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Modeling Land Use Change Process by Integrating the MLP Neural Network Model in the Central Desert Regions of Iran

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Abstract

To understand and manage the natural and human-made ecosystems and develop long-term planning, it is necessary to model Land Use Change (LUC) and predict future changes. Therefore, we used Landsat satellite imagery, Multilayer Perceptron neural network (MLP) and Markov Chain model (MCA) to monitor the regional changes over 30 years in the central arid regions of Iran. In the present research, the stratified maps derived from the object-oriented algorithm were used to detect and map the changes of land use classes from 1986 to 2016. Furthermore, the land use in 2030 was predicted using Land use Change Modeler (LCM). Slop, contour elevation lines, distance from river, road, afforestation, agricultural lands/gardens, barren lands, poor rangelands, residential lands, rocky land, and sand dunes were considered as factors influencing the changes in the ANN. The Cramer's V coefficient was employed to select appropriate parameters with the highest significant correlation. Our results showed that the sub-models performed well (75-85%). Besides, the highest and lowest accuracy of sub-models were related to the distance from barren lands and distance from residential areas (75.23 and 85.91%, respectively). The results of land use change monitoring from 2016 to 2030 revealed that land use such as forest, residential lands, gardens, and sand dunes would be increased by about 0.11, 1.53, 2.36 and 0.56 %, respectively, by 2030 compared to 2016. On the other, the area of barren land and poor rangeland would be reduced by 2.88 and 1.68 %, respectively. Our results can be used in land change evaluations, environmental studies, and integrated planning and management regarding appropriate and logical use of natural resources and reducing resource degradation.

Keywords: Simulation; Land use change modeler; Spatial variables; Cramer's V test; Yazd-Ardakan plain

1. Introduction

Earth is a natural capital through which development humans form their social life. Environmental threats such as climate change, desertification, deforestation and loss of biodiversity in general, and Land Use/Land Cover (LU/LC) change have attracted the attention of environmental experts in the studies of the recent decade (Kuemmerle *et al*., 2009). LU/LC change is the result of the interaction between social and cultural factors as well as the potential ability of the land. In other words, LU/LC change can be considered as the beginning of humans' dynamic use of natural resources to meet their needs (Oñate-Valdivieso and Sendra, 2010). Land use is an important example of human impact on the environment, and in the last half-century, Land use has witnessed the most changes (Thapa and Murayama, 2011; Gómez *et al*., 2011). The intensity of land use changes in developing countries and arid and semi-arid regions is more than other areas. Land use changes comprise natural and human types and are caused by the irrational exploitation of human resources. However, human-induced changes are taking

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place more rapidly than natural changes due to increased human activities.

To better manage natural and human ecosystems and develop long-term planning, it is crucial to model Land Use Change (LUC) and predict future changes. Over the past two decades, a wide range of LUC models have been developed to help land management and better understand and assess the role of such changes in the performance of the land system (Mas *et al*., 2014). For land-use planning, it is necessary to utilize land-use predictive models (Mas *et al*., 2014), particularly in developing countries where activities such as deforestation, irregular land development, and rangeland degradation have intensified the desertification phenomenon (Amiraslani and Dragovich, 2011). Accordingly, detection and modeling of LUCs via remote sensing data can contribute to a better understanding of how LUCs are made and provide appropriate managing tools for its management (Bakr *et al*., 2010; Coppin *et al*., 2004).

Various land-use predictive models such as GEOMOD, Conversion of Land Use (CLUE), DYNAMIC, Land Change Modeler (LCM), and CA-Markov have been designed and employed by researchers in many studies (Mas *et al*., 2014). Another model for the prediction of land use changes is the Artificial Neural Network model in which the user is to specify the number of parameters such as network architecture, training rate, number of epoch, and the training algorithm. Selecting each of the above parameters has a significant effect on the performance of the method.

Over the recent years, experts have modeled LUCs and used these models such as GEOMOD, CLUE, DIANAMIC, Land Change Modeler (LCM) and CA-Markov to predict LUCs for accuracy and future planning. Researchers have mostly employed Multilayer perceptron neural network model and Markov-Cellular Automata to model and predict LUC processes over different regions. Mas *et al*. (2004) predicted the location of deforestation in tropical areas through GIS and artificial neural distribution networks using Landsat satellite images associated with the years 1974, 1986, and 1991. They used many different location variables such as distance from road and residential areas, forest sections, elevation, slope, and soil type as variables of the neural network. The comparison of the risk maps related to deforestation and real deforestation showed that the prediction map of the former was prepared with two levels of deforestation and lack of deforestation with a 69% accuracy. Maithani *et al.* (2009) devised a model based on artificial neural networks, aiming to predict the spatial variations in Saharanpur city over the period of 2001-1993. In this model, remote sensing data were used to obtain land use changes, GIS was employed to prepare urban land use map, and input variables were utilized to enter ANN with input, hidden, and output layers. The results of the performance evaluation of the model showed that the model was able to predict the growth of urban areas with a general accuracy of 66.56%. Perez-Vega *et al*. (2012) used the Land-Change Model (LCM) to model the degradation and regeneration of Mexican tropical deciduous forest. They modeled the transfer force with the neural network, and sub-models of regeneration, deforestation, and disorder were obtained with an accuracy of 59.2%, 235% and 59.6%, respectively. Fonji and Taff (2014) employed Landsat satellite images over a 15-year period between 1992 and 2007 to evaluate land use changes in the northeast of Latvia. Their results showed that by integrating the satellite data and demographic data, it is possible to efficiently simulate the process of land use change. In 2014, Tudun-Wada *et al*. analyzed the forest cover changes in Nimbia, located in Nigeria, between 1986 and 2010 and forecasted them for the next 21 years using GIS, remote sensing techniques, and the Markov chain model. Their findings showed that the area of forest lands decreased due to human activities such as illegal tree-cutting and agricultural activities. Yang *et al*. (2015) investigated land use change simulations using ANA-CA model and land-surface pattern indicators in the Changping region, China. Based on the land use maps in 1988 and 1998, the land use map of 2008 was simulated using the proposed model. The actual land use map of 2008 was compared with the simulated map obtained from the artificial neural network automata model. The comparison showed that the proposed model had a good performance in simulating land use changes in the studied area.

