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Original Research Paper

Land use and land cover spatiotemporal dynamic pattern and predicting changes using integrated CA-Markov model

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ABSTRACT: Analyzing the process of land use and cover changes during long periods of time and predicting the future changes is highly important and useful for the land use managers. In this study, the land use maps in the Ardabil plain in north-west part of Iran for four periods (1989, 1998, 2009 and 2013) are extracted and analyzed through remote sensing technique, using the land-sat satellite images. Then, the future land use changes are simulated for 2030 using integrated CA-Markov model according to the scenario of continuing current management process. The results show that in the period between 1989 and 2009, i.e. since two-thirds of the plain was declared restricted till all of it was declared thus, the study area has experienced a total of about 58645.08 ha changes. After the whole plain was restricted (since 2009 till 2014), the changes have been estimated to be 22466.88 ha. The prediction also indicates that the changes will equal 8908.83 ha by 2030. Agricultural lands and human-built environment constitute the majority of changes and are increasing continuously. The obtained Kappa values for the model accuracy assessment (higher than 0.8) indicated the model's capability to predict future Land use/cover changes in the study area. Thus, analyzing Land use and cover changes trends from past to near future using CA-Markov model can play a significant role in land use policy making, planning, and managing of the restricted plains especially in the proposed study area.

KEYWORDS: *Ardabil plain; CA-Markov; Land use change; Remote sensing; Restricted plain*

INTRODUCTION

Maintaining sustainability of the environment is one of the main factors of sustainable development (Luo *et al.*, 2015). Land use and cover changes (LUCCs) are among the most important changes on the land surface which have considerable influence on the environment and environmental processes. Thus, LUCCs are recognized as the main driving force of the global ecosystem change (Behera *et al.*, 2012; Zhang *et al.*, 2015). Land use change is rooted in the spatiotemporal interaction between biophysical and human aspects (Arsanjani *et al.*, 2013; Dubovyk *et al.*, 2011; Poelmans and Van Rompaey, 2010; Veldkamp and Verburg, 2004), which has increased in recent years due to the increasing human activities and the loss of balance between human and nature (Memarian *et al.*, 2013; Halmy *et al.*, 2015). Forest destruction, desertification, destruction of fertile agricultural lands and uncontrolled urban development are some of the phenomena that threaten the environmental balance directly and indirectly (Farsaei, 2012). These changes will finally influence significant aspects such as human health, ecosystem quality and natural resources (Milà *et al.*, 2015). Identifying LUCCs dynamics from the past to the future can be an important step towards recognizing potential effects. The models for analyzing and simulating the LUCCs provide a suitable tool for identifying the spatial pattern and dynamics of land use/cover (Gong *et al.*, 2015, Jiang *et al.*, 2015). Though

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static model of land use changes is an important tool towards the management of the changes, the nature of the issue requires long-term and strategic planning and necessitates the analysis of the past periods and simulating the future. The need for the dynamic land use system management highlights not only the complexity of the issue (Subedi *et al.*, 2013), but also the necessity of employing robust models. A variety of land use modeling methods exist: mathematical models (linear and static), systems models (stocks and flows), statistical models (regression), cellular models (cellular automata (CA), Markov chain, evolutionary models (neural networks) and modeling with an agent-based approach (Agarwal *et al.*, 2002; Parker *et al.*, 2003; Subedi *et al*., 2013; Al-sharif and Pradhan, 2014). The Markov chain and cellular automata are widely used because of their bottom-up approach, simulation capability, and high flexibility (Amini Parsa, 2014; Nejadi *et al.*, 2012). Both Markov chain and cellular automata are models that are discrete in time and space. The Markov chain model fails to provide spatially referred output (Behera *et al*., 2012), so cellular automata can be used to overcome this deficiency (Nejadi *et al*., 2012).

The Ardabil plain is one of the restricted plains of Iran, which has experienced many land use changes due to urbanization and the physical development of cities and villages as well as agricultural development. These changes have brought about many problems, e.g. the destruction of the fertile agricultural lands due to the expansion of cities and villages and the depletion of the groundwater resources due to their exploitation for agricultural and human usage (Aalipour Erdi, 2014; Kord and Moghaddam, 2014; Maali Ahari, 2011). Since land use change is an influential factor in the decline of the groundwater resources, identifying the previous process of spatiotemporal land use changes and predicting the future process is an effective step towards managing the LUCCs, and thereby, preventing further decline in groundwater levels of the plain and destruction of the fertile agricultural lands. Therefore, this paper aims to analyze the previous land use changes in the plain, as well as simulate the changes in the near future years using integrated CA-Markov model. This study has been performed in Ardabil plain in north-west part of Iran during 2015.

