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Integrating logistic regression and cellular automata–Markov models with the experts' perceptions for detecting and simulating land use changes and their driving forces

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Abstract Modeling spatial-temporal dynamic of land use change is of great necessity for understanding the status of the past, causes of the change, and prediction of the future. This study aims to objectify three topics which include identifying the past land use changes, modeling the future changes, and subsequently considering their driving forces. The change detection analysis has shown that about 12,081.8 ha of the study area has changed since 1984 to 2014. Moreover, the models of cellular automata (CA) and Markov chain were applied in order to predict the land use changes of 2024 and 2034. The simulated transition matrix showed that about 6780 ha and 10,835 ha would change during the periods of 2014–2024 and 2014–2034, respectively. Furthermore, the results of the logistic regression model showed that the human driving forces of distance to roads, distance to wells, distance to streams, and distance to residential areas have had a negative effect on the process land use changes. Additionally, a questionnaire was used to obtain information considering the management factors of preventing land use changes, the perception of the natural resources' experts and in turn finding some socioeconomic and policy forces on land use changes. The Friedman's test analysis indicates that the factors of the official rules of government, economy, weakness of regulatory systems, and development activities, e.g., infrastructure and industrial projects, were identified as the leading causes of converting natural ecosystems to other land uses, particularly to cropland. Therefore, the decision-makers and managers should be assigned comprehensive planning for the protection, restoration, and development of natural resources, especially in this region.

Keywords Remote sensing · Driving forces · Land use · Questionnaire · Cropland · Natural ecosystems

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Introduction

Change in land use/cover is one of the most crucial environmental issues on a global scale (Lambin and Meyfroidt 2011; Meyer and Turner 1992; Meyer and Turner 1994; Turner et al. 1994), indicating the relationship between human activities and environmental variables in aspects of time and space (Agarwal et al. 2002). Land use changes have been among the most significant factors by which human beings have affected the environment (Aaviksoo 1995); these changes have resulted in the intensification of environmental disasters, e.g., deforestation, biodiversity reduction, and global warming (Reis 2008). Therefore, it is necessary to understand how to use the land and how to change it during a time-scale in order to plan and to develop the

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natural ecosystems. Over the last few decades, the land cover has been mostly converted from forests to agricultural and residential lands (Lausch and Herzog 2002). Hence, identification of different human activities is an essential factor, one that is significantly influential on land use changes. For this purpose, finding a suitable model is regarded as a tool for detecting land use changes in relation to the influential factors.

Satellite images of remotely sensed data are the most common sources which can be used for detecting, mapping, and modeling different patterns of land use change (LUC) (El-Kawy et al. 2011). The support vector machine (SVM), which was developed by Vapnik (2013), is a supervised classification method with a high accuracy for the classification of satellite imagery data (Kavzoglu and Colkesen 2009; Huang et al. 2002; Samardžić-Petrović et al. 2016). The SVM can be applied to the change detection analysis. This method is a statistical learning-based model that detects the boundary of various classes optimally (Pal and Mather 2005; Vapnik 2013). The SVM supplies the best separation between two classes (Petropoulos et al. 2012) due to its ability to separate the satellite imagery data into different classes with limited training sites (Mountrakis et al. 2011). Furthermore, for simulating LUC, three major models of empirical estimation, dynamic simulation, and rule-based simulation have been mostly used (Hu and Lo 2007). Logistic regression is an empirical estimation model which can be applied for simulating natural ecosystem (Viedma et al. 2015). This model is generally used to detect the statistical relationships between a dependent factor and various independent variables (McCullagh and Nelder 1989). Besides, by using an appropriate model, it is possible to explain the relationships between different variables, in order to estimate the relative importance of major parameters and to extract the probability map of land use changes (Jokar Arsanjani et al. 2013; Verburg et al. 2004). Nonetheless, the logistic regression (LR) is not a suitable model for measuring the variation of time, space, and human factors (Hu and Lo 2007). Hence, a different kind of the rule-based simulation model, e.g., cellular automata (CA), is the most adaptable option for combining effects of spatial and temporal factors and their interactions (Hu and Lo 2007; Jokar Arsanjani et al. 2013). In the current study, various driving forces of LUC were characterized by using three principal approaches, which include the LR model, CA model, and the questionnaire method to find a better understanding of the changes' main causes in natural resources. Furthermore, the LUC was detected by using SVM classification method from 1984 to 2014. The integrated CA and Markov chain models were applied for simulation of LU maps of 2024 and 2034. An integration of the CA and Markov chain was recommended as a suitable method for simulating urban expansion (e.g., Deep and Saklani 2014; Jokar Arsanjani et al. 2013) and modeling urban areas and other land uses such as forest and crop lands (e.g., Guan et al. 2011; Moghadam and Helbich 2013).

Materials and methods

Study area

Mehran plain was selected as the study area which is located in Ilam province in west of Iran (33° 03′ to 33° 13’ N and 46° 05′ to 46° 15′ E) with an area of 317.1 km^2 (Fig. 1). The center of population in the region includes Mehran county, Eslamieh town, and Banrahman village. This region has a semi-arid climatic condition based on de Martonne aridity classification (De Martonne 1926) with annual precipitation of about 238 mm. The absolute temperature ranges from − 6 to

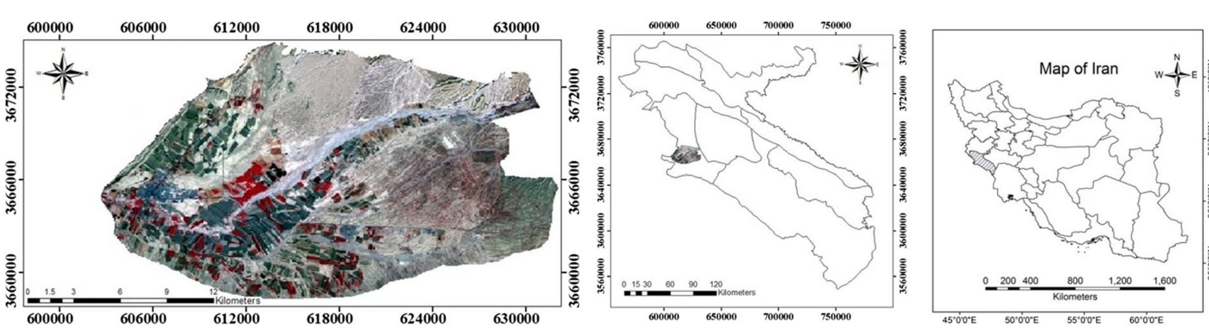

Fig. 1 The research area on the maps of Iran and Ilam province (RGB false color composite, extracted from Landsat ETM, 2014)

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25 °C. About two thirds of Iran's whole area has a precipitation of approximately less than 250 mm which is classified as either arid or semi-arid areas. These areas, where the land use is changing rapidly under the driving forces, are environmentally fragile (Cao et al. 2011). Moreover, in many areas of Iran, human factors such as population growth, high grazing intensity, excessive extraction of groundwater, and industrial development have led to the intensification of destruction trend in natural resources (Faramarzi et al. 2010; Zare et al. 2017).