The study area of the current research is Yazd-Ardakan plain, Iran, which has undergone many changes over the recent years, including urban population growth, physical expansion of urban settlements, and industrial development. Accordingly, providing human needs requires extensive use of natural resources due to population growth, and the demand for land resources in both agricultural and non-agricultural sectors will be increased. Undoubtedly, unplanned development in this plain will result in the loss of its rare and vital resources, which are fertile soils and water resources. Given the foregoing problems, it is necessary to understand how to use the land and determine the spatial patterns of land use and the future land covers in the studied area. Therefore, the main purpose of this study was to investigate LUC over a period of 30 years (1986-2016) using Landsat satellite images and simulate the changes using MLP neural network and MCA up to 2030 in the region. Furthermore, the most important questions answered in this study were: (i) how much LUC occurred between 1986 and 2016?, (ii) In what areas of the plain do these changes occur and which spatial area was affected??, and (iii) in 2030, what changes will occur in the land use of the study area??

2. Maretials and Methods

2.1. Study area

With maximum and minimum altitudes of 2684 and 997 m, respectively, Yazd-Ardakan plain is located in the central plateau of Iran with a total area of 482900 hectares. The rainfall in this region is low and irregular (the mean rainfall is 118 mm per year) and its evaporation rate is between 2200 and 3200 mm per year (Fathizad *et al*., Hakimzadeh and Vahdati, 2018). In the middle section of the Yazd-Ardakan plain, which is the most important sand dunes north of Yazd and Rastaq area (Fig. 1).

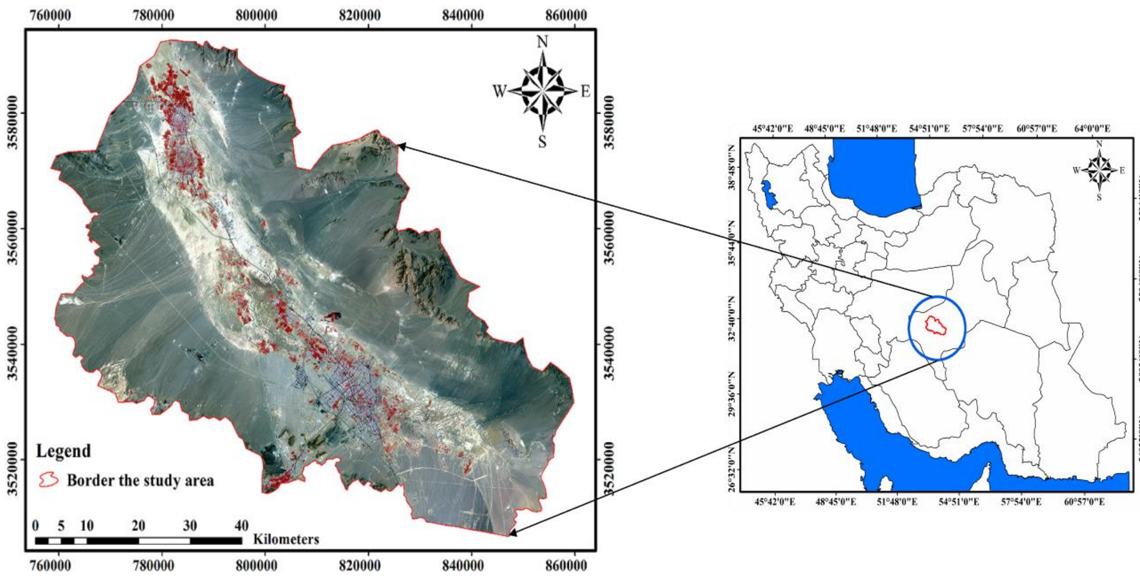


Fig. 1. Location of the study area in Iran and Yazd province

2.2. Data and image processing

Figure 2 shows the research process flowchart. In this study, Landsat satellite images (MSS) of 1986, Landsat (TM) of 1999, Landsat (ETM) of 2010 and Landsat 8 (OLI sensor) of 2016 were used.Landsat images published by the US Geological Survey (USGS) were downloaded from the EarthExplorer website (http://earthexplorer.usgs.gov). The land use map was prepared and extracted after performing geometric and radiometric corrections in the dark subtraction method (Chavez, 1988) on the satellite image and. Then Object-oriented supervised classification method was used to prepare and extract land use maps of satellite images and 7 land uses class (forestry, agricultural area and gardens, barren lands, poor rangeland, residential lands, rocky lands, and sand dunes) were extracted.

To investigate the accuracy of the classification, a comparison was drawn between existing land use maps and field visits. In this way, the reference or ground truth map was prepared from all parts of the study area using other such methods as field visit. In this study, a random sampling method was used to assess the accuracy of the obtained maps. The samples were randomly selected and recorded from each land use group based on the land use map and local visits of the study area by use of the GPS in the polygons mods (due to the large area of each land use). To evaluate the accuracy of image classification based the training site samples, statistical indices such as overall accuracy, kappa coefficient, user’s accuracy, and producer’s accuracy were calculated using the error matrix (Lu, 2004).