MATERIALS AND METHODS

Case study

The Ardabil plain is located at the north west part of Iran, the east part of the Azerbaijan plateau, and the center of Ardabil province (Fig. 1). It lies between $38^0$00'– $38^0$30' N and $48^0$00'– $48^0$40' E. The area under

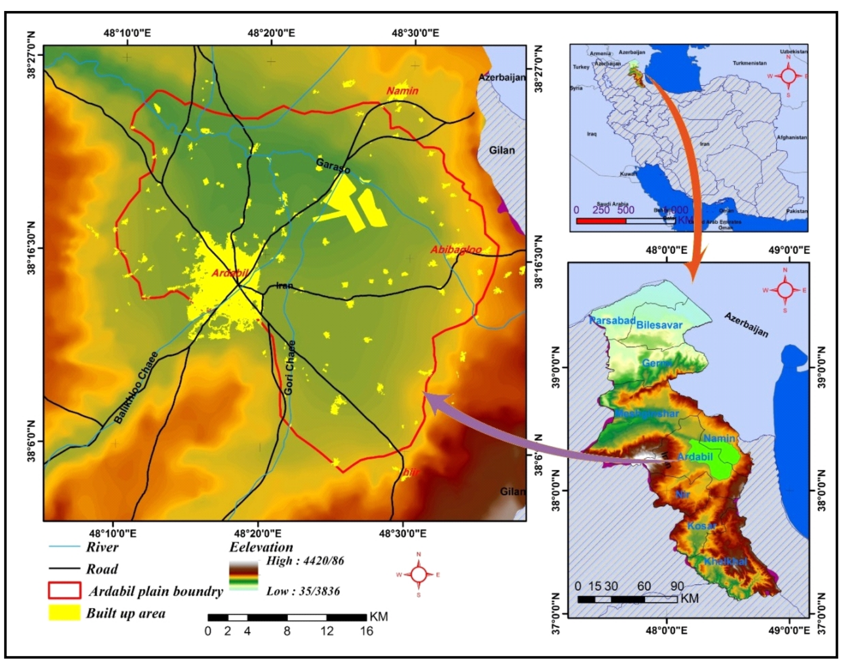

Fig. 1: Location of Ardabil Plain

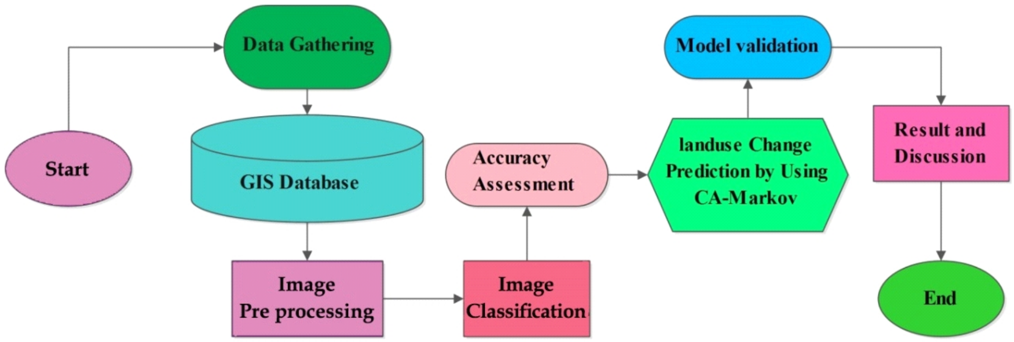

Fig. 2: The research methodology as a flowchart

Table 1: Landsat data sources

satellite	Sensor	Spatial resolution (m)	Total Bound	Date
Landsat 4 and 5	TM	30	7	14-05-1989
Landsat 4 and 5	TM	30	7	26-07-1998
Landsat 7	ETM+	30	8	24-07-2009
Landsat 8	OLI	30	11	22-07-2014

study has an average elevation of 1400 meter and about 564,365 inhabitants (Daneshvar Vousoughi and Dinpashoh, 2013). With its vast area, the plain is the main center of inhabitation and work in Ardabil province, and has an important place in the economy and agriculture of Iran (Ghodsniroo, 2009). Its lands, with their fertile soil and adequate water, grow strategic products such as potatoes. The plain's drainage basin is about 900 km^2 and stretches from the north to mountains at Iran-Azerbaijan border, from the east to Talesh Mountains, from the south to Arpa Chay River, and from the west to the Sabalan mountain range (Aalipour Erdi, 2014). The average precipitation is 300 mm per year.