Study framework

This part discusses the required features of the model, procedures for preparing LU maps, environmental variables, and some socioeconomic and management factors that influence LUC (Fig. 2). For this purpose, the Landsat satellite imagery of 1984, 2001, and 2014 were used for further analysis. Landsat images have suitable resolutions (e.g., spatial resolution of 30 m and 8-bit radiometric resolution) which have been used by many researchers in modeling LUC (e.g., Fathizad et al. 2015; Jokar Arsanjani et al. 2013; Yaghobi et al. 2019). Initially, LU maps of these years were prepared by applying a supervised classification method of SVMs. Then, the principal environmental factors and human activities affecting LUC were determined and analyzed using the LR model. In the next stage, probability matrix of LUC was acquired using the Markov chain model, and finally, the combined CA and Markov chain model was applied in order to simulate the LU map. Besides, some socio-economic and management factors were assessed by distribution of questionnaires among land affair experts in the study area.

Image classification and LUC

The objective of classifying the satellite imagery data is to convey the spectral values of images to useful and comprehensible information (Khatami et al. 2016; Mountrakis et al. 2011). In the current study, three

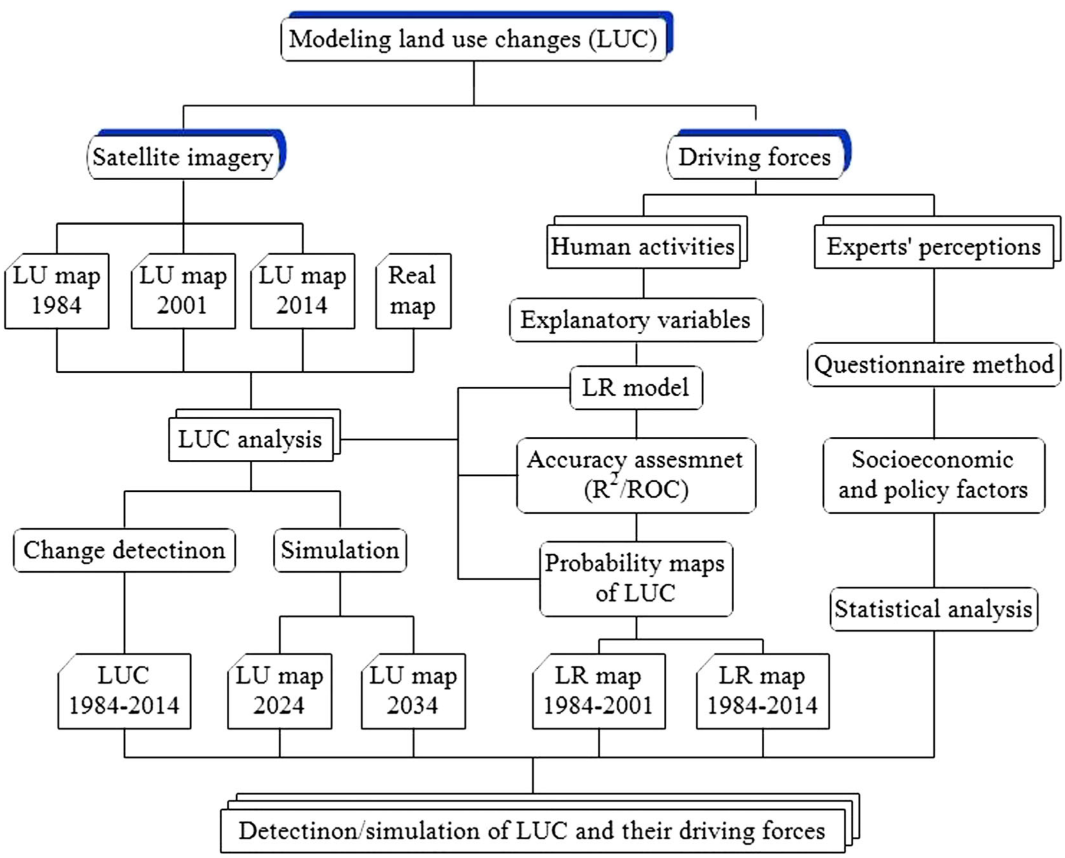

Fig. 2 Flowchart of the study structure for modeling LUC

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supervised classification methods of maximum likelihood, fuzzy ARTMAP, and the SVM were applied for the purpose of finding a method with higher-order accuracy to detect land use changes. The SVM method showed a higher accuracy (kappa coefficient and overall accuracy of about 0.89 and 91%, respectively) than other methods in producing the LU maps of 1984, 2001, and 2014. The SVM method is a binary classifier that separates two classes by a linear boundary (Wu and Wang 2009). In the binary analyses, the SVM is designed to locate an optimal separating hyper plane that aims to maximize the margin between different classes (Kavzoglu and Colkesen 2009; Vapnik 2013; Wu and Wang 2009). Assuming that the training dataset (the experimental observations) belongs to two separated classes, $T = \{(x_1, y_1), (x_2,y_2),\ldots,(x_n,y_n)\}$, $x€R^n$, $y€\{-1,+1\}$, $i = 1,2,\ldots,n$, where yi is the class of sample i, xi is the number of variables in sample i, and $x€R^n$ is a real n-dimensional space (Huang et al. 2002; Vapnik 2013; Yang et al. 2008). In the current study, yi and xi demonstrate the LUC of pixel i and the set of feature changes, respectively.

The main objective of this algorithm is to find the maximum distance between two classes, and hence, to increase the classification accuracy mean, while extrapolation is reduced as far as possible (Mountrakis et al. 2011; Otukei and Blaschke 2010). The SVMs minimize classification errors in unobserved data without prior assumption from data loss probability whereas statistical techniques like maximum similarity recognize data destruction (Mountrakis et al. 2011). Following initial image classification, a ground truth map was prepared for the field data collection to evaluate the accuracy of the maps (Fig. 3). For this, a random sampling method was used for ground data collection, from which the samples were chosen randomly in each land us. In the present study, the kappa coefficient and the overall accuracy were used to assess the classification accuracy. Kappa coefficient is one of the principal and common methods, which is used for accuracy assessment of satellite imagery data classification (Boyce et al. 2002).

