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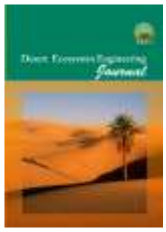

Analysis and Prediction of Land Use Change in Yazd-Ardakan Plain

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Abstract

Land use maps provide a large fragment of the information required by planners for basic decision-making. Detection of changes as well as prediction of land use changes play a critical role in providing a general insight into better management and conservation of natural resources. This study aimed to simulate land use and land changes using the automatic cell model and Markov Chain in a 30-year period (1986-2016) in the Yazd-Ardakan plain, Iran. In this regard, the object-oriented classification technique, Landsat satellite images (MSS) of 1986, Landsat (TM) of 1999, Landsat (ETM^+) of 2010, and Landsat 8 (OLI) of 2016 were employed to create the land use maps, including seven land use types (afforestation, agricultural land and garden, barren land, poor rangeland, residential land, rocky land and sand dune). To validate the model accuracy, the simulated land use map of 2010 was compared to the actual map obtained by mapping of the satellite image of the same year. The Kappa coefficient obtained showed that the CA-Markov chain model had a high ability (81%) in simulation of land use changes in the Yazd-Ardakan plain. Based on the results, it is likely that, at the interval of 2016-2030, 80% of afforestation land, 55% of agricultural land and gardens, 41% of barren land, 34% of poor rangeland, 47% of residential land, 43% of sand dune, will be 93% unchanged. Additionally, from 2016 to 2030, the conversion of barren lands to afforestation (55%) as well as poor rangeland to agricultural lands and gardens (43%) is highly probable. Based on the area obtained from each land use in 2030 compared to 2016, the areas of afforestation, agricultural land and gardens, residential land and sand dune will increase, and the barren land and poor rangeland will decline. The excessive growth of the population and the increasing need for food and new energy sources as well as the need for residential areas lead to unconventional and extreme exploitation of the natural resources of the Yazd-Ardakan plain.

Keywords: Land use, Landsat satellite imagery, Object-oriented classification, CA-Markov, Yazd-Ardakan plain.

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1. Introduction

Desertification is recognized as the main threat of sustainable development, which is defined as the destruction of lands occurred in the extent range of climate such as in arid and semi-arid to dry-wet areas, due to various effects of destructive human actions (UNEP[5], 1991). In this regard, land use change is recognized as important processes in evaluation of land susceptibility to desertification. Land use is special human use of the earth that will change over time. In arid and semi-arid regions, these changes typically increase and accelerate desertification processes. Land use change is one of the obvious examples of human impacts on the environment, and in the last half of the century, land use has seen considerable changes (Thapa & Murayama, 2011). Given the increase of land use changes as well as the necessity of managers and decision-makers to be aware of how the changes occured, we must seek and use a new approach such as remedy to detect changes and determine the trend of changes over time (Parker et al., 2003). In addition, simulation and modeling of land use changes are also vital tools to be aware of the quantity and quality of future changes. Therefore, detection and prediction of changes are required for conservation of an ecosystem, especially despite the rapid changes of the new world.

The spatial prediction of land use changes can be determined by the empirical models based on the extrapolation of change patterns occurred in the past (Lambin, 1997; Parker et al., 2003). Land use changes prediction models are essential to plan for the sustainable use of land types (Kamusoko et al., 2009; Sohl & Claggett, 2013; Mas et al., 2014). This issue is especially required in developing countries, where activities such as deforestation, irregular expansion of agricultural land and conversion of rangelands to other land uses result in intensification of desertification processes (Amiraslani & Dragovich, 2011; Upadhyay et al., 2006). The Land use and Land cover (LUCC) model are fundamentally different from their pros and cons. Therefore, calibration of the LUCC model is very difficult as reported by Verburg et al. (2004), Gilmore Pontius and Chen (2006), and Luo et al. (2010). Models of land use change can be categorized into three main groups, including: empirical estimation models, dynamic simulation models, and rule-based simulation models (see more details in He & Lo, 2007). Cellular Automata (CA)–Markov model is recognized as a combination model to combine the Markov chain model (from the category of empirical estimation models) and the cellular automata model (from the category of dynamic simulation models) (López et al., 2001; Baysal, 2013; Behera et al., 2012). Although the Markov chain model can successfully detect the rate of land use changes regarding their spatial distribution, it cannot describe the number of land use changes. Therefore, the combination of the models is recommended to overcome this challenge (Sang et al., 2011; Houet & Hubert-Moy, 2006).