In Ardabil province especially in restricted Ardabil plain, the groundwater resources are the main source of the drinking, agricultural and industrial water (Kord and Moghaddam, 2014). 89% of the drinking water demand is provided by the groundwater. The groundwater level declines 20-30cm per year, which places the plain in the first rank of groundwater decline among the plains of Iran (Abanpajoh, 2015). As agriculture developed, and the uncontrolled use of the groundwater increased from 1980s, the ground water resource began to decline from 1984 on. The continuing of this condition in the following years made the plain's condition even more critical. This has had environmental consequences such as the saltiness of the groundwater resources, and the subsidence of the land. In order to control the decline, in 1989 two thirds of the plain and then in 2009 all of the plain was declared restricted by the Ministry of Power (Maali Ahari, 2011). Land use change is an influential factor of groundwater resources decline in the plain (Abanpajoh, 2015).

Method

The research process is shown in Fig. 2. In this study, the images of the Landsat satellite are used to analyze the land use changes in Ardabil plain (Table 1). Criteria such as accessibility, cloud-freeness, same resolution and time period have been considered in selecting images. The images have been collected from the Landsat satellite in a time span of 25 years (1989, 1998, 2009 and 2014). It is important to note that the time period chosen for the study corresponds to the times the plain of Ardabil was declared restricted, with the two images coinciding with 1989 when two thirds of the plain was declared restricted and with 2009 when all of it was declared thus. This approach allows us to examine the efficiency of the management of the plain before and after it was declared restricted. It is also important to note that the area under study for land use changes is 5 km away from the border of the restricted area.

In the preprocessing stage, atmospheric correction, geometric correction and enhancement were done. Then the unsupervised classification was conducted to have a general understanding of the land use classes in the area under study and to serve as an assistant tool for identifying the training samples. The training samples were gathered for the expected classes according to the previous knowledge of the area under study, the results of the unsupervised classification, GPS and field sampling, and the web based Google Earth tool. Then the supervised classification was conducted for each individual image by the Maximum Likelihood method in Erdas Imagine Environment; and the initial land use map was extracted for each image. After the images were classified, the accuracy assessment was determined using 256 points by stratified random sampling based on the relative knowledge of the study area and using Google Earth and GPS in field studies. Then the land use changes in the Ardabil plain were predicted for 2030 using the integrated Markov and the cellular automata model in IDRISI Selva software. In the next step, the results of the model were validated and presented. In order to investigate similarities between actual images and the simulated ones, the output was compared to the actual land use map (2014) based on KIA (Kappa Index of Agreement) approach using VALIDATE module in IDRISI Selva. The cross tabulations method was used to determine the quantity of conversions that occurred regarding each particular LULC.

Markov model

Markov model is widely used in ecological modeling (Brown *et al.*, 2000; Muller and Middleton, 1994). Markov chain is a stochastic model in which the state of one system in the future (t_2) can be predicted according to its previous state (t_1) and to the probability of the transition (Adhikari and Southworth, 2012; Behera *et al.*, 2012; Houet and Hubert-Moy, 2006). The application of Markov model in the modeling of land use change is due to its ability not only to quantify different states between different land uses, but also to quantify the transition rate between different land uses (Sang *et al.*, 2011). Homogeneous Markov model for predicting land use changes are shown mathematically as Eq. 1 (Subedi *et al.*, 2013):

$$L_{(t+1)} = P_{ij} \times L_{(t)} \text{ and } P_{i_i} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_m \end{bmatrix} \quad (1)$$

$$(0 \le P_{ij} < 1 \text{ and } \sum_{j=1}^{m} P_{ij} = 1 \text{ , i,j= 1,2,…, m})$$

In Eq. (1), $L_{(t+1)}$ and $L_{(t)}$ are the states of land use in t and t+1 periods, respectively and P_{ij} is a matrix of transition probability in one state. In other words, the Markov chain as Eq. 2 is created from the distribution of land use in the beginning (M_t) and the end of a discrete time period (M_{t+1}) as well as from a transition matrix (M_{Lc}) which shows the changes that have occurred in the intended time period. Given this presupposition, change of use in a piece of land is estimated based on estimated probabilities and in the transition matrix (Muller and Middleton, 1994):

$$\begin{bmatrix} LC_{uu} & LC_{ua} & LC_{uw} & .. \\ LC_{au} & LC_{aa} & LC_{aw} & .. \\ LC_{wu} & LC_{wa} & LC_{ww} & .. \\ .. & .. & .. & .. \end{bmatrix} \begin{bmatrix} U_t \\ A_t \\ W_t \\ .. \end{bmatrix} = \begin{bmatrix} U_t \\ A_t \\ W_t \\ .. \end{bmatrix} \quad (2)$$