Driving forces of LUC

The LR is an empirical model of estimating the relationship between land use changes and driving forces by using statistical methods (Hu and Lo 2007). This model is a binary regression which is suitable for interval censored data which contains data coded as 1 (e.g., TRUE) or 0 (e.g., FALSE) (Kleinbaum and Klein 2010). Furthermore, the relative operating characteristic (ROC) will be used as a quantitative measurement to validate a land cover change model (Pontius and Schneider 2001). The LR model has been used in

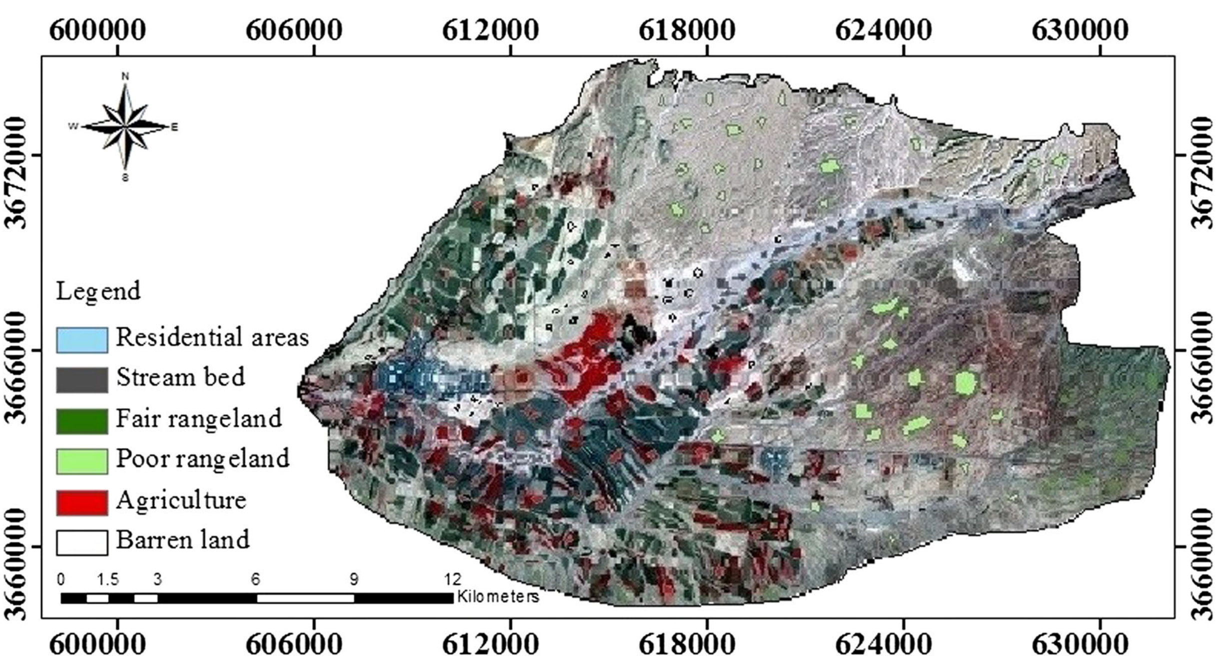

Fig. 3 Ground truth map

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different studies, for instance, in order to analyze the natural resources' degradation (Chowdhury 2006; Rueda 2010). The LR model is mainly aimed to prepare the probability maps of LUC to find an adaptable model to convey the relationships between the presence/absence of dependent variable and groups of independent variables (Kleinbaum and Klein 2010). If the dependent variable has binary values, it will only equal zero or one (Kleinbaum and Klein 2010). The values of one and zero represent the occurrence and nonoccurrence of the event, respectively. The output of the relevant model includes the probability surface maps of the dependent variable based on coefficients of independent variables (Hu and Lo 2007).

According to the logistic curve, the probability value of a cell changing to other land uses (e.g., to the rangeland area) can be estimated through following the logistic regression model (Hosmer Jr et al. 2013; Serneels and Lambin 2001):

$$Prob(Y = 1|Xi) = \frac{Exp(b0 + b1X1 + b2X2 + \ldots + b2X2)}{1 + Exp(a + b1X1 + b2X2 + \ldots + b2X2)}$$

where X_i is an independent variable representing the driving components of LUC and b is the estimated parameter.

Probability ranges from 0 to 1 which demonstrate the lowest and the highest likelihood of dependent variable changes, respectively. Moreover, the relevant probability map will be integrated with the models of Markov chain and cellular automata for the simulation of LUC (Jokar Arsanjani et al. 2013).

Simulation of LUC

Markov chain model and CA were used for simulating different aspects of LUC. Markov chain is a probabilistic modeling method (Baker 1989; Agarwal et al. 2002) which represents the probability of variation within a state, for instance, a class of LU to other states (Fathizad et al. 2015; Neal 1993). Inputs of this model are various LU maps from different times. The maps of different time intervals are compared with each other in the form of matrices, which are based on maximum values of probability (Baker 1989). Afterwards, the maximum likelihood for each pixel either to remain in a class or to convert to another class will be estimated. This model is quantitatively run to determine the LUC. The Markov chain model projects a transition probability matrix as well as the transition maps of each class to another class by using the initial LU areas (Baker 1989; Neal 1993). The problem in using Markov chain model is considered to be the lack of any possible discussion for the spatial element in the process of the modeling (Jokar Arsanjani et al. 2013). Therefore, the CA model will be applied in order to add a spatial element to the model.

CA represents the models that generate large-scale patterns from small-scale processes (Sakieh et al. 2015). This modeling technique deals with spatial and dynamic phenomena and consists of continuous cells whose following states vary in different iterations by the imposed rules and status of their neighboring cells. In a CA system, there are four elements including cells, states, neighborhoods, and rules (Li and Yeh 2000). The state of a cell—the smallest unit—can be changed based on the transition rules (Li and Yeh 2000) that define the basis of the quantification of the neighborhood functions (Verburg et al. 2004). The CA model determines the interaction among the LU in a cell, the cell conditions, and the LU types in the neighborhood (Verburg et al. 2004).

Perception survey of natural resources' experts

In the present research, library study and search via electronic references were used to determine the theoretical, fundamentals and literature review. Following these research in parallel with regular theoretical surveys, a questionnaire was prepared as a research tool to target the members of the statistical population for the means of gathering information and insights about the research objectives and questions. A researcher made questionnaire (Yu and Cooper 1983) method was used in the present research for obtaining the required data. The questions were posed via an interview with well-informed residents of the study area to analyze the research objectives. The questionnaire included a series of both open and closed questions (Foddy 1994; Schuman and Presser 1979) for each objective. The closed questions were designed as a multi-choice Likert scale, and the open questions were such that accurate information could be derived from the statements. The Likert scale is an easy tool to use by responders of the questionnaire (Laerhoven et al. 2004) in which the scale is ranged from "strongly agree" to "strongly disagree" (Hills and Argyle 2002). The nonparametric Friedman's test (Conover 1980; McCrum-Gardner 2008; Roa 1992)

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Table 1 Accuracy amounts of the SVM supervised classification for 1984, 2001, and 2014

Year	Kappa coefficient	Overall accuracy
1984	0.8776	89.35
2001	0.8923	91.45
2014	0.8998	93.31

was conducted to analyze different factors that were scaled from 0 to 4. This can be successfully used for analyzing the ranked-based data (e.g., Rasher et al. 2013). In the present study, the questionnaire was presented to the experts who worked in relation to LU in several organizations and universities. The total population of the research comprises all LU experts of the study area of Mehran city. The number of samples was estimated to be 40 people based on the table of Krejcie and Morgan (1970). The samples were selected randomly by a stratified sampling method with a proportional allocation.