This model simulates land use changes for future lifespan by adding spatial contiguity to the random CA-Markov chain model. CA models can produce large-scale patterns by small-scale local processes (Verburg et al., 2004). Compared to the other models that are commonly used in LULC (land use land cover) change studies, the CA-Markov model has its own advantages and limitations. A key advantage of the CA-Markov model is its easy structure to calibrate and its power to simulate different land use patterns as well as simulate complex patterns (Eastman, 2003; Memarian et al., 2012). This advantage can result in a more comprehensive simulation, compared to other LULC change models. Furthermore, the CA-Markov model has some limitations, including inability to consider social dynamics, human and economic impacts on the simulation, which can be considered later, especially in agent-based modeling systems (Arsanjani et al., 2011). Failure to combine the new changes leads to underestimation of CA-Markov's prediction, since this model uses a uniform transfer rule during the simulation period to predict longer periods (Samat, 2009)

Therefore, simulation of land use changes can be determined by expansion rate of changes and destruction of resources (Brown

1. United Nation Environmental Program

et al., 2000; Hathout, 2000; Jenerette & Wu, 2001). Mubea et al. (2010) studied the use of the CV-Markov chain model to predict land cover changes in the Nakuru region of Kenya. The results of this study indicated an increase in urban land use from 19.04 km^2 in 1973 to 37.31 km^2 in 2000. Additionally, the results of the Markov model showed that for 2005, water use had the highest stability (68.44%), while the least stability (0.6%) was observed in land use without covering. Al-Bakri et al. (2014) modeled land use changes in Oman using Landsat imagery and the Markov model for 2043. The results of this study indicated conversion of natural use to residential use. The study results suggested that modeling and evaluation of land use changes could be used as an important tool to manage plans and land use policies.

Tudun-Wada1 et al. (2014) analyzed Nimbia Nigeria's forest cover changes in 1986 and 2010 and predicted the next 21 years using the GIS, remote sensing and CV-Markov modeling techniques. The results showed that the area of the forest lands was decreasing due to human activities such as illegal cutting of trees and agricultural activities. In another research, Fonji and Taff (2014) used Landsat imagery in a 15-year period from 1992 to 2007 to evaluate land use changes in northeastern Latvia. Their results indicated that the land use changes process could be simulated by integration of satellite data and demographic information.

The main cause of desertification in different regions is due to several different processes. In some areas, degradation of vegetation and in other areas, the decline of the groundwater table are the major causes of desertification. In most studies, human intervention has been introduced in the form of degradation of vegetation due to excessive grazing of livestock as a major cause of desertification (Hill et al., 1998; Puigdefabregas & Mendizabal, 1998). While grazing in the Yazd-Ardakan plain is not a challenge, the main cause of land degradation in the region is the uncontrolled development of urbanization and the conversion and change of agricultural land and garden to residential areas. Undoubtedly, in the meantime, the land use in this region has been affected by some changes that can be a considerable danger for the inhabitants of the region. The aim of this study was to investigate land use changes in a 30-year period (1986-2016) using Landsat satellite imagery and simulation of changes using a CA model and Markov chain by the year 2030 in the Yazd-Ardakan plain Iran. Therefore, in the current study, we use the Markov chain and CA-Markov model to predict and provide a map of prediction of changes in different land use patterns. Indeed, the ability of the object-oriented classification method to examine the process of changes is another important aspect of innovation in this research.

2. Materials and Methods

2.1. Study area

Yazd-Ardakan plain is a closed basin located in the central part of Iranian plateau and is a part of Yazd province. Yazd-Ardakan plain with a total area of 482900 ha, located in the central part of Yazd province (extended from 53° 08' 36" to 54° 85' 32" E to 32' 21° 31 to 32° 61' 02" N). The range of altitude varied between 997 (min) and 2684 (max) meters. The Yazd-Ardakan plain can also be considered the Shirkou-Sinkoukh pond. The precipitation in this region is low and irregular (average rainfall is 118 mm/y), and its evaporation rate is between 2200 and 3200 mm/y. This plain contains several cities, including Ardakan, Meybod, Ashkezar, Mehriz and Yazd County (Fig. 1).