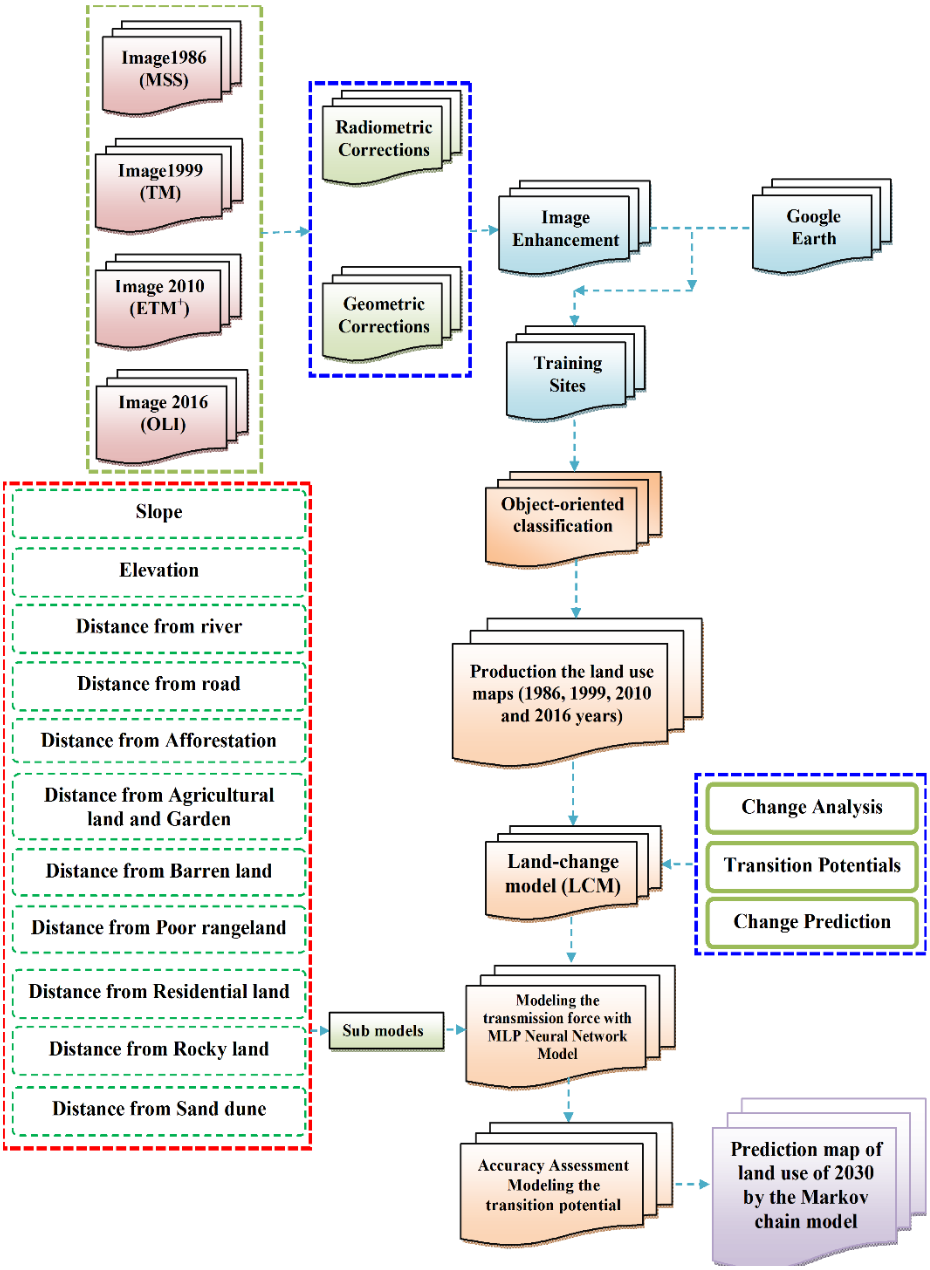


Fig. 2. Research process flowchart

2.3. Object-oriented classification

Object-oriented classification is a process that relates land cover classes of visual objects (Blaschke and Lang, 2006; Yan, 2003). In this method, the basis of analyzes instead of pixels is a set of pixels called image phenomena that result from the segmentation process. After Segmentation, classification is done based on training sites samples or threshold definition based on fuzzy logic (Rafieyan *et al*., 2011). In this process, pixels with different membership degrees are categorized in more than one class, and classification is performed based on the degree of membership for each class according to the nearest neighbor's algorithm.

2.4. Training sample Objects

Object-oriented classification further requires training sites like the pixel-based classification. For both classification methods (pixel-based and object-oriented), it is necessary to select a class of educational samples as the spectral specifications of the classes (Wang *et al*., 2004). In the Idrisi Selva software (Simbangala *et al*., 2015), the range of training sites is determined by sample pictorial objects. Therefore, we selected a sample of the classes which were appropriate and proportional to the frequency and dispersion of each class in the region and based on field information. The training sites required for classification in the Idrisi Selva software environment are implemented on the surface of the images, and their corresponding pictorial objects are chosen as educational sample objects for classification classes.

2.5. LUC modeling

Land-change model (LCM) is a software tool for creating an ecologically sustainable development, designed to understand and identify the LCCs and the conservation and environmental requirements caused by these changes. This software is a vertical application program in the IDRISI software system. This model has a good performance in simulating the complex process through combining the capabilities of the Markov chain model, the Multi-Layer Perceptron (MLP) neural network approach with error backpropagation training, logistic regression, and Multi-Objective Land Allocation (MOLA) (Mas *et al*., 2014; Fathizad *et al.*, 2018; Eastman, 2009). The modeling of LCCs is carried out over four main stages using the land-change model:

1. Change analysis
2. Transition potentials
3. Change prediction
4. Accuracy assessment

The classified maps of 1986, 1999, 2010, and 2016 were utilized to understand the manner of the changes in the region over the 30 years and determine which classes were expanded and which ones were reduced. By comparing these maps, the percentage of change in each class was determined and mapped. Using the provided LU/LC map for each period, the area percentage of the LC class was calculated in the study area. The percentage of each class was further compared to the whole region to understand the changes occurring from 1986 to 2016. To model the transmission potential of LU/LC, the transfer force from one user to another was modeled according to the desired variables. This refers to the level of potential each image pixel has for changing from one user to another. The output from this section will be a force map for each change. To select models with the highest accuracy, it is essential to run the model several times with different scenarios. The sub-models selected in this study were: 1- afforestation on residential land, 2- agricultural lands and gardens to residential lands. 3- poor rangelands to residential lands, 4- barren lands to residential lands, 5- rocky lands to residential lands, and 6- sand dunes to residential areas.

Eleven variables were introduced to model the transfer potential to the land-change modeler. Variables used in this study were employed in most LUC modeling studies (Hamdy *et al*., 2016). These variables (Figure 3) included: 1- slope (%), 2- elevation (m), 3- distance from the river (m), 4- distance from the road (m), 5- distance from afforestation (m), 6- distance from agricultural land and garden (m), 7- distance from barren land (m), 8- distance from poor rangeland (m), 9- distance from residential land (m), 10- distance from rocky land (m), and 11- distance from sand dune (m).

The main steps of the approach are:

1- Determining the role of variables affecting the changes through calculating overall Cramer’s V coefficient

2- Preparation of transition potential maps based on the LU/LC maps of the previous period and its effective variables using MLP-ANN

3. Providing the future LU/LC map based on the modeled changes obtained from the Markov chain analysis, transition potential maps, and limiting and stimulating variables

First, the role and ability of each spatial variation were evaluated in predicting possible Lu/LC changes by calculating Cramer's V coefficient. These changes were used to determine the correlation between two nominal variables, or one nominal and one ordinal variable. This value of this coefficient is up to 1 and calculated using equation 1:

$$V = \sqrt{\frac{x^2}{N * Min(k-1, l-1)}} \tag{1}$$

Where X^2 is the Chi-Score statistics, N is the number of samples, and k and l are the number of rows and columns in the table.