Results

The current study was aimed to examine different aspects of driving forces, including environmental variables, human activities, and some socioeconomic and management variables on LUC in semi-arid rangelands of western Iran. In order to detect LUC in the past, TM and ETM+ Landsat satellite images were used for the period of 1984, 2001, and 2014. The images were classified using the SVM supervised classification method and based on the information gathered of the training sites using GPS (GARMIN 62s). These sites were selected randomly in each LU class. In order to assess the accuracy of the classification, the statistical factors of the kappa coefficient and overall accuracy were calculated (Table 1). Overall accuracy is estimated by summing the number of pixels classified correctly divided by the total number of pixels (Congalton 1991). After finding an acceptable accuracy (Table 1), the study area was classified to six classes for each year which include residential land, stream bed, fair rangeland, poor rangeland, agricultural land, and barren land (Table 2 and Fig. 4). The results showed that the agricultural land class with an increase of 4160 ha went through a high amount of change, while the minimum variation of land use was observed for the class of barren lands, which area increased to about 1091 ha, during 1984 to 2014 (Table 3).

Detection of LUC

The results of LU classification in different years indicated that the areas of agricultural, barren, and residential lands have increased, while the classes of poor rangeland, fair rangeland, and river-bed have declined (Table 3). Overall, about 12,081.8 ha of different LU classes have changed from 1984 to 2014 (Table 3). Furthermore, change/nonchange maps of different land uses were obtained by overlaying the classified maps of the periods 1984–2001 and 1984–2014 from which the amount and the location of LUC and nonchanges were acquired (Fig. 5).

LUCs in relation to driving forces

LR

Logistic regression was applied to determine the impact of the relevant factors on changes in land uses. For

Table 2 Area of land use classes for 1984, 2001, and 2014

Class	1984		2001		2014	
	ha	%	ha	%	ha	%
Residential area	199.8	0.63	525.2	1.66	989.6	3.12
Stream bed	1561.7	4.93	1428.2	4.5	1337.5	4.23
Fair rangeland	7239.8	22.48	5435.6	17.15	4458.6	14.06
Poor rangeland	15,103.5	47.64	14,252.8	44.96	12,068.0	38.06
Agriculture	6189.7	19.52	8347.9	26.33	10,349.7	32.6
Barren land	1408.6	4.44	1713.6	5.4	2499.7	7.88

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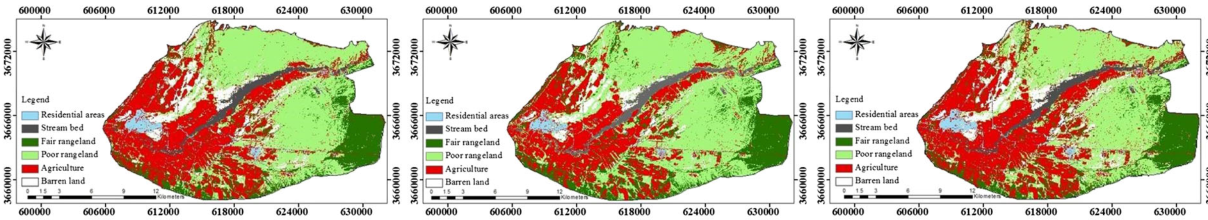

a b c

Fig. 4 Land use change detection maps in **a** 1984, **b** 2001, and **c** 2014

modeling the transition potential of land uses, LU change/nonchange maps of two periods of 1984–2001 and 1984–2014 were chosen as the dependent variables of the model. Besides, the independent variables included the layers of slope percentage, slope aspect, elevation, distance from residential areas, distance from the road, distance from streams, and distance from exploitation wells (Fig. 6). The maps of elevation, slope percentage, and slope aspect were extracted from a high-resolution digital elevation model (DEM). The resolution (grid size) of the DEM was 10 m^2 which was prepared by Iran's National Cartographic Center (NCC). Elevation map was generated in five classes. To determine the probable relationship between the percentage of slope and destruction phenomena, the slope map was divided into five classes of 0–5%, 5–15%, 15–25%, 25–35%, and over 35% (Fig. 6a). The Natural Breaks (Jenks) method (Jenks 1967) was used for the classification of slope which was extracted from the DEM layer. The Jenks Natural Breaks was proposed as a suitable method for data classification (e.g., Osaragi 2002; Sema et al. 2017; Stefanidis and Stathis 2013) which benefits from low information loss and a high accuracy (Osaragi 2002). Moreover, the slope aspect map was prepared in five classes, including four main geographical directions (north, south, east, and west) and one class, including the flat areas for which the slope percentage is zero. Based on the frequency and distribution, thirty 200-m buffer zones were generated for each human factor, including residential areas, roads, wells, and streams. Figure 5 shows different raster independent variables used in the regression model.

The probability maps of LUC based on the LR model were prepared for two periods of 1984–2001 (Fig. 7a) and 1984–2014 (Fig. 7b). According to these maps, darker areas (green color) represent more variations in the region, and lighter colors reflect lower levels of variations in the region. Moreover, the coefficient values of the raster variables (Fig. 7) during periods of 1984–2001 and 1984–2014 are shown in Table 4. The amount of coefficients indicates an impact degree on the LUC from which the positive measures have the highest effect on LUC (Jokar Arsanjani et al. 2013). In the current study, the slope aspect and elevation have positive effects, while the distance to roads, distance to wells, the percentage of slope, distance to streams, and distance to residential areas have negative impacts on LUC. The scale and sign of coefficient value indicate the amount and direction effects of the variables, respectively, on LUC. For instance, the stability of LUC will increase with increasing the distance from the human activities, e.g., road, residential area, stream, and well (Table 4).