$$M_{LC} \times M_t = M_{t+1}$$

Cellular Automata

Cellular Automata (CA) is a model for spatial dynamics which is widely used to study the land use changes (Adhikari and Southworth, 2012). It is a well-known simulated model in which space and time are discrete and the interactions are local (Arsanjani *et al.*, 2013). Cellular automata shows a landscape as a network in which each cell is updated in each T+1 time stage using the transition law based on the state of the adjacent cells in t time and according to the predetermined transition laws (Wolfram, 1983). Cellular automata, as a method with spatiotemporal dynamicity, can simulate the changes in a two-dimensional space. This method is widely used in many geographical fields, especially in order to predict urban development and land use change (Arsanjani *et al.*, 2013). Cellular automata consists of four elements: cell space, cell states, time stages, and transition laws (White and Engelen, 2000). Decision laws can be expert opinions or the result of statistical analyses. The approach adopted in using the cellular automata model is known as the bottom-up approach. Among the features of this model, their simplicity can be mentioned. Using the cellular automata, we can identify the dynamics of the complex systems and propose them in the form of simple laws. Then, using these laws, we can model spatially the future of the system (Singh, 2003; Torrens and O'sullivan, 2001).

CA -Markov

In this study, CA Markov chain model and the cellular automata model are integrated. Both are models discrete in time and space. Markov chain adds no knowledge about the random spatial distribution within each land use group (Behera *et al*., 2012; Houet and Hubert-Moy, 2006). In other words, there is no spatial component in the modeling output (Nejadi *et al*., 2012). Moreover, other than its failure to provide information about the spatial distribution in the probability Markov model, another issue is the consideration of the homogeneous transition probability for the use classes in this model, whereas the transition probability is not fixed in each class (Houet and Hubert-Moy, 2006). Therefore, cellular automata can be used a complement to this model (Nejadi *et al*., 2012), especially when the analysis of different processes is conducted in various spatial and temporal scales (Houet and Hubert-Moy, 2006). The integrative model of Markov-cellular automata (M-CA) is an interesting approach to modeling of the changes in space and time for several reasons (Behera *et al*., 2012):

a) The Markov model controls the dynamics of time among various land covers through transition probability.

b) Space dynamics is controlled through local principles using CA mechanism and according to the state of vicinity and transition probability of each land use.

c) The capacity to connect to geographical information system and remote sensing techniques.

RESULTS AND DISCUSSION

LUCCs of the area under study were analyzed based on the management of restricted Ardebil plain. The land use map of 1989, when two thirds of the plain was declared restricted, was analyzed. This was the initial point of the land use changes within the area under study. Also, in order to study the dynamics of the land use changes, the condition of the land uses between the periods of declaring the plain restricted was also studied in order to have a better understanding of the change processes. Thus, almost the same time periods were chosen and studied for analyzing LUCCs according to limitations in data accessibility. Land use maps illustrate the distribution of the land use/covers classes in the plain during the time span (Figs. 3 to 6). Land use maps include, 1989 land use map when the two-thirds of the plain was declared restricted, ten years after that (to examine the effect of the management of the restricted plain on land use changes), when all of plain was declared restricted (2009), and the present condition of the region. This 25-year period is studied in order to analyze to the process of land use change in the Ardabil plain. Five land use/covers classes were extracted from the images under study: forests, human-built environment (such as urban and industrial area), agricultural land, barren/range land (including pastures and dry faming land) and water bodies; and the land use maps were obtained for 1989, 1998, 2009, and 2014. Table 2 shows the area of each land use in the different studied periods and the covering percentage of each land use. This table shows that, in the period between 1989 and 2009, the coverage of the human-build environment has increased from 2.52% to 5.69% (almost doubled). This increase has also continued from 2009 to 2014, reaching 7.62% of the area under study.

In the years between 1989 and 2014, the agricultural lands increased from 46.49% in 1989 to 50.84% in 2009 and 57.06% in 2014. In contrast, the barren land decreased from 47.83% in 1989 to 40.47% in 2009 and 33.05% in 2014. Also in the years 1989-2014, the water body coverage increased from 245.61 ha in 1989 to 295.81 ha in 2009, but decreased to 241.69 ha by 2014. This statistic also shows that the changes in the agricultural and urban land uses experienced net increasing rate. The form and degree of the land use changes can itself show the degree of the probable need for various land uses according to the biophysical features of the region and the possibility of the transition of the land uses.

The main purpose of the accuracy assessment is to provide an index for determining the correctness degree of the classified map or image (Foody, 2002). In this study, the kappa index is used for validating the classification of the satellite images (Table 3). The results show a high degree of classification accuracy for each map. The overall accuracy of each image is more than 85%.