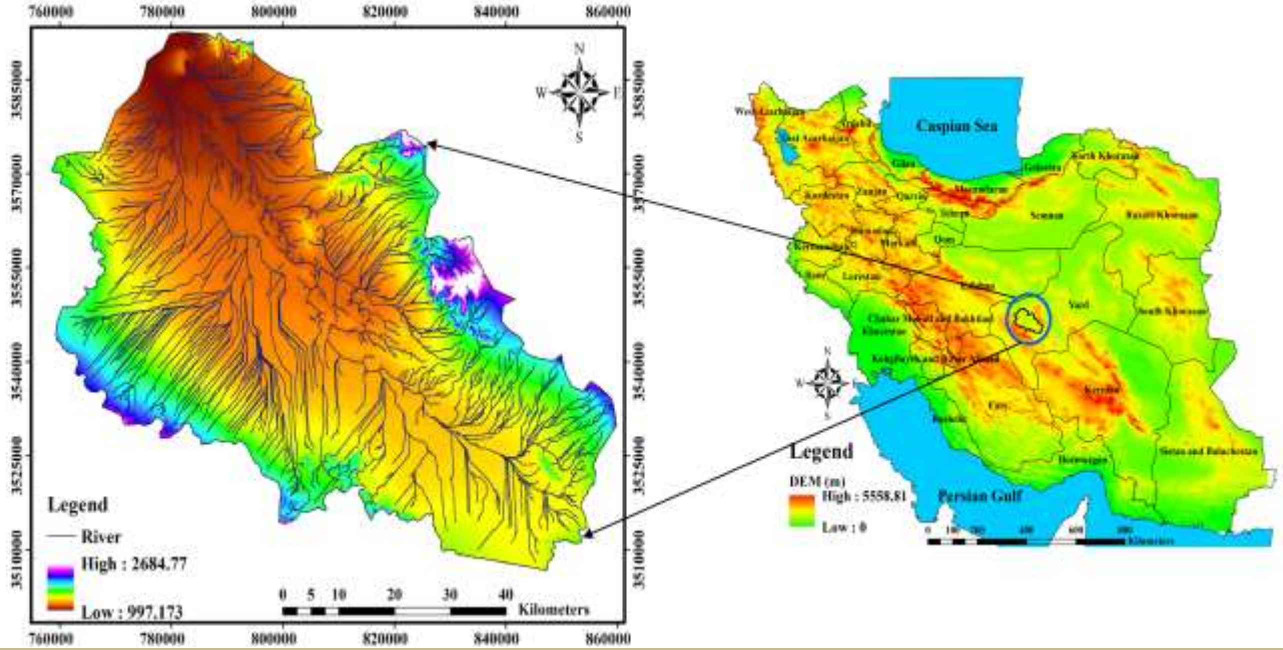


Figure 1: Location of the study area in Iran (right) and digital elevation model with a drainage network (left)

2.2. Data and image processing

To investigate the quantitative and qualitative of land use changes occurred in the studied area, Landsat satellite images (sensors MSS, TM, ETM^+ and OIL) were used, for the three periods of 1986, 1999, 2010, and 2016, respectively. The reason for the time interval between the 2010 and, 2016 images was to examine the effects of human activities. Table 1 presents some characteristics of the selected images.

Since the mentioned sensor images had different pixel size in some bands in the current study, bands with 30 *30 m pixel size as well as ENVI ver. 4.8, Idrisi Selva ver. 18.30 and ArcGIS ver. 10.3 software were used. The preprocessing work such as geometric and radiometric corrections and cutting images was performed in the ENVI software. Then, to map and model land use changes, the corrected images were transferred into the Idrisi Selva software, which can classify the images by different algorithms such as object-oriented and CA-Markov methods. Finally, the Arc GIS software was used to generate the output in the map format.

Before using the satellite images in digital analysis, their quality was examined for geometric distortion and radiation such as striped become, under each other not perch scan lines, duplicate pixels, the atmospheric noise, such as the presence of cloud patches. For a radiometric correction, the dark subtraction method was used. (Chavez & Mackinnon, 1994). To perform radiometric correction, in the first step, digital values were converted into spectral radiation, this was carried out using the calibration coefficients of the sensor using Equation 1 (Bruce & Hilbert, 2004):

$$L = Gain \times DN + Offset \qquad (1)$$

Where L is the spectral radiance ($1Wem^{-2}$ $Ster^{-1}$ μm^{-1}) of the digital pixel value (0 to 255) and the gain and offset of the calibration coefficients of the sensor. In the next step, according to Equation 2, the amount of spectral irradiation is converted into spectral reflection (Richards, J.A., 1993; Lillesand & Kiefer, 1994).

$$p = \frac{\pi L d^2}{ESUN.COS(SZ)} \qquad (2)$$

P: Spectral reflection without unit from zero to one.

π: 3.14.

L: Spectral radiation in sensor valve

d^2: is the distance between the earth and the sun based on astronomical units.

ESUN: Height of the sun.

SZ: The angle of the sun during radiation when recording a satellite image.

After performing geometric and radiometric corrections, the study area was subtracted. Then, the land use maps were generated using the object-oriented supervised classification method in seven land use categories, including afforestation, agricultural land and garden, barren land, poor rangeland, residential land, rocky land, and sand dune. To select an optimum number of the training site for each category, we randomly used the proportion of each class area to study area and select the suitable number of training samples using field studies and false color composite images. We then used the transformed divergence index to investigate the similarity of the classes and the degree of differentiation and distinction of the classifications.

To investigate the accuracy of the classification, a comparison was made using existing land use maps and field visits. For this purpose, the reference or ground truth map was prepared from all parts of the study area using other methods, including field visit. In this study, a random sampling method was used to assess the accuracy of the obtained maps. The samples were randomly recorded from each of the land use groups based on the land use map and local visits of the study area using GPS several polygons. Accuracy and the statistical parameters, including overall accuracy, Kappa coefficient, producer and user accuracy (extracted by error matrix) were employed to evaluate the accuracy of images and the classification of the experimental samples (Lu, 2004). Figure 2 shows the research process flowchart.