Table 3 Area of land use changes during the period of 1984 to 2014

Class	1984–2001		2001–2014		1984–2014	
	ha	%	ha	%	ha	%
Residential area	325.3	1.03	464	1.46	789.7	2.62
Stream bed	− 133.5	− 0.43	− 90.7	− 0.27	− 224.19	− 0.7
Fair rangeland	− 1805	− 5.96	− 976.9	− 3.09	− 2781.2	− 8.78
Poor rangeland	− 850.8	− 2.68	− 218.6	− 6.9	− 3035.5	− 9.58
Agriculture	2158.2	6.81	2001.8	6.32	4160	13.13
Barren land	305	0.96	786	2.48	1091	3.44
Total	4627	17.87	4538.6	20.52	12,081.8	38.25

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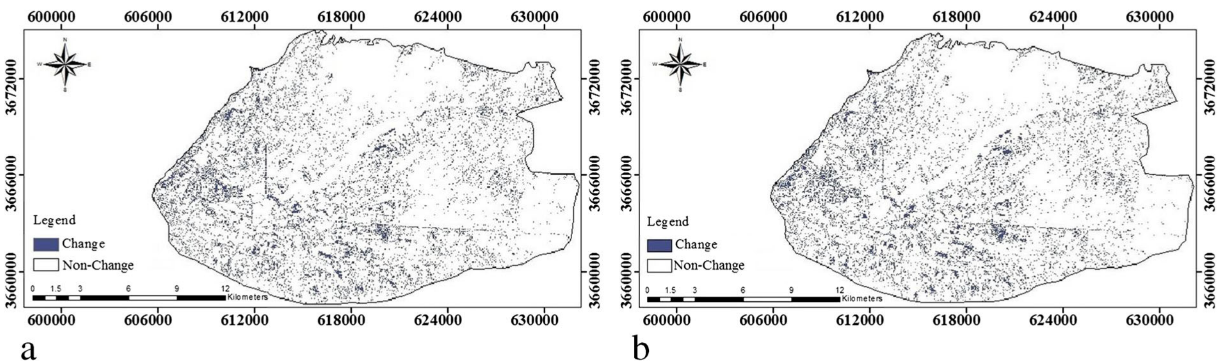

Fig. 5 Change/nonchange maps of the land use classes as a dependent variable in the model for **a** 1984–2001 and **b** 1984–2014

Logistic regression accuracy

Validating land use change models have been recognized as an essential tool for determining the accuracy of predictive modeling (Pontius and Schneider 2001). In this study, the ROC and pseudo-R^2 indices were used to validate the prepared model (Table 5). The value of ROC ranged from 0.5 to 1 from which greater amounts show a higher accuracy of the model prediction. The accuracy of the model can be grouped according to the ROC values into low accuracy (ROC = 0.5–0.69), acceptable (ROC = 0.70–0.9), and high accuracy with the ROC more than 0.9 (Manel et al. 2001; Jiang et al. 2015).

Moreover, the pseudo-R^2 index was used for the evaluation of the model precision. This index ranged between 0 and 1. The values of 0 and 1 represent no significant correlation between dependent and independent variables, and fitness of the model, respectively. In spatial studies, the higher than 0.2 amounts in pseudo-R^2 can be relatively considered as the goodness-of-fit indices for simulating the model (Clark and Hosking 1986; Hemmert et al. 2018). In this study, the ROC index was acquired during the period of 1984–2001 with a value of 0.8253, and for the period of 1984–2014 with a value of 0.8323, which indicates a high fit and presence of the significant relationship between variables (Table 5).

The perception survey of natural resources' experts

A questionnaire was used to attain the opinion of experts of natural resources considering the factors affecting LUC in the study area. The Friedman's test measurement was used to compare the scale factors from 0 to 4. Therefore, if the mean value of each factor is equal to or greater than three, it can be derived that the respective factors influence the LUC. On the other hand, if the mean value of each factor is less than three, it can be concluded that the relevant factors do not affect or poorly affect the LUC. In the current study, a number of ten factors (Table 6) have been considered within a questionnaire that was designed to include 63 questions in total. The statistical analysis indicated that the measured factors were significantly ($x^2 = 45.08$, p value < 0.001) influential on LUC (Table 6). The highest mean values of the measured factors include the official rules of government (3.781), economy (3.761), weakness of regulatory systems (3.759), and environment (3.665) to be considered as the main causes influencing LUC (Table 6). The natural resources' experts, moreover, suggested that some aspects which include social factor (3.414), technicality (3.375), and the Iran–Iraq War (3.117) had lower impacts on the LUC than the factors mentioned above (Table 6).

Simulation of LUC

The combined model of CA and Markov chain was run to determine the LUC quantitatively. The model was calibrated using the real area in each LU class for further analysis. For this, initially, the transition matrix of the first period of 1984–2001was applied to simulate LUC in 2014 (Table 7a). Then, the model was validated by comparing the simulated map with the actual LU classes in 2014 for which an acceptable accuracy (the kappa coefficient of 84.25%) was obtained. This value demonstrated that the model has a high ability in the simulation of LUC. Besides, a multi-objective land allocation (MOLA) analysis was used to produce the prediction maps. The MOLA, CA, Markov chain, and LR were applied to integrate different datasets for simulating different LU maps of 2014 and 2024 (Table 7). For instance, the transition probability matrix of the period

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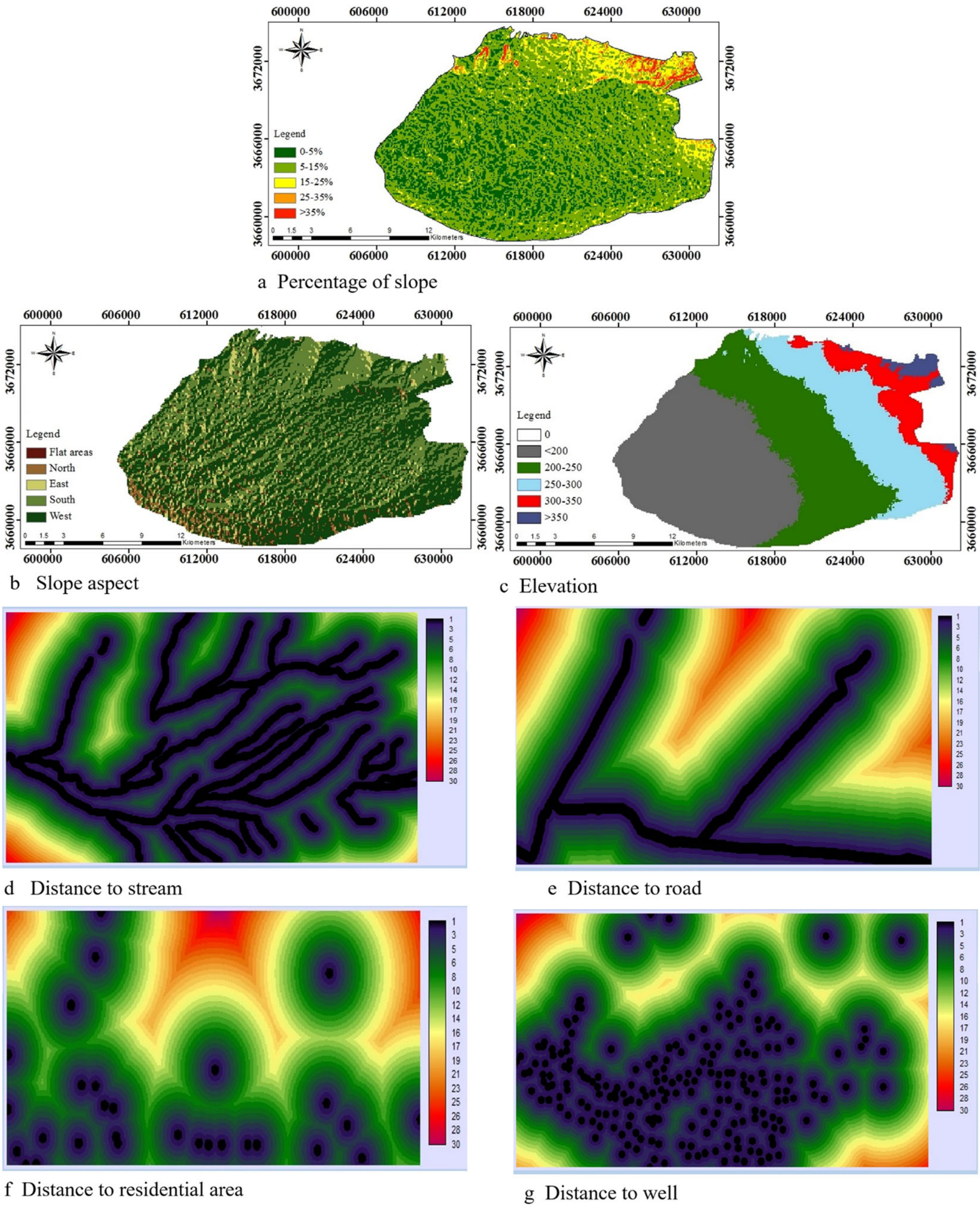