Predicting the future land use changes

The integrative model of Markov chain and cellular automata are used to predict the future land use pattern of the study area. Then, land use map for 2030 are simulated using the CA-Markov model under the scenario of the continuing the current management (Fig 7). The results of analyzing the future land use show that, in the period between 2014 and 2030 the human-built environment will increase from 7.62% to 10.71% in the area under study (Table 2). Also agricultural land will reach 59.02% in the future 16 years, which indicates an increase trend. But, the predicted land use shows a decrease for the barren land from 33.05% in 2014 to

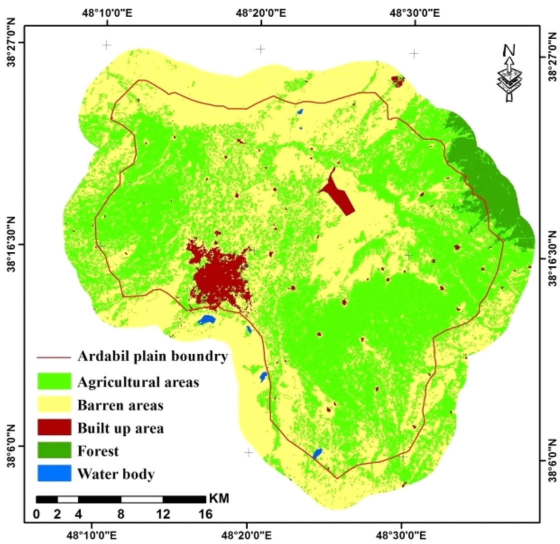

Fig. 3: Landuse/cover classification map 1989

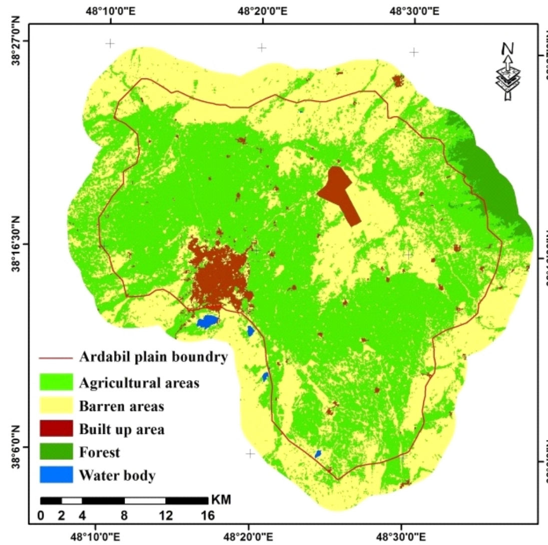

Fig. 4: Landuse/cover classification map 1998

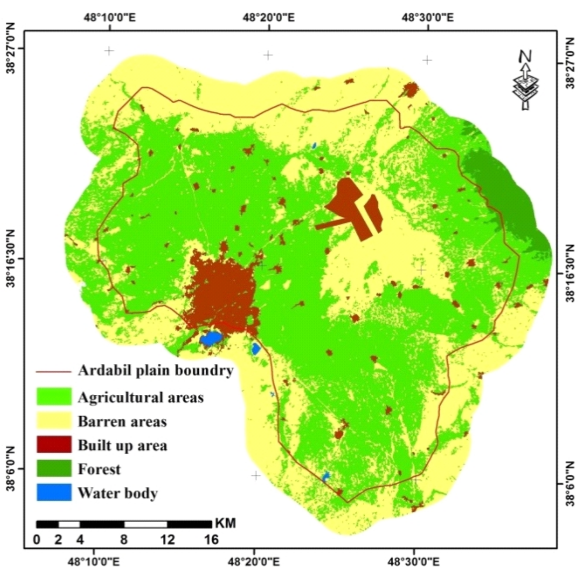

Fig. 5: Landuse/cover classification map 2009

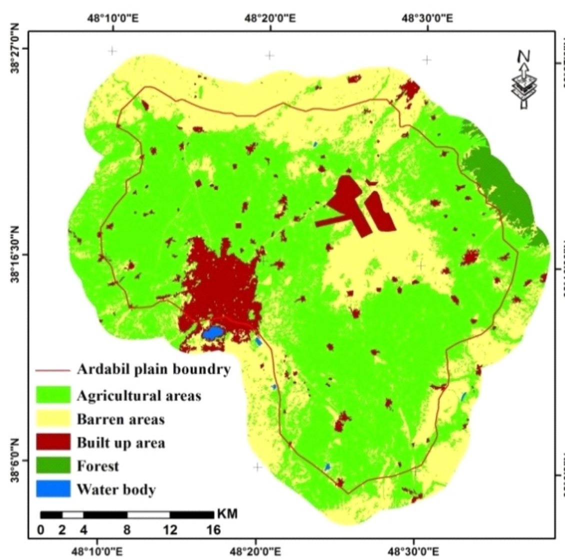

Fig. 6: Landuse/cover classification map 2014

28.08% in 2030. Meanwhile, the water body will also decrease to 196.92 ha. These results show the intrusion of the human-built environment and agricultural land in the barren land.