In general, values closer to and more than 0.4 are considered as appropriate for a variable and values less than 0.15 indicate lower prediction ability (Eastman, 2009).

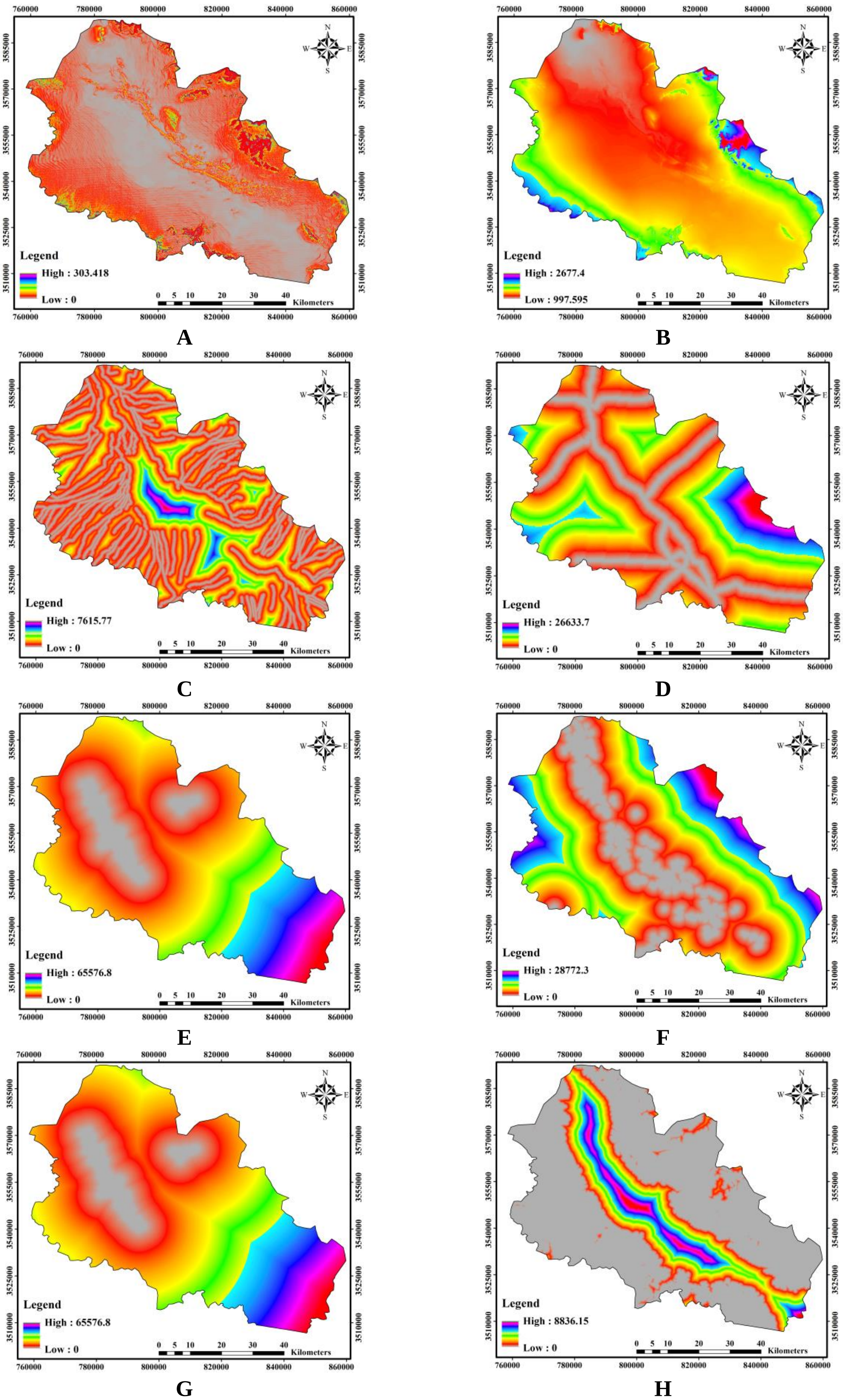
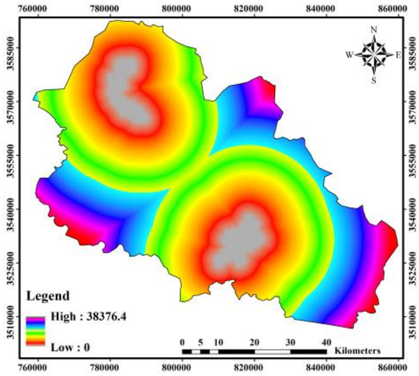


Fig. 3. The variable maps used in this research: A: Slope (%); B: Elevation (m); C: Distance from river (m); D: Distance from road (m); E: Distance from Afforestation; F: Distance from Agricultural land and Garden; G: Distance from Barren land; H: Distance from Poor rangeland; I: Distance from Residential land; J: Distance from Rocky land; K: Distance from Sand dune



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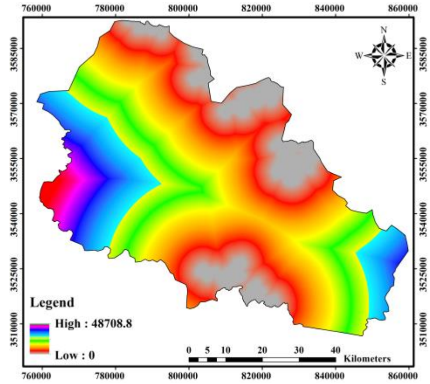

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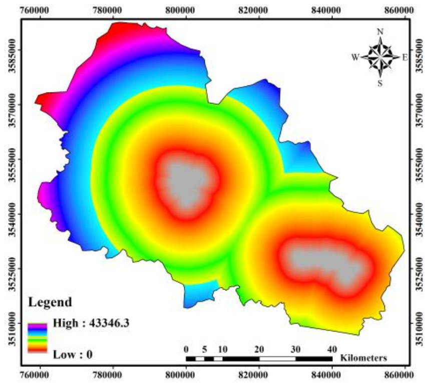

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Continued Fig. 3. The variable maps used in this research: A: Slope (%); B: Elevation (m); C: Distance from river (m); D: Distance from road (m); E: Distance from Afforestation; F: Distance from Agricultural land and Garden; G: Distance from Barren land; H: Distance from Poor rangeland; I: Distance from Residential land; J: Distance from Rocky land; K: Distance from Sand dune

There are several methods for modeling the transition potential, and previous studies have shown that ANN is the strongest method among them (Eastman, 2006). ANN is an information processing pattern inspired by the human brain (Mas *et al*., 2004). This network is a mathematical structure that can represent desired non-linear compounds to connect the inputs and outputs of each system. It is trained with the existing data during the learning process and is utilized for future prediction. ANN consists of neural cells called neurons and communication units called axons. Neurons of ANN are very simple forms of biological neurons. Networks consisting of these neurons have a higher speed but less potential compared to biological neurons.