Fig. 6 Raster independent variables used in the regression model. The units of the layers of **c**–**g** are defined in "meters"

of 1984–2014 was used to simulate the LU map of 2024 (Table 7b). In this year, probably about 99.4%, 97.7%, 93.9%, 81.3%, 90.5%, and 99.6% of the residential land, agriculture, stream bed, fair rangeland, poor rangeland, and barren land, will respectively remain unchanged (Table 7b).

Furthermore, the area of both different LU classes for 2024 and 2034 and LUC from 2014 to 2024 and 2014–2034 were calculated for a better understanding of the simulated LUC (Table 8 and Fig. 8). The highest areas of LUC were related to agriculture and poor rangeland with the amounts of + 3544.7 ha (an

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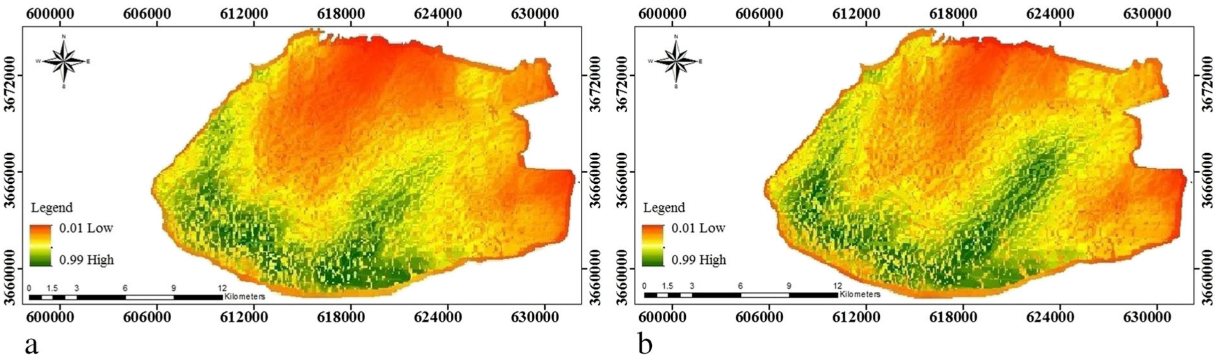

Fig. 7 Map of logistic regression probability of land use changes for **a** 1984–2001 and **b** 1984–2014

increasing trend) and − 4822.9 ha (a decreasing trend), respectively, in 2034 (Table 8).

Discussion

Modeling and simulating LUC have been recognized as necessary to evaluate different environmental and human impacts (Brown et al. 2000). Conventional surveying techniques are not time and cost efficient to assess the land cover changes, especially at a large scale and for a vast area. Remote sensing tools and techniques offer a high-resolution method for detection, identification, and zonation of natural resources, particularly for the purpose of mapping land uses (Fathizad et al. 2015; Jiang et al. 2015). For the investigation at hand, first the analysis of LU change detection will be discussed; next, the relevant driving forces of the measured variables of environmental factors, human activities, and the socio-economic and management variables will be presented. Finally, the simulation of LUC in the study area will be interpreted.

Table 4 Coefficient values of the independent variables during periods of 1984–2001 and 1984–2014

Variable	Coefficient	
	1984–2001	1984–2014
Slope aspect	0.2718	0.2798
Percentage of slope	− 0.1009	− 0.1053
Elevation	0.1082	0.1148
Distance to stream	− 0.0492	− 0.0831
Distance to residential area	− 0.0453	− 0.0198
Distance to road	− 0.1322	− 0.1393
Distance to well	− 0.1108	− 0.0960

Change detection analysis

In the current study, the LUC was, firstly, detected via the supervised classification method of SVMs. In order to determine the influence of relevant factors on the LUC, the LR model and a questionnaire method were used. Moreover, the Markov chain model and cellular automata were applied in order to simulate the LUC in the future.

The SVM analysis has classified the study area into six classes of residential land, stream bed, fair rangeland, poor rangeland, agricultural land, and barren land (Table 2), after achieving a relatively high accuracy of kappa coefficient that is more than 0.87 for 1984, 2001, and 2014 (Table 1). The results indicated that the highest and lowest changes had occurred in the classes of agricultural land and barren land which was an increase of about 13.13% and 3.44%, respectively (Table 3). On the other hand, the rangeland areas of both fair and poor conditions had a decreasing trend of 18.36% during periods of 1984–2014 (Table 3). Conversion of rangeland to cropland has been recognized as the main problem in the natural resources of Iran (Faramarzi et al. 2010). Expansion of cropland is a major problem of LUC worldwide, which has been mainly related to population growth and the growing demand for agricultural productions (Lambin et al. 2001; Lambin and Meyfroidt 2011). In the present study, the residential

Table 5 Evaluation of the logistic regression model using ROC and Pseudo-R^2

Index	1984–2001	1984–2014
ROC	0.8253	0.8323
Pseudo-R^2	0.2473	0.2536

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Table 6 Statistical analysis of different socioeconomic and management factors affecting land use changes according to the perception of the natural resources experts. Evaluated by the ranked-based Friedman's test (for all factors: p value < 0.00, $K^2 = 45.075$, degrees of freedom = 9)

No.	Factor	Mean ± SD
1	Official rules of government	3.781 ± 0.674
2	Economic	3.761 ± 0.535
3	Weakness of regulatory systems	3.759 ± 0.480
4	Environment	3.726 ± 0.569
5	Development activities, e.g., infrastructure and industrial projects	3.665 ± 0.522
6	Population	3.617 ± 0.621
7	Culture	3.478 ± 0.489
8	Social condition	3.414 ± 0.562
9	Technicality	3.375 ± 0.721
10	Iran–Iraq War	3.117 ± 0.625

area has expanded about 2.49%, which is mainly due to the population growth.