Table 1: Specifications of the used Landsat satellite imagery

Sensor	Data	Pass/Row	Resolution (m)	Number of bands
MSS	1986. 10. 7	162/38	60	4
TM	1999. 8. 19	162/38	30	7
ETM+	2010. 9. 3	162/38	30	7
OLI	2016. 9. 10	162/38	30	11

2.3. Object-oriented classification

Object-oriented classification is a process relating land use classes to visual objects (Blaschke & Lang, 2006; Yan, 2003; Ghazizadeh, 2007). Object-Oriented Processing of Satellite Images is an applied method in digital image processing that has been recently developed in conjunction with the basic pixel analysis (Blaschke, 2003). Object-oriented analysis has been increasingly used to analyze images with high resolution to detect changes in heterogeneous environments. In this method, the spectral information of textual information is also used to improve map accuracy and computational value (Tong et al., 2013; Wang et al., 2017). This method considers an object or homogeneous group of pixels (known as a segment) as the main processing unit and simultaneously incorporates, in addition to spectral properties, non-spectral features such as shape, texture, geometry, pattern, and communications with neighboring objects (Bouziani & Goita, 2010, Feizizadeh et al., 2017). In other words, the object-oriented method can use the same features that are visible and understood by the human eyes. For this reason, the output of these methods better represents the reality of objects and phenomena in the world (Blaschke, 2010).

Object-Oriented Operations on an image as typically include three steps:

1) Production of image objects using an image segmentation algorithm.

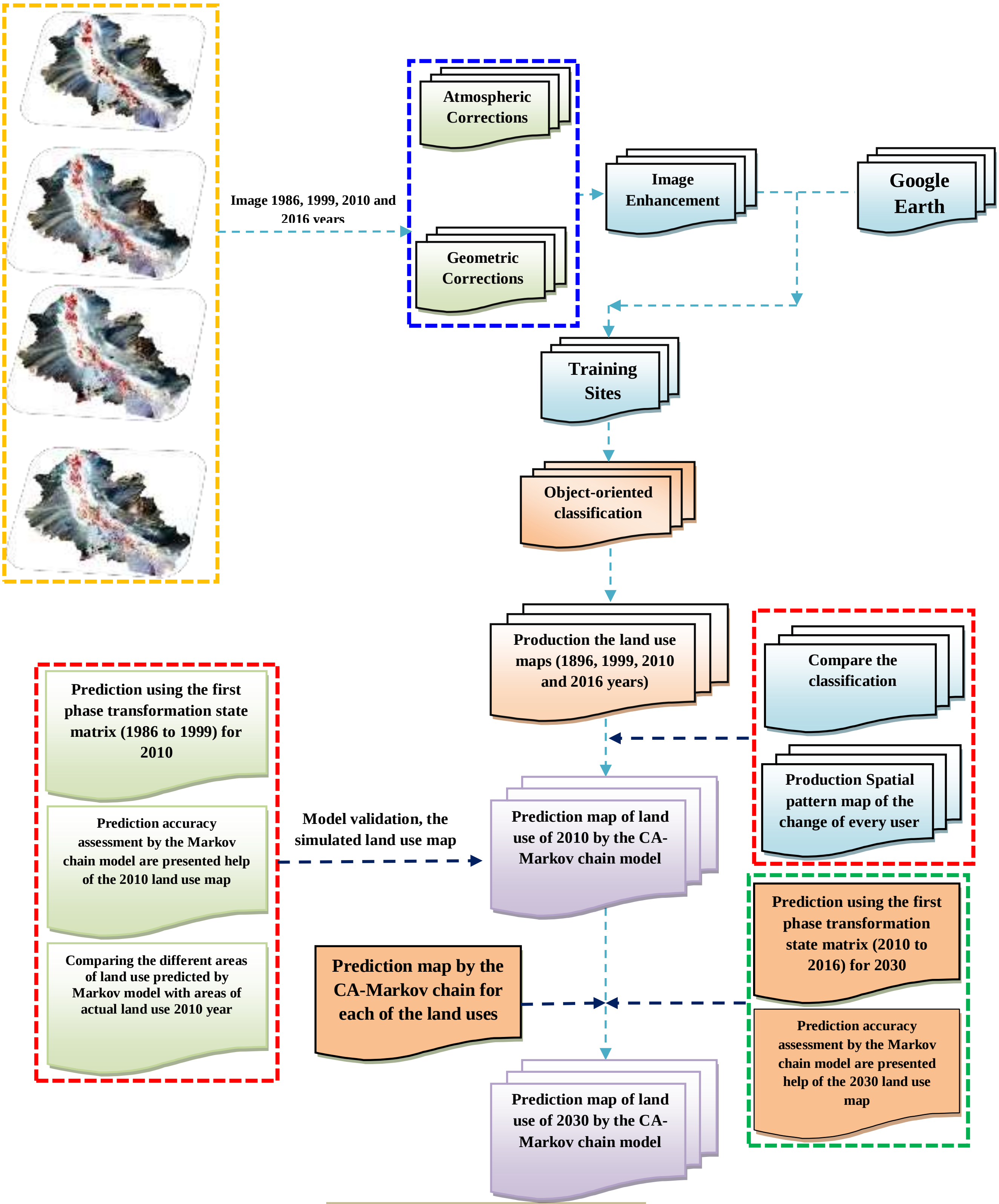
2) Object-based criteria extraction.