In the next step, the probability of changing each land-use to another use was calculated using the Markov chain (Haibo *et al*., 2011). The Markov chain is a sequence of random processes where the outcome of any process at any time depends only on the outcome of the process at its adjacent times (Norris, 1997). Markov-based models are capable of collecting complex information in the form of a state change matrix. Accordingly, complicated systems with unidentifiable underlying processes can be modeled using the Markov chain (Balzter, 2000). In the Markov analysis, cover classes are used as the chain states. In this analysis, two raster maps are employed as the model inputs. The time interval between the two images and the simulation time interval are further considered in the model. The output of the model also includes the probabilities of the state transformation, transition area matrix of each class, and the conditional probabilities images for converting different uses (Gilks, 1996). The classified images of 1986, 1999, 2010, and 2016 were used as land cover maps for modeling. Using the land cover maps obtained for each period, the state transition matrix of the land cover classes was obtained between every two periods. The cover maps of 1986 and 1999 were employed to model 2010 using a hard prediction model (Khoi and Murayama, 2010). The land cover maps of 2010 and 2016 were utilized to predict the land use change in 2030.

3. Results and Discussion

Land use maps of the Yazd-Ardakan plain pertaining to 1986, 1999, 2010, and 2016 were generated using the object-oriented categorization method in seven land use categories (Figure 4). The statistical parameters of the producer and user accuracy, overall accuracy, and kappa coefficient were further extracted (Tables 1 and 2).

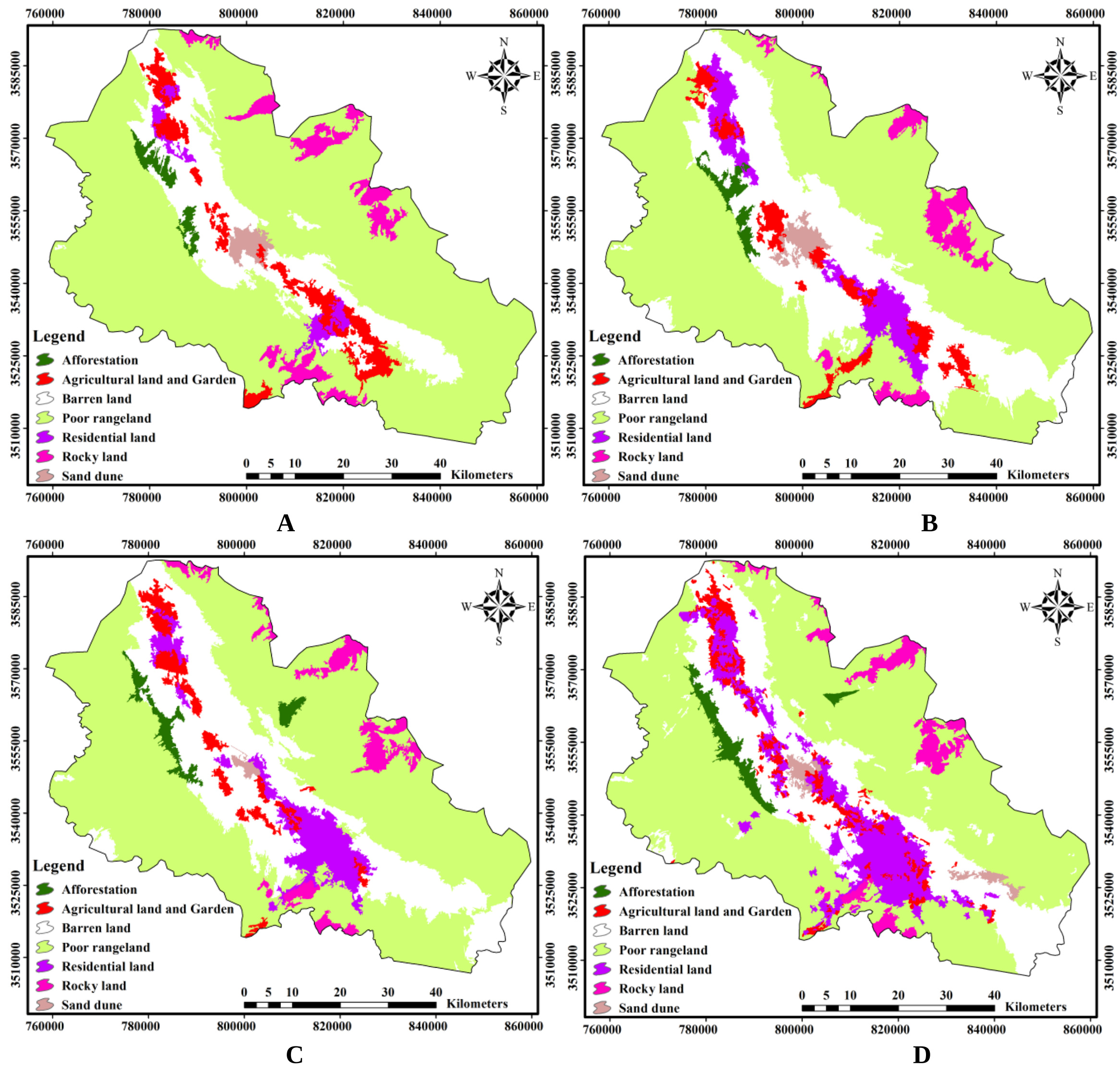

Fig. 4. The land use map of desert area of Yazd-Ardakan plain (A: 1986 B: 1999 C: 2010 D: 2016)

Table 1 Statistical characteristics of producer and user's accuracy to classify the images of 1986, 1999, 2010 and 2016