Driving forces of LUC

The LR model deals with the relationships between the dependent variable (land use) and the independent variables (driving forces) in order to determine the probability levels and locations of changes, which can be then recognized as useful parameters (Jokar Arsanjani et al. 2013; Park et al. 2011). In the current study, the measured environmental variables of the slope, aspect and elevation have positive effects on LUC, of which the logistic coefficients are about 0.2798 and 0.1148, respectively, in the second period (1984 to 2014). The positive coefficient of a variable means that it has a considerable effect on the probability of LUC (Park et al. 2011). This condition seems to be due to the climatic situation of the study area which is located in a semi-arid climate based on the de Martonne aridity classification (de Martonne 1926). In this condition, the most limiting factor should be the amount of humidity for agriculture. Rainfall is the main source of water for rain-fed agriculture, which has a decreasing trend with the decrease of elevation in arid and semi-arid areas (Modarres and da Silva 2007). In the north-facing aspects of the northern hemisphere, the vegetation cover receives more water, and the evapotranspiration is lower as it gets less solar radiation (Maren et al. 2015). Therefore, in the hope of obtaining the most amount of productions, local people have tried to convert the rangeland area to cropland in whichever area that has a high-water availability. Furthermore, the human activity variables which include distance to roads, distance to wells, distance to streams, and distance to residential areas have negative impacts on the LUC. The negative coefficient for these variables (Table 4) indicates that if and

Table 7 Probability values of Markov transition matrix for (a) 2014 based on 1984–2001, and (b) 2024 based on 1984–2014

Class	Residential area	Agriculture	Stream bed	Fair rangeland	Poor rangeland	Barren land
(a)						
Residential area	0.9838	0.0162	0	0	0	0
Agriculture	0.0127	0.9873	0	0	0	0
Stream bed	0.0008	0.0172	0.9728	0	0.0036	0.0056
Fair rangeland	0	0.0623	0	0.9084	0.0288	0.0005
Poor rangeland	0.0005	0.0232	0	0	0.9704	0.0059
Barren land	0	0.0035	0	0	0	0.9965
(b)						
Residential area	0.9939	0.0061	0	0	0	0
Agriculture	0.0227	0.9773	0	0	0	0
Stream bed	0.0054	0.0379	0.9395	0	0	0.0172
Fair rangeland	0.0012	0.152	0	0.8126	0.0306	0.0036
Poor rangeland	0.0054	0.062	0.0004	0	0.9052	0.027
Barren land	0	0.0042	0	0	0	0.9958

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Table 8 Area of both different land use classes for 2024 and 2034 and land use changes during 2014 to 2024, 2014–2034, and 2024–2034

Year class	2024		2034		2014–2024		2014–2034		2024–2034	
	ha	%	ha	%	ha	%	ha	%	ha	%
Residential area	1261.7	3.98	1530.9	4.83	272.1	0.86	541.3	1.71	269.2	0.85
Agriculture	12,508.3	39.46	13,894.4	43.82	2158.6	6.86	3544.7	11.22	1386.1	4.36
Stream bed	1262.8	3.98	1153.3	3.64	− 74.7	− 0.25	− 184.2	− 0.59	− 109.5	− 0.34
Fair rangeland	4229.8	13.34	4047.5	12.77	− 228.8	− 0.72	− 411.1	− 1.29	− 182.3	− 0.57
Poor rangeland	8981.5	28.33	7245.3	22.85	− 3086.5	− 9.73	− 4822.7	− 15.21	− 1736.2	− 5.48
Barren land	3458.9	10.91	3831.7	12.09	959.2	3.03	1332.0	4.21	372.8	1.18
Total area/changes	31,703	100	31,703	100	6779.9	21.45	10,836.0	34.23	4056.1	12.78

when these values decrease, the probability of LUC will increase (Park et al. 2011). For instance, the negative value of slope percentage (about − 0.10) shows that the most LUC is occurring in the flat areas. The highest negative coefficient was related to the distance to the road (coefficient = − 0.1393) in second period (1984 to 2014) (Table 6). This condition demonstrates development in manmade facilities in order to expand the road network, for example, agricultural land and the residential area had an increasing trend during 1984 to 2014 (Table 4). Some variables that provide facilities for human, e.g., distance to road, distance to the nearby cities, distance to stream (Jokar Arsanjani et al. 2013), and distance to the markets (Verburg et al. 2004), might change LU patterns.

Perception of the natural resources' experts on LUC

Land use changes are mostly related to the socioeconomic drivers and demographic variables in many ecosystems (Grau et al. 2003; Hansen et al. 2002; Meyfroidt et al. 2013). In the current study, a questionnaire method was applied for understanding the perceptions of the experts concerning the impacts of different socioeconomic and