Generally, the statistics show an increasing trend in human-built environment, which is due to the growth of population in recent years and also emigration to the city of Ardabil. As the results show, the city of Ardabil is increasingly expanding. As the center of the province, it attracts migrants from different cities of the province. The increase of the agricultural lands is also inevitable and leads to the over-exploitation of the water resources of the Ardabil plain for agriculture. It is important to note that the two land uses of human-built environment and agriculture are ones whose developments generally increase water usage. Against the increasing trend of the human-built environment and agricultural use, the barren land have, and will face,

Table 2: Area (ha) and percentage of LULC type during the time span

Land-use \ Year		1989	1998	2009	2014	2030
Human built environment	Area	3310.19	4799.42	7472.42	10003.48	14068.69
	(%)	2.52	3.65	5.69	7.62	10.71
Agriculture land	Area	61067.33	68145.02	66779.38	74951.88	77530.27
	(%)	46.49	51.88	50.84	57.06	59.02
Water body	Area	245.61	293.67	295.81	241.69	196.92
	(%)	0.19	0.22	0.23	0.18	0.15
Barren/range land	Area	62825.15	55117.91	53517.45	43407.63	36874.14
	(%)	47.83	41.96	40.74	33.05	28.07
Forrest land	Area	4107.87	3200.04	3434.85	2951.46	2680.12
	(%)	3.13	2.44	2.61	2.25	2.04

Table 3: Results of Classification accuracy assessment

Image	The overall statistical Kappa	The overall classification accuracy (%)
Landsat 1989	0.862	90
Landsat 1998	0.881	91
Landsat 2009	0.876	92
Landsat 2014	0.893	92

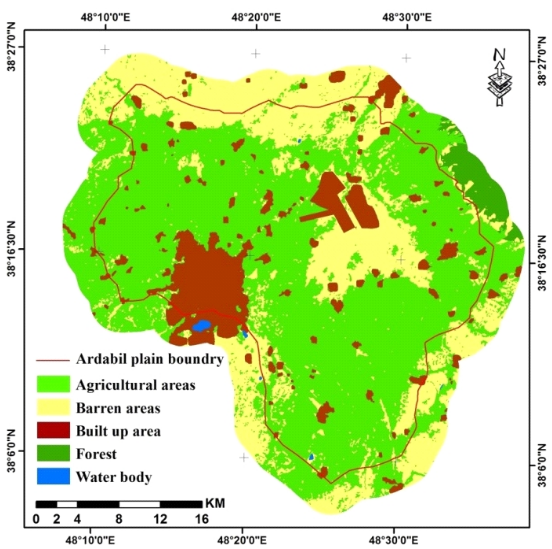

Fig 7: Predicted landuse map for 2030

a decreasing trend, as they are being devoured by the other two above-mentioned land uses (Fig 8).

Validation of the land use prediction model was conducted through simulating a past time period. Thus, the land use was simulated for the year 2014 (Fig 9). The predicted land use map was compared to the actual land use map of 2014 (Table 4). The comparison shows that the area of the human built environment and agricultural land has been estimated smaller than its real area, but the area of the water body and barren land are slightly larger than their real areas in 2014 (Table 4). The forest land is almost equal. It has to be noted that these differences in estimations of percentage and area of the land uses can be neglected. Since the comparison of the percentage and area of the land uses in the real maps with those predicted is done numerically and visually, it is not adequate. Therefore, a more reliable method is needed to validate the model. Kappa statistics measure the goodness of fit between the simulated and the actual maps (Foody, 2002; Omar *et al.*, 2014; Pontius and Schneider, 2001; Van Vliet *et al.*, 2009; Batisani and Yarnal, 2009), the upper and lower limit of kappa is +1.00 (occurs when there is total agreement) and -1.00 (represents agreement which is less than chance). The Kappa statistics higher than 0.8 show the reliability of the simulation process (Viera and Garrett, 2005). In this study, Kappa statistics were used in order to assess the agreement between the actual and simulated land use maps of 2014. Since all the Kappa statistics (Table 5) were higher than 0.8, CA-Markov model is suitable for accurate prediction of future LUCCs in the plain of Ardabil. Due to the necessity of considering the precautionary principle on the role of the land use managers, this prediction seems to have a cautionary vision against depleting the groundwater resources of the plain.