Year	1986		1999		2010		2016	
Class	Producer's accuracy	User' accuracy	Producer's accuracy	Producer's accuracy	Producer's accuracy	User' accuracy	Producer's accuracy	User' accuracy
Afforestation	73.9	32.4	64.9	35.0	49.1	33.8	81.7	43.9
Agriculture land and Garden	99.6	100.0	97.9	99.1	96.9	99.1	96.8	98.1
Barren land	84.1	99.7	93.7	98.7	88.5	89.5	88.3	94.5
Poor rangeland	97.4	93.3	96.0	94.5	91.3	89.8	89.8	95.0
Residential land	84.5	36.4	93.5	92.6	95.7	89.3	95.5	93.3
Rocky land	86.6	98.5	93.3	98.0	93.4	98.8	96.0	94.0
Sand dune	27.9	28.0	98.2	84.5	76.1	88.0	92.3	77.5

Table 2 The evaluation of classification accuracy for the derived user maps to classify the images of 1986, 1999, 2010 and 2016

Year	Total accuracy (%)	Kappa coefficient (%)
1986	69.74	90.26
1999	86.05	94.64
2010	84.04	91.29
2016	85.18	91.77

After analyzing the results of Table 1, several important conclusions were drawn: firstly, it was found that the agriculture class and the gardens were obtained with high producer and user accuracy of over 96%, indicating the high spectral separation capability of this class. Secondly, the lowest accuracy of the producer and user (27.9% and 28%, respectively, in 1986) was observed to be related to the sand dune class. The classification results are presented in Table 2 using the object-oriented method for the considered years. According to this table, the year 1999 with total accuracy and kappa coefficients of 86% and 94% had the highest accuracy in classifying land use in Yazd-Ardakan plain.

Kappa and overall accuracy, particularly in pixel-based methods, are influenced by inputs or educational samples. Moreover, if the training samples of each Garber are adequately designed and distributed to represent the entire image, obtain the correctness and high precision is expected. For instance, Whiteside and Ahmad (2005), Qian *et al*. (2007), Bello *et al*. (2017), Fathizad *et al*. (2018) and many researchers reported high Kappa coefficients and accuracy in their study areas.

The results showed the efficiency and reliability of the object-oriented method for the extraction of the LU/LC maps (Kappa coefficient above 90% for all studied years). However, the limitations in selecting the optimal fragmentation parameters and the potential error in fragmentation are considered as the problems associated with fragmentation and object-oriented method. Segmentation errors can cause error sin classification (deletion or addition), thereby posing a serious challenge regarding the use of object-oriented method.

3.1. Analyzing and highlighting the changes

After preparing the LU/LC maps for 1986, 1999, 2010, and 2016, the areas of seven LU/LC categories were obtained. For a better comparison of the changes occurring in these four periods, they are shown in Figure 5. As observed, during this period (1986-2016), the areas of agricultural lands and free rangelands of the region were 5696 and 579888 hectares (reduced by -1.81 and 12.12%); however, barren lands, residential lands, and sand dunes were 2419, 35454 and 457 hectares (5.16, 7.34, and 0.99%increase, respectively). In other words, after 30 years, the most changes were related to poor rangelands and residential lands. A remarkable point associated with this region is the implementation of the forestry plan to deal with desertification. Forested lands increased from 3367 hectares (0.7%) over the 30-year period. The trend of changes in land use revealed a general trend of destruction in the region caused by replacing the agriculture land and poor pasture by land use and residential areas as well as sand dunes. Reduction in the extent of poor rangeland coverage and the increasing trend of other uses implied a general deterioration in the region. This indicates increased population and human pressure in the study area.

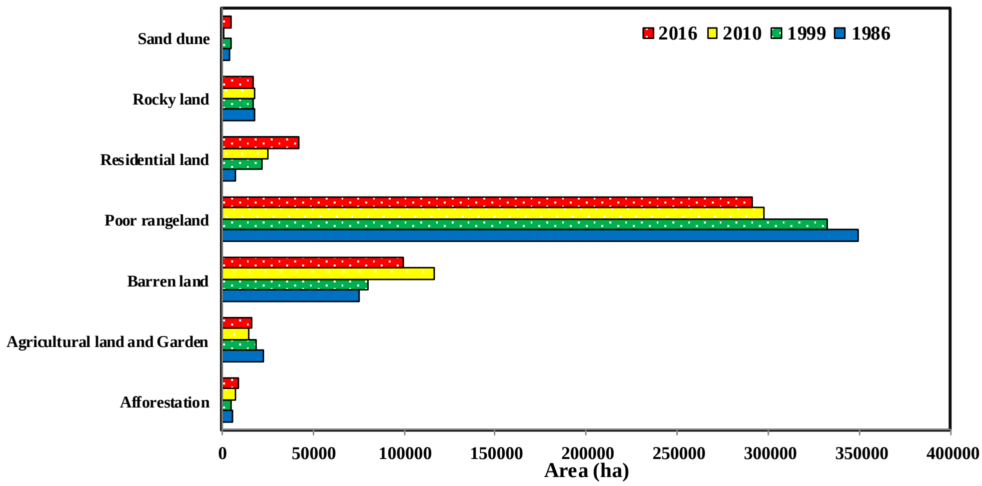

Fig. 5. Graph area of land use classes in the 1986, 1999, 2010, and 2016 years

3.2. Modeling of the land use transition potential

At this stage of LUC modeling in Yazd-Ardakan plain, the potential for transfer from one land use to another was modeled according to the variables introduced to the land-change modeler. In other words, in this stage, the potential of each image pixel was converted to other land uses.

The maps of the sub-models employed in this study are presented in Figure 6. The transition potential of LU/LC was modeled via MLP-ANN method. The transition potential modeling was evaluated using the accuracy factor (Table 3). The highest accuracy of sub-models was related to the distance from barren lands (85.91%), and the lowest belonged to the distance from the residential area (75.23%), which represents acceptable accuracy all sub-models. The total accuracy of the MLP-ANN method was about 85%, indicating a good accuracy for modeling (Arekhi, 2014). Table 4 shows the Cramer's coefficients which show the relationship between variables and land cover classes calculated for each variable. As can be seen, the highest and lowest values of the Cramer's coefficients pertained to slope (0.0425) and distance from poor rangeland (0.4000), respectively.