3) Classification using object-based criteria extraction (Jawak et al., 2015).

In the process of object-oriented classification, many options, including image types, segmentation methods, precision evaluations, classification algorithms, training sample collections, input characteristics, and target classes should be evaluated.

Segmentation means a group of neighboring pixels inside the zone in which similarity (such as numerical value and texture) is the most important common criterion. In the object-oriented processing of images, objects are formed by a group of pixels by the homogeneity and heterogeneity criteria that are the most important process in the object-oriented processing of images (Huang & Ni, 2008; Baatz & Schape, 1999). The parts must be homogeneous within themselves and represent only one floor, not a combination of multi-class, and at the same time, in the whole image, heterogeneity and differences between adjacent phenomena exist (Definiens Imaging Gmb, 2006). In this research, we used 6, 70, 5, and 0.8 for the weight of window width, similarity tolerance, weighted mean factor, and weight variance factor, respectively.

Object-oriented classification also requires training site, as in the common pixel-based classification. In the Idrisi Selva software, the range of training site is determined by sample image objects. Therefore, the training site needed for classification in the Idrisi Selva software is implemented on the surface of the images, and their corresponding visual objects are selected as training sample objects for classification classes.



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2.5. Detection of changes

To understand how the region has changed over the 30 years, and which classes have been expanded and which have had a decrease in area, classified maps were used. By comparing these maps and the error matrix table, the percentages of each class change were determined, and its map was plotted.

The percentage of the land use class was calculated in the study area, using the coverage map of each period. In addition, the percentage of each class to the whole region was obtained to be aware of the changes occurring in subsequent periods.

2.6. Markov model

The Markov chain is a random process that in its random variables, transitions from one mode to another will be done. The Markov feature (property states) expression that is the next state of a variable depends only on the current state of the variable and does not depend on previous events (Higgins & Keller-McNulty, 1995). Random process in which the feature applies Markov, Markov process

(Markov process) and such processes which have discrete modes, Markov chain is called. The Markov chain is considered a memory-based approach. Thus, as an order is named, the length of memory in which the possible probability values for the next mode are calculated. Therefore, the probability of changing a one-stage mode based on conditional probabilities is defined as Equation 3:

$$P(i \longrightarrow j) = P\left[X = 1 \middle| X - 1 = i\right] \qquad (3)$$

The probability of a one-step mode change is equal to the probability of the transition from step i to j step. The probability of a one-step change, in the theory and application of the Markov chain plays a key role. The use of the one-step model change matrix is an efficient tool to provide the probabilities of changing the mode of a Markov chain.

2.7. Cellular Automata-Markov model (CA-Markov)

The CA-Markov model is a combination of cellular automata, Markov chain, and Multi-Objective Land Allocation (MOLA) that is used to predict future changes in land use (Myint & Wang 2006). Cellular Automata is a discrete dynamic model used in simulation of various natural and human processes. In the CA model, space is defined as a network containing cells. CA cells are simultaneously updated at discrete times by a local rule. The value of each cell is determined based on the values of the neighboring cells and it self-cell. The Cellular Automata model can be obtained by Equation 4 (Sang et al., 2011).

$$S\ (t, t+1) = f\ (S\ (t), N) \qquad (4)$$

where S; limited and distinct sets of cellular modes, N; cell field, T and t + 1 represent different times, and f the rules of transferring cellular modes in the local space.

Initially, the probability of land use map classes changes to each other in the form of the probability matrix of land use status change the and based on the area changes occurring between time t_0 and t_1 are calculated using the Markov chain model.

The output of the Markov model (matrix of the land use state change) is non-spatial (not product a map); in other words, there is no knowledge about the geographic location of land use. To predict the spatial location of the land use (land use and cover map), at the time t + 1, CA technique was used. Accordingly, the future land use map is prepared using transition suitability maps of coverage and applying the filter contiguity during the MOLA process (Eastman, 2006).

The CA-Markov model adds the spatial contiguity components and user's knowledge about the spatial distribution of the probability of land use transformation to the Markov chain model. In this research, the existing models in the Idrisi Selva software were used to simulate land use changes in the desert region of the Yazd-Ardakan plain.

3. Results

Figure 3 shows the relevant maps land use images 1986, 1999, 2010, and 2016 using object-oriented classification.