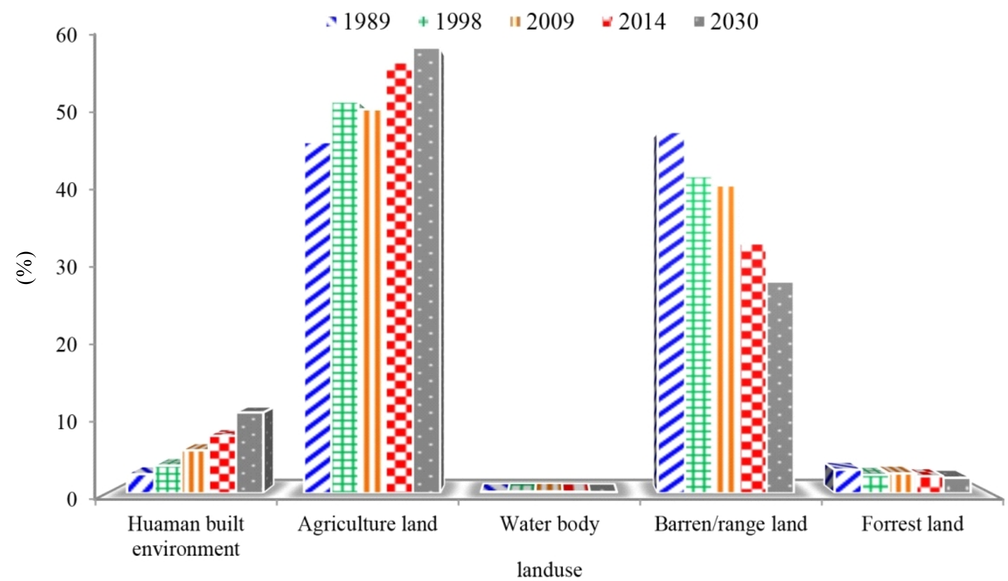

Fig. 8: Area changes of LULCs in study area during the study period

Land use changes

Table 6 indicates the changes and transitions of land use type categories in the different studied periods. The results show that in the period between 1989 and 1998, 20466.54 ha of barren land changed into human-built environment and agricultural land. Also in the period between 1998 and 2009, 12352.41 ha of barren land changed into human built environment and agricultural land. In other words, since Two-thirds of the plain was declared restricted till all of it was declared thus, about 32818.95 ha of barren land converted to agricultural land and human built environment. Since all the plain was declared restricted (2009) till now (2014), the plain has experienced a total 15900.39 ha of barren land change to agricultural land and human built environment. These changes are significant as regards water resources, because the barren land is penetrable and allow surface waters to recharge and replenish groundwater tables. The agricultural land and human built environment, on the other hand, not only prevent the penetration of the surface water into the ground, but also have an extensive water usage.

In 1989 and 1998, more than 12889.52 ha of agricultural land converted to residential and barren land, while 18962.82 and 973.53 ha of barren land and forests changed to agricultural respectively. These numbers show that the agriculture has increased by 7046.82 ha. In other words, even after two-thirds of the plain were declared restricted, the agricultural land has still increased. This increasing trend continued even after all the plain was declared restricted, and the coverage of the agricultural land reached to 7956.9 ha in the period between 2009 and 2014. It is predicted that this process will continue and there will be about 210.42 ha of increase in the agricultural land. Fig. 6

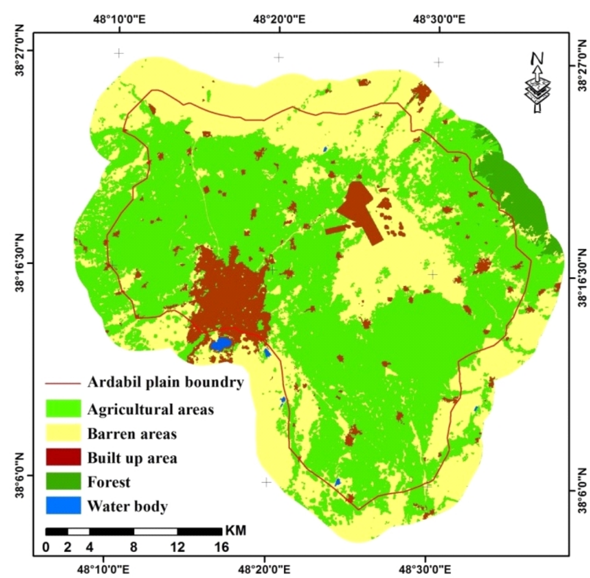

Fig. 9: Simulated land use map for 2014

Table 4: Comparison of actual and simualted land use map of 2014

Land use / Year		Actual (2014)	Predicted (2014)
Human built environment	Area (ha)	10003.48	9251.51
	(%)	7.62	7.04
Agriculture land	Area (ha)	74951.88	70655.35
	(%)	57.06	53.79
Water body	Area (ha)	241.69	249.12
	(%)	0.18	0.19
Barren/range land	Area (ha)	43407.63	48243.39
	(%)	33.05	36.73
Forrest land	Area (ha)	2951.46	2958.99
	(%)	2.25	2.25