Table 3 Results of the evaluation of the accuracy of the models created from different scenarios

Scenario	1	2	3	4	5	6	7	8	9	10	11	Total
Accuracy (%)	85.14	85.21	85.21	85.21	82.96	75.38	85.91	83.45	75.23	85.39	83.88	85.21

Table 4 Relationship between variables and land cover classes

Class / Sub model	Afforestation	Agricultural land and garden	Barren land	Poor rangeland	Residential land	Rocky land	Sand dune	Overall Cramer's V
Slope	0.0311	0.0048	0.0472	0.0593	0.0505	0.0632	0.0233	0.0425
Elevation	0.0796	0.1527	0.2294	0.2668	0.1247	0.2294	0.0595	0.1668
Distance from river	0.0486	0.1255	0.0953	0.3271	0.2955	0.1329	0.3457	0.2168
Distance from road	0.1496	0.1529	0.2212	0.3596	0.3698	0.1568	0.0852	0.2199
Distance from afforestation	0.6113	0.1172	0.2643	0.2098	0.2649	0.2403	0.1509	0.3194
Distance from agricultural land and Garden	0.1573	0.4461	0.4312	0.6593	0.4389	0.2845	0.1081	0.3654
Distance from barren land	0.6113	0.1172	0.2643	0.2098	0.2649	0.2403	0.1509	0.3149
Distance from poor rangeland	0.1863	0.3096	0.6048	0.8291	0.4550	0.2061	0.2055	0.4000
Distance from residential land	0.1004	0.2101	0.2700	0.4770	0.5126	0.0949	0.1476	0.2799
Distance from rocky land	0.2881	0.2132	0.3923	0.4175	0.1551	0.6980	0.2274	0.3781
Distance from sand dune	0.1064	0.1167	0.3520	0.3494	0.1387	0.2283	0.5856	0.3103

Figure 6 shows the land use transition potential map obtained from the MLP-ANN model. The potential change probability was from 0 to nearly 100%. In this map, moving from the center of the study area towards the corners, changes are observed in land use while the changes are zero in the center. The gray color indicates that the potential change probability is minimum.

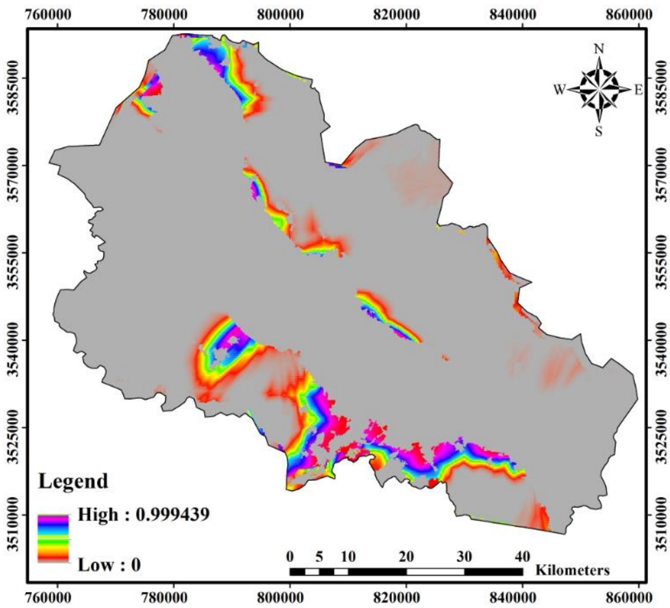

Fig. 6. The land use transition potential map obtained from the MLP-ANN model

Results of Cramer's correlation coefficient showed that the most important independent variables accounting for the changes in the Yazd-Ardakan plain of Yazd province with a Cramer's coefficient above 0.30 were distance from: poor rangelands, rocky lands, agricultural lands and gardens, afforestation, barren lands, and sand dunes.

The evaluation of transition force modeling using Multi-layer perceptron neural network showed high accuracy in most of the sub-models (75-85%). Similarly, Pereza-Vega *et al.* (2012) used this method to model the transition power. However, the accuracy of their model was lower because certain variables were not available on appropriate scales in their study, hence not studied.

3.3. Results of Markov chain analysis

Table 5 shows the results obtained from the prediction of land use changes using the state transition matrix of the first period (1986 to 1999) for 2010 used to evaluate the Markov model using the available land use map for this year. In this table, the sum of each column represents the area of each class in 2010. Table 5 also shows the evaluation results of the prediction accuracy through the MCA using LU/LC maps of 2010. According to Table 6, there existed differences between various classes. This difference magnitudewas generally less than 1%, indicating the usefulness of the Markov model and its ability for simulating land use changes (Baker, 1989).

Table 5. Prediction of the area of different land use (ha) for 2010 using MCA and transition matrix for the period of 1986-1999 (ha)

Class	Afforestation	Agricultural land and Garden	Barren land	Poor rangeland	Residential land	Rocky land	Sand dune	Total
Afforestation	6600	415	101	500	48	0	0	7664
Agricultural land and garden	164	14106	0	380	0	0	68	14718
Barren land	79	0	116505	1435	14	74	0	118107
Poor rangeland	784	538	675	295331	893	20	78	298319
Residential land	0	0	0	83	24484	0	65	24632
Rocky land	102	0	0	0	0	17846	78	18026
Sand dune	90	77	0	176	22	0	1069	1434
Total	7819	15136	117281	297905	25461	17940	1358	482900

Table 6. Comparison of different areas of land use predicted by the Markov model with actual land use areas

Class	Afforestation	Agricultural land and garden	Barren land	Poor rangeland	Residential land	Rocky land	Sand dune	Total
Prediction for 2010 (ha)	7816	15097	116964	298166	25366	18136	1355	482900
Area in 2010 map (ha)	7819	15136	117281	297905	25461	17940	1358	482900
Area differences (ha)	-2.53	-39.05	-316.80	260.86	-94.61	195.61	-3.08	0
Differences (%)	-0.03	-0.26	-0.27	0.09	-0.37	1.08	-0.23	0.00

To validate the model, the simulated land use map of 2010 was compared with the actual map obtained from the classification of satellite images in the same year. Kappa coefficient was 81% regarding the simulation of land use changes in the desert area of Yazd-Ardakan plain (Figure 7).