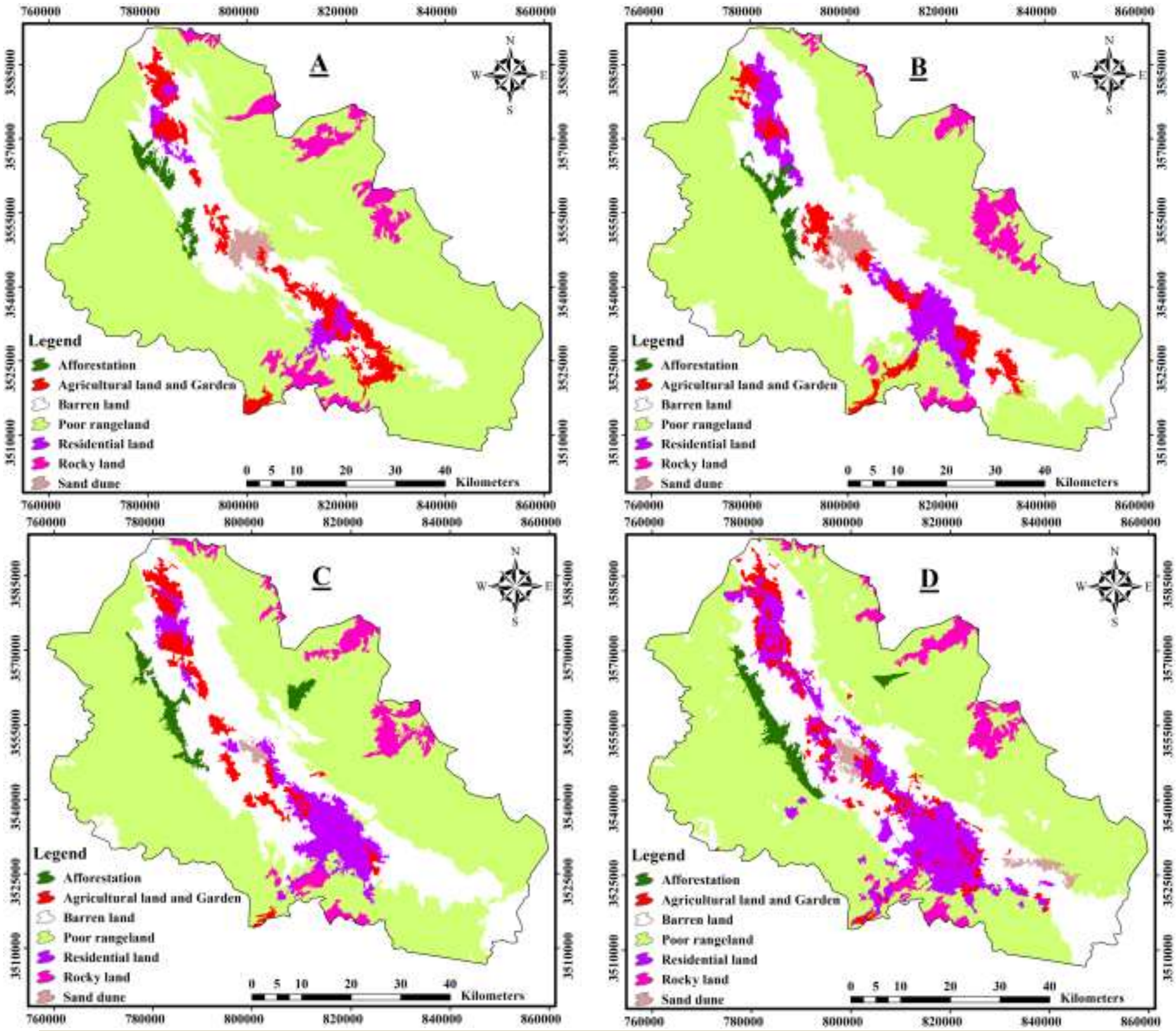


Figure 3: The land use map of the Yazd-Ardakan plain (A: 1986 B: 1999 C: 2010 D: 2016)

Statistical parameters of Confusion Matrix Analysis, producer and user accuracy, overall accuracy and Kappa coefficient were extracted as tables (2, 3), using field operations, aerial photographs, Google Earth satellite images, random sampling, as well as recognizing the researcher by inquiring from people of the study area. The low accuracy of the land use classification of sand dunes in 1986 was due to spectral overlapping, resulting in reduction of accuracy and relative similarity in the land use pattern.

Table 2: Confusion matrix analysis in classifying the images of 1986, 1999, 2010 and 2016

1986	Afforestation	Agricultural land and garden	Barren land	Poor rangeland	Residential land	Rocky land	Sand dune	Total	Error C
Afforestation	27077	105	210	0	461	85	79	28017	0.0336
Agricultural land and garden	272	661	111	3	0	40	687	1774	0.6274
Barren land	12	0	6026	12	57	0	0	6107	0.0133
Poor rangeland	0	0	0	5613	0	0	0	5613	0
Residential land	21	0	494	0	210	0	0	725	0.7103
Rocky land	40	11	0	2	0	434	822	1309	0.6684
Sand dune	1	1	2	2	0	23	10925	10954	0.0026
Total	27423	778	6843	5632	728	582	12513	54499	
Error O	0.0126	0.1504	0.1194	0.0034	0.7115	0.2543	0.1269		0.0652

1990	Afforestation	Agricultural land and garden	Barren land	Poor rangeland	Residential land	Rocky land	Sand dune	Total	Error C
Afforestation	55510	104	536	2	7	187	302	56648	0.0201
Agricultural land and garden	38	2832	21	71	2	0	86	3050	0.0715
Barren land	137	2	8881	9	0	0	18	9047	0.0183
Poor rangeland	0	30	5	4981	2	0	5	5023	0.0084
Residential land	3	3	0	14	731	0	113	864	0.1539
Rocky land	593	15	2	1	0	438	184	1233	0.6448
Sand dune	43	36	2	6	2	45	12298	12432	0.0108
Total	56324	3022	9447	5084	744	670	13006	88297	
Error O	0.0145	0.0629	0.0599	0.0203	0.0175	0.3463	0.0544		0.0297

2010	Afforestation	Agricultural land and garden	Barren land	Poor rangeland	Residential land	Rocky land	Sand dune	Total	Error C
Afforestation	36997	111	614	0	33	415	1169	39339	0.0595
Agricultural land and garden	154	6357	49	245	196	5	53	7059	0.0994
Barren land	3	6	13501	7	3	0	123	13643	0.0104
Poor rangeland	2	59	4	9336	1	0	9	9411	0.008
Residential land	4	70	24	3	866	0	16	983	0.119
Rocky land	271	5	13	0	0	438	544	1271	0.6554
Sand dune	1536	12	101	16	35	21	19716	21437	0.0803
Total	38967	6620	14306	9607	1134	879	21630	93143	
Error O	0.0506	0.0397	0.0563	0.0282	0.2363	0.5017	0.0885		0.0637

2016	Afforestation	Agricultural land and garden	Barren land	Poor rangeland	Residential land	Rocky land	Sand dune	Total	Error C
Afforestation	42271	67	297	0	147	236	498	43516	0.0286
Agricultural land and garden	50	13093	35	205	31	47	442	13903	0.0583
Barren land	680	22	13450	1	4	1	31	14189	0.0521
Poor rangeland	0	117	0	6669	1	0	3	6790	0.0178
Residential land	732	1	0	0	2706	0	26	3465	0.219
Rocky land	825	88	17	0	7	1527	936	3400	0.5509
Sand dune	397	242	129	2	29	45	18326	19170	0.044
Total	44955	13630	13928	6877	2925	1856	20262	104433	
Error O	0.0597	0.0394	0.0343	0.0302	0.0749	0.1773	0.0955		0.0612

Table 3: The evaluation of the classification accuracy for the derived user maps to classify the images of 1986 1999, 2010 and 2016

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

When the results of Table 2 are analyzed, several important conclusions are taken: First, it was observed that the agricultural and gardens class was obtained by more than 96% producer and user accuracy, indicating the high spectral resolution for this class. Second, according to the results, it was observed that the lowest producer and user accuracy was regarding the sand dunes class. This class has been classified with 27.9% and 28% producer and user accuracy for 1986, respectively. Table 3 presents the classification results. According to Table 3, the overall accuracy and Kappa coefficient of 1999 were 86% and 94%, respectively, indicating the highest accuracy of classification land use in the Yazd-Ardakan plain.

3.1. Comparison of the classification

After land use mapping in 1986, 1999, 2010 and 2016, the area of 7 land use class was obtained. To better compare the changes occurring in these four periods, it is shown in Fig. 4 drawn up, that during the period (1986-2016), the area of agricultural lands and impoverished rangelands of the region was 5696 and 579888 ha. (-1.16 and 12.01%, respectively) decreasing, while the barren land, residential land and sand dune areas with increasing trend were 2419, 35454 and 457 ha. (5.16, 7.34 and 0.09 %, respectively), has encountered. In other words, in a 30-year period, most changes were related to poor rangeland and residential land. A noteworthy point is the implementation of the afforestation plan to deal with desertification. Afforestation lands within 30 years increased approximately 3367 ha (0.7%).

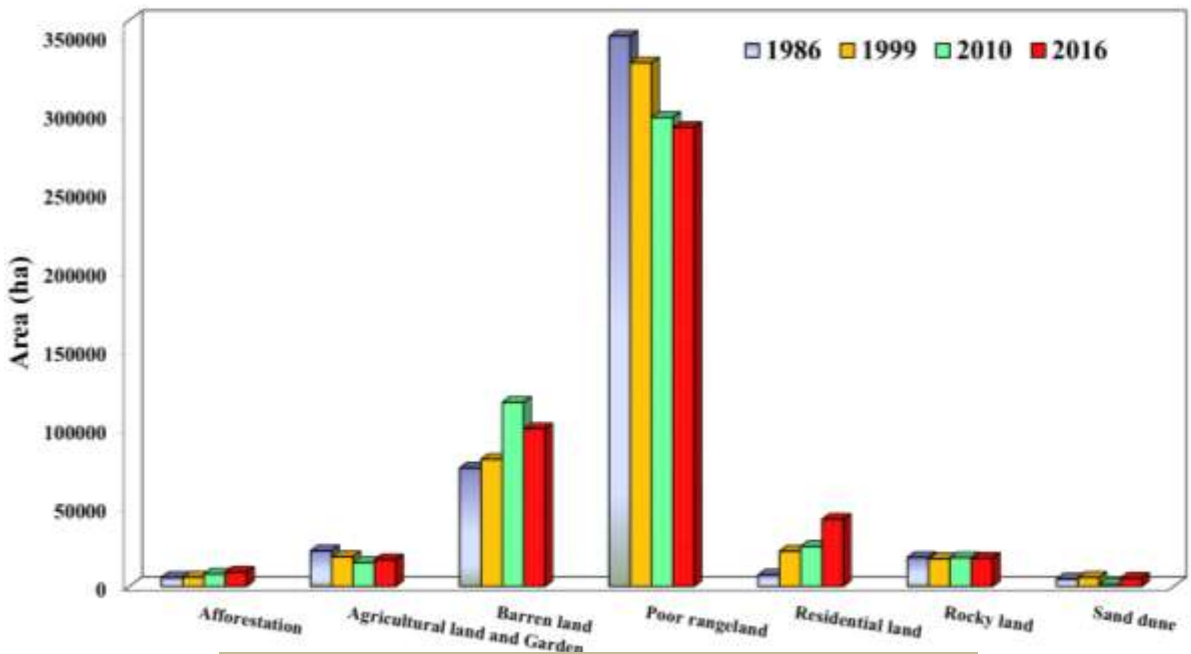


Figure 4: Graph area land use classes in 1986, 1999, 2010 and 2016

3.2. Results of the Markov chain analysis

Table 4 shows prediction of the results of land use changes using the first phase transformation state matrix (1986 to 1999) for 2010, which was conducted to evaluate the Markov model using the existing land use map for this year. In this table, the sum of each column represents the area of each class in 2010. With the help of the 2013 land use map, Table 6 presents the results of the prediction accuracy assessment by the Markov chain model. According to Table 5, the variation between the variant classes is different and its magnitude is generally less than 1%, indicating the usefulness of the CA-Markov model and the ability to use it in simulating land use changes (Baker, 1989).

Table 4: Prediction of the land use area for 2010, using the CA-Markov chain model and transformation matrix for the period of 1986-1999 (ha)

	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 5: Comparison of the different areas of land use predicted by the Markov model with areas of actual land use

Class	Afforestation	Agricultural land and garden	Barren land	Poor rangeland	Residential land	Rocky land	Sand dune	Total
Prediction for 2013 (ha)	7816	15097	116964	298166	25366	18136	1355	482900
Area in 2013 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

For model validation, the simulated land use map of 2010 was compared to the actual (truth) map obtained from the classified satellite image of the same year. The obtained Kappa coefficient indicates (Arsanjani et al., 2011, Kityuttachai et al., 2013, Sayemuzzaman & Jha, 2014) the high ability of the CA-Markov model (81%) to simulate land use changes in the Yazd-Ardakan plain (Fig. 5). The research was conducted in desert areas with poor vegetation, which undoubtedly had a direct effect on lowering the accuracy of validation.

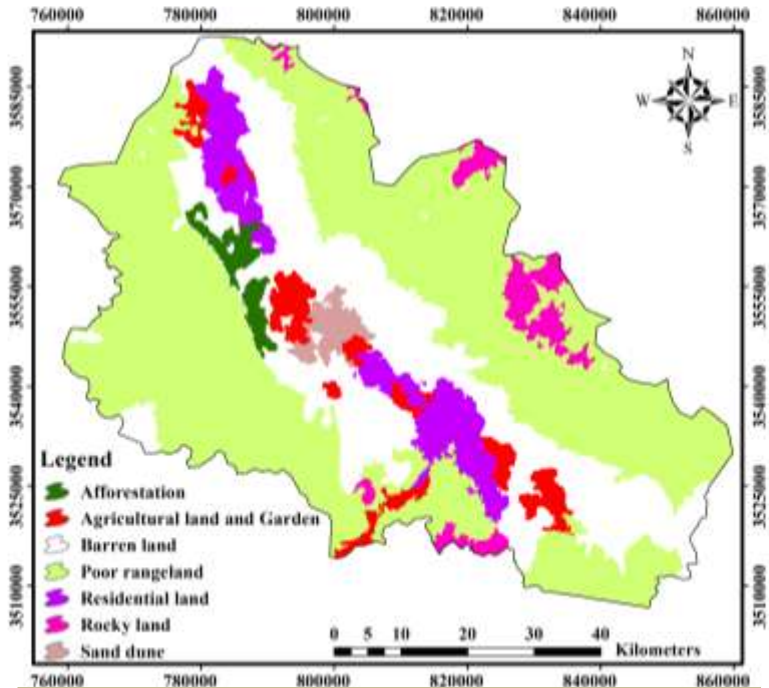
