure 7 shows the distribution of the environmental impact index in the study area.

Conclusions

In this paper, using Landsat Satellite images in 1989 and 2008, land use changes in Zanjan city, Iran were evaluated. For classification of the images, Fuzzy Artmap classification method was applied, which has very high confidence comparing with other classification methods. In addition, combined Cellular Automata with Markov Chain method was employed to forecast human impacts on land use change until 2015 for the study area.

The results revealed that the land use change has occurred for the area of about 8300 hectares in the period 1989-2008. About 5143 hectares of these changes due to developments of settlements on orchards and agriculture lands, which occurred mostly in the urban fringe of Zanjan city, are recognized as highly impacted areas from the environmental point of view.

According to Cellular Automata and Markov Chain Forecasting model, built-up areas will increase from 6619.6 hectare in 2008 to 8453 hectare in 2015. The continuation of such a trend may endanger the surrounding land as well as the agricultural lands and orchards in the area. Hence, it is recommended to protect these critical areas.

Table 5 Weights assigned for land use and land cover

Land use	Built-up area	Orchard	Artificial forest	Irrigated agriculture	Stone area	Water	Dry farming	Vegetation cover	Waste land
Weights	9	1	1	5	3	1	4	3	7

Table 6 Expected environment impacts in Zanjan city, Iran

Variable	Level	Area (hectare)	Percent
Low Impact	1-3	1529.15	18.35
Medium Impact	3-5	1458.12	17.50
Low Impact	5-7	158.51	1.90
Very High Impact	7-9	5183.38	62.23
Total		**8329**	**100**

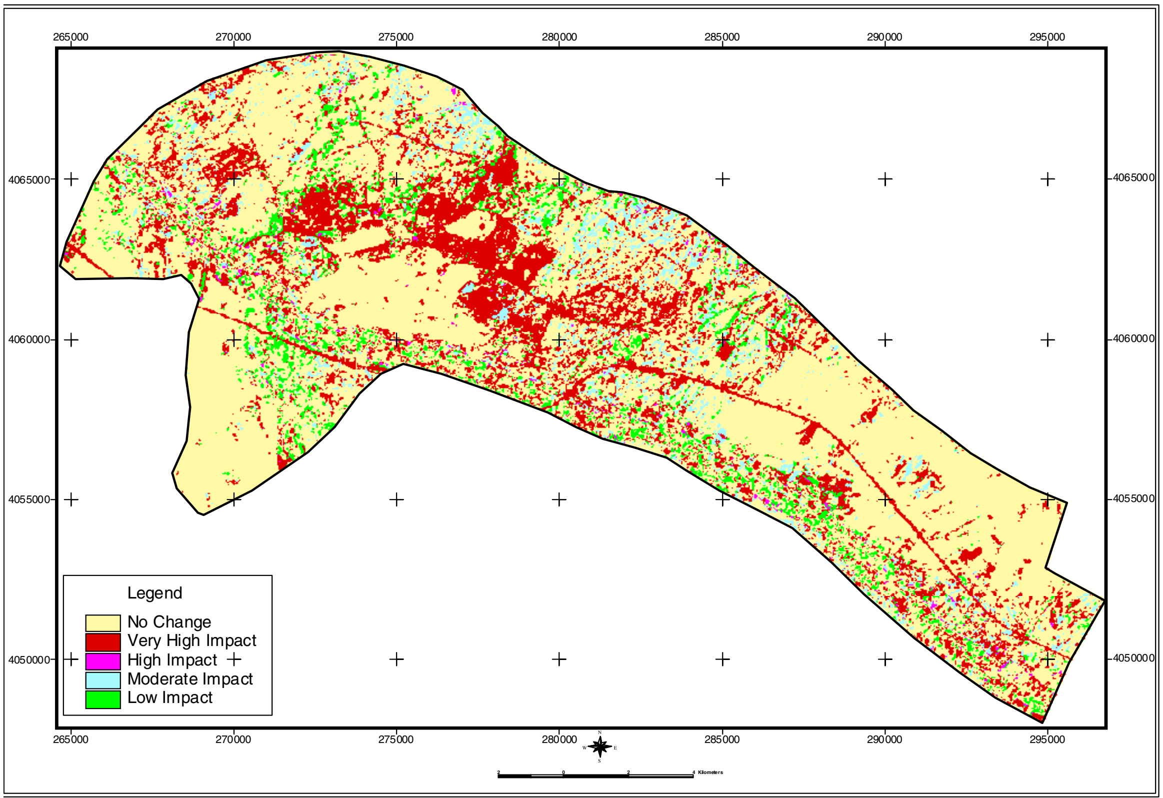

Fig. 7 Environment impact map in the study area.

The results of this study also revealed that agricultural land around major towns and settlements are recognized as critical regions in terms of land use changes, and special protection measures are needed to be taken. In case of improper planning, these regions will be changed to settlements in a very short time, which is totally in contradiction to sustainable development.

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