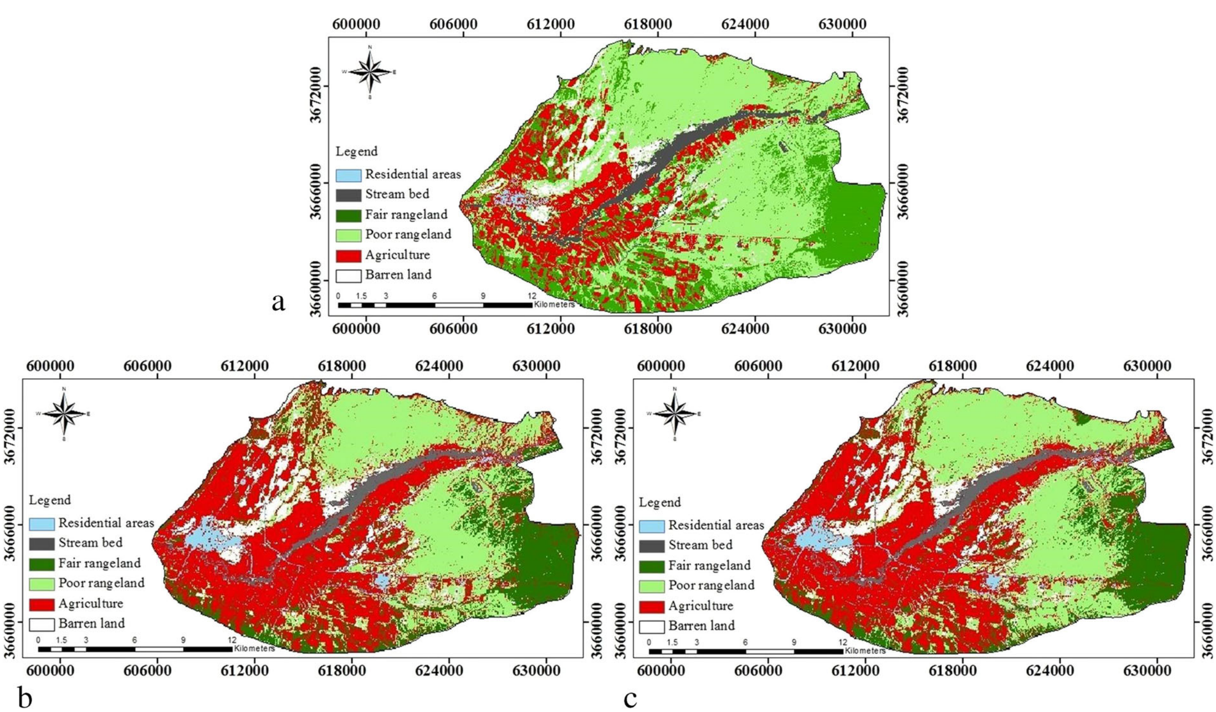

Fig. 8 Simulated land use maps of 2014 (**a**), 2024 (**b**), and 2034 (**c**)

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management factors on LUC. Friedman's analysis showed that there were significant differences between the effects of various factors. The interviewees suggested that factors such as the official laws of the government, economy, weakness of regulatory systems, and the environment have the main impacts on LUC (Table 6). Management factors have been recognized as the main variable influences on the conservation of natural resources (Faramarzi et al. 2010) which indicates that a law must be legislated in order to confront the people who have made a private use of the natural resources (Cooter and Ulen 2016). In the present study, strong law enforcement could be principally considered as an essential task of relevant organizations for controlling the conversion of the natural resources to other land uses, e.g., cropland. Because, in Iran, natural resources are categorized as public lands, which belong to the government. Otherwise, if local people can transfer these lands to either cropland or residential area in any way, they will be changed into private ownership. Although it has been suggested that transferring public rangeland to private ownership can help in improving natural resources of Iran (Faramarzi et al. 2010), it cannot propose a suitable method when the locals want to convert the natural resources to other land uses. Besides, the economic conditions are an important factor which can affect either the conservation, or the degradation of natural resources. A population with a low income does not care for the improvement of natural resources, e.g., afforestation (Barbier and Burgess 2001; Ewers 2006). Furthermore, several environmental factors are also leading to LUC, for example, climate change (Dale 1997; Olesen and Bindi 2002) and topographic variables (Ellickson 1973). There are also some variables such as developmental activities, e.g., infrastructure and industrial projects, as well as population growth, have been considered by experts of natural resources to have less remarkable effects than the previous components.

Various development projects can negatively affect natural resources by converting them to other land uses. Infrastructure projects of the road, water and electric, and also the health services that are mostly provided by the government have also resulted in the loss of natural resources (Lambin et al. 2001). Therefore, developing and improving natural ecosystems should be programmed through the development projects by both the governmental and nongovernmental organizations. Social and cultural factors, as well as the Iran–Iraq War, were stated in the lowest influential variables of LUC. Cultural traits indirectly affected LUC through economic and demographic factors (Meyer and Turner, 1994). The war between Iran and Iraq (1980–1988) has the lowest impacts of land use change considering the study area is located on the border of Iraq. However, the war ended about 28 years ago and it was the main cause of immigration in this area.

Simulating the LUC

Forecasting LUC of the future is essential for better decision making in management, development, and planning of natural resources (Fathizad et al. 2015). The CA-Markov model, which was used in the present study, has a high accuracy in simulating the LUC (Guan et al. 2011; Sang et al. 2011; Yang et al. 2012). The model was initially validated by comparing the simulated and the real land uses for the study area in 2014 with an acceptable accuracy of about 84.25. Afterward, the simulated maps were carried out for forecasting the changes of the next both 10 and 20 years that is years 2024 and 2034. The simulated transition matrix showed that in total about 6780 ha (21.5%) and 10,835 ha (35%) would change during 2014–2024 and 2014–2034, respectively, in the study area (Table 8). The results of Markov matrix of 2024 indicates that barren land, residential area, and agricultural lands were the most stable land classes, i.e., with probabilities of 0.9958, 0.9939, and 0.9773, respectively, for the year 2024 (Table 7b). On the other hand, fair rangeland, poor rangeland, and stream-bed were recognized as the most unstable categories with 0.8126, 0.9052, and 0.9395 probabilities, respectively, in 2024 (Table 7b). These classes were replaced by other land uses mainly agricultural land (Fig. 8). Conversion of rangeland to farmland has been introduced as the main problem of semi-arid rangelands in western Iran (Faramarzi et al. 2010; Fathizad et al. 2015). Grassland areas were from the most dynamic categories which were mainly changed to agriculture in Morelia city in Mexico (López et al. 2001). Human activities and population growth could be the reasons behind the degradation of natural resources (Fathizad et al. 2015; Meyer and Turner 1992). This kind of LUC will generally influence the reduction in biodiversity and in turn leads to global warming (Reis 2008) and soil degradation (Lambin et al. 2001). Management factors, e.g., education of the farmers concerning their ecosystem, especially experimental learning was suggested for improving the rangelands (Faramarzi et al. 2010).

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Conclusion

The SVM analysis for detecting LUC showed that the rangeland area is mostly encroached by agricultural land during 1984–2014. An LR model examined various environmental and human activities influencing LUC. The human driving forces of distance to roads, distance to wells, distances to streams, and distance to residential areas negatively influenced the temporal stability of the land use. On the other hand, the slope, aspect, and elevation that were included in the measured environmental variables had a positive impact on the LU stability. Moreover, the simulated transition matrix extracted from CA-Markov indicated that about 6780 ha and 10,835 ha would change during 2014–2024 and 2014–2034, respectively. The rangeland and barren land had the highest and the lowest stability, respectively.

The perceptions of the experts of natural resources emphasize the importance of management factors in order to prevent the LUC. The factors of the official laws of government, economy, weakness of regulatory systems, and developmental activities, e.g., infrastructure and industrial projects were identified as the main socioeconomic and policy forces behind converting natural ecosystems to other land uses, particularly to cropland. Further factors that were significantly influential on LUC include economy, environment, social elements, and culture.

Overall, the natural ecosystem of rangeland was mostly encroached by cropland in the past. The simulated analysis indicates that the lowest stability area was related to the rangeland area. The management of spatial human activities has been known as the main driving forces of LUC. According to the perceptions of the experts of natural ecosystems, applying the mandatory public regulations will also be required of organizations and agencies that are related to natural resources. All management activities must be specified towards conservation and prevention of LUC.

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