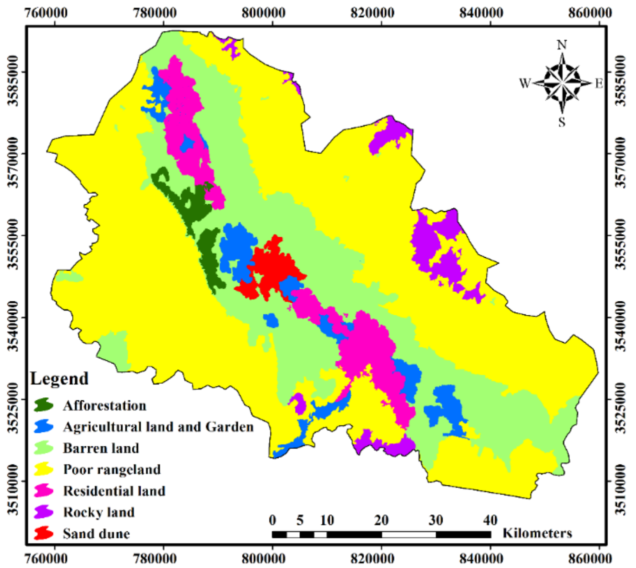

Fig. 7. Map of 2010 resulted from validation using Markov Model

If the process of future changes is considered as equivalent to the current changes, the probability matrix derived from the maps of the years 2010 and 2016 can be calculated using the Markov chain to simulate changes in the next 14 years (2030) (Table 7). Furthermore, Figures 8 and 9 show the map obtained from the prediction via the Markov chain and the area of land use in 2030.

Table 7. Matrix of Probability of LUC in Statistical Period of 2016-2030 Using Markov Chain Model

Class	Afforestation	Agricultural land and garden	Barren land	Poor rangeland	Residential land	Rocky land	Sand dune
Afforestation	0.80	0.05	0.03	0.01	0.01	0.01	0.09
Agricultural land and garden	0.04	0.55	0.02	0.23	0.02	0.00	0.14
Barren land	0.55	0.01	0.41	0.00	0.00	0.00	0.03
Poor rangeland	0.05	0.43	0.01	0.34	0.01	0.00	0.16
Residential land	0.02	0.14	0.00	0.25	0.47	0.00	0.12
Rocky land	0.54	0.04	0.01	0.01	0.01	0.14	0.25
Sand dune	0.25	0.17	0.00	0.06	0.04	0.03	0.43

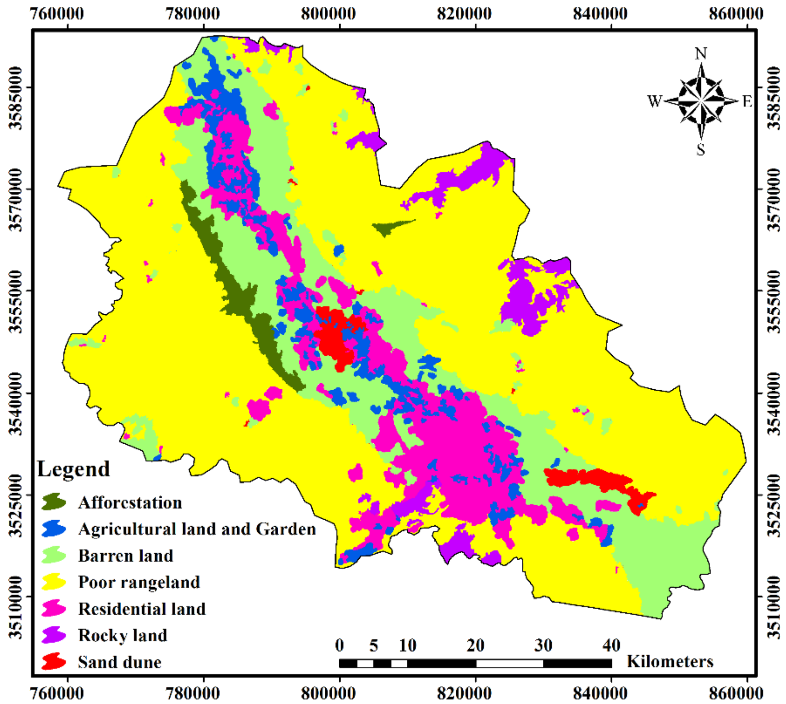

Fig. 8. Prediction map of land use of 2030 by the Markov chain model

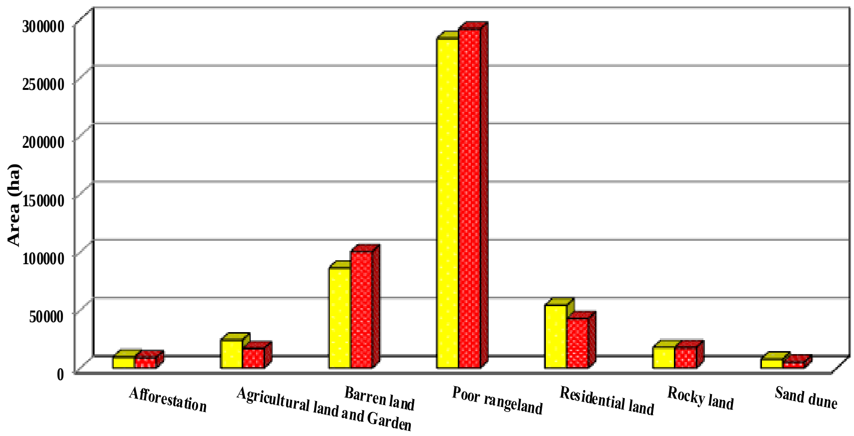

Fig. 9. Graph of land use area of 2030 Yazd-Ardakan Plain

Based on the results of modeling, the area obtained from each application in 2030 showed that by 2030, the land use area of forests, residential land and gardens, and sand dunes would increase by approximately 544, 7365, 11398 and 2681 hectares, respectively, compared to 2016. Also, the area of barren lands and poor rangelands would decrease by 139921 and 8099 hectares, respectively. Rocky lands were almost constant. The reason for the reduction in the barren lands and poor rangelands is the increase in the amount of agricultural and residential lands, indicating an increase in population and human pressure in the studied area. This shift in land use and the increase in human pressure on agricultural lands and pastures are currently called tectogenetic desertification.

4. Conclusion

The present study presents an empirical model between the dependent variable (LUC variables) and the independent variable (descriptor of the changes).ANN was employed due to the presence of nonlinear relationships between variables, and the network was trained using the previous year's data. Moreover, the most important assumption in this modeling (considering the experimental nature) was that the nature of development and changes would be the same over time; in other words, pervious changes can predict future changes based on historical scenarios. The maps simulated in this study can be good guides for managers and planners in the natural resources sectors. The simulated LU maps can be further utilized as a warning system for outcomes and the impact of future LUC. The results obtained from studying the LUC process can be used in land evaluation, environmental studies, and integrated planning and management so as to appropriately and logically utilize natural resources and reduce resource degradation**.**

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