Table 5: Validation of projected 2014 land-use map with actual 2014 land-use map

Row	K indexes	Value
1	Kno	0.9508
2	Klocation	0.9766
3	KlocationStrata	0.9766
4	Kstandard	0.9411

shows the land use changes during studied periods. The results also show that in the period between 1989 and 2009, the area under study has experienced about 58645.08 ha of changes. Also between 2009 and 2014, the changes equal 22466.88 ha. The predictions suggest that the changes will equal 8908.83 ha by 2030 (Fig. 10).Comparing the results of the predicted changes and transitions of the land uses in the period between 2014 and 2030 shows that if the current trend continues with the same management, the barren lands will change into human built environment and agricultural land by 2872.71 and 4169.7 ha, respectively. In this period, the total amount of changes will equal 8908.83 ha.

Table 6: Land use class change and conversion during the time span (ha)

Land use conversion / Period	1989-1998	1998-2009	2009-2014	1989-2014	2014-2030
Forest to agriculture	973.53	147.78	119.7	676.71	5.67
Forest to barren land	20.79	26.28	475.47	540.27	245.88
Agriculture to Human built environment	324.63	982.08	749.61	1798.74	1565.37
Agriculture to barren land	12564.9	10609.2	5157.54	8852.67	35.37
Barren land to forest	5.22	0	5.85	1.71	0.09
Barren land to Human built environment	1503.72	1923.12	2156.04	4978.89	2872.71
Barren land to Agriculture	18962.82	10429.29	13744.35	23855.76	4169.7
Barren land to Water body	69.66	30.6	23.94	59.58	0
Water body to barren land	37.35	34.11	34.38	63.63	14.04
Total changes	34462.62	24182.46	22466.88	40827.96	8908.83

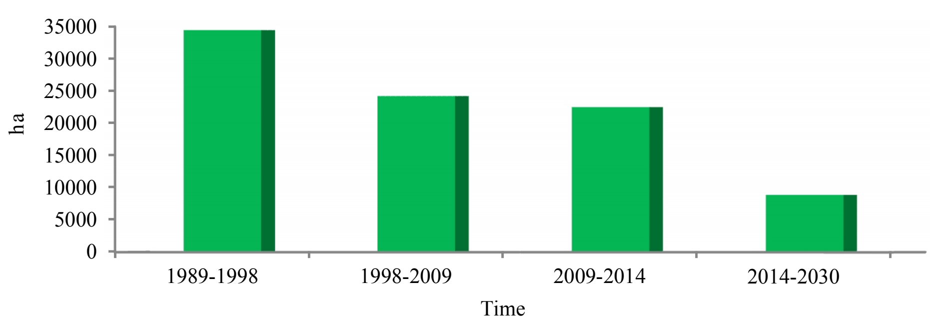

Fig. 10: Total and overall landuse changes trend during different periods

CONCLUSION

Analyzing the process of land use change is highly important in a sustained management of water resources spatially in arid and semi-arid area (Maali Ahari, 2011). The growing increase of population and, thereby, the growing need for the development of human built environment and agriculture lands, influence the quality and quantity of water resources, especially the groundwater resources. On the other hand, due to the increase of population, food demand, and the shortage of surface water resources especially in the last decades, the land areas under irrigation have increased in all the country, and especially in the Ardabil plain. This has completely changed the policy of water and soil resource uses. Land use change is a major factor and a driving force of the groundwater level changes, because the concept of land use shows how human beings use the land. Land use changes cause changes in groundwater levels. For example increase in the area under cultivation will increase the water usage, especially the groundwater resources. These changes have various effects on the management of the restricted plains; and the results of the studies on land use play an important role in decreasing the environmental effects and in managing the decline of the groundwater levels in Ardabil plain. Therefore land use/cover maps will give highly important information for applying management plans. Given the approach of the study based on presenting appropriate data for managing Ardabil plain, the study of land use change was conducted in this regard. This study was conducted using RS data, GIS and CA-Markov model for modeling the dynamics of land use in Ardabil plain. Using this model and assuming the scenario of continuing the current process, the future land use was predicted for 2030. The overall accuracy of the model was higher than %90 in all the Kappa statistics. This indicates that CA-Markov model can be used to analyze and predict the future spatiotemporal dynamics of the land use change in the restricted plains especially in Ardabil plain. The results showed that human-built environment and agricultural use constitute the main dynamics of changes in the plain (Table 6) due to increase of population and agricultural, urban, and industrial development. Assuming the continuation of the current process, it is predicted that these two land uses will still increase. Given the fact that agriculture and human built environment are the major users of the groundwater resources in the Ardabil plain, analyzing LUCCs can provide valuable information for the planners and managers in order to manage and prevent the groundwater resources depletion as well as to reduce its environmental effects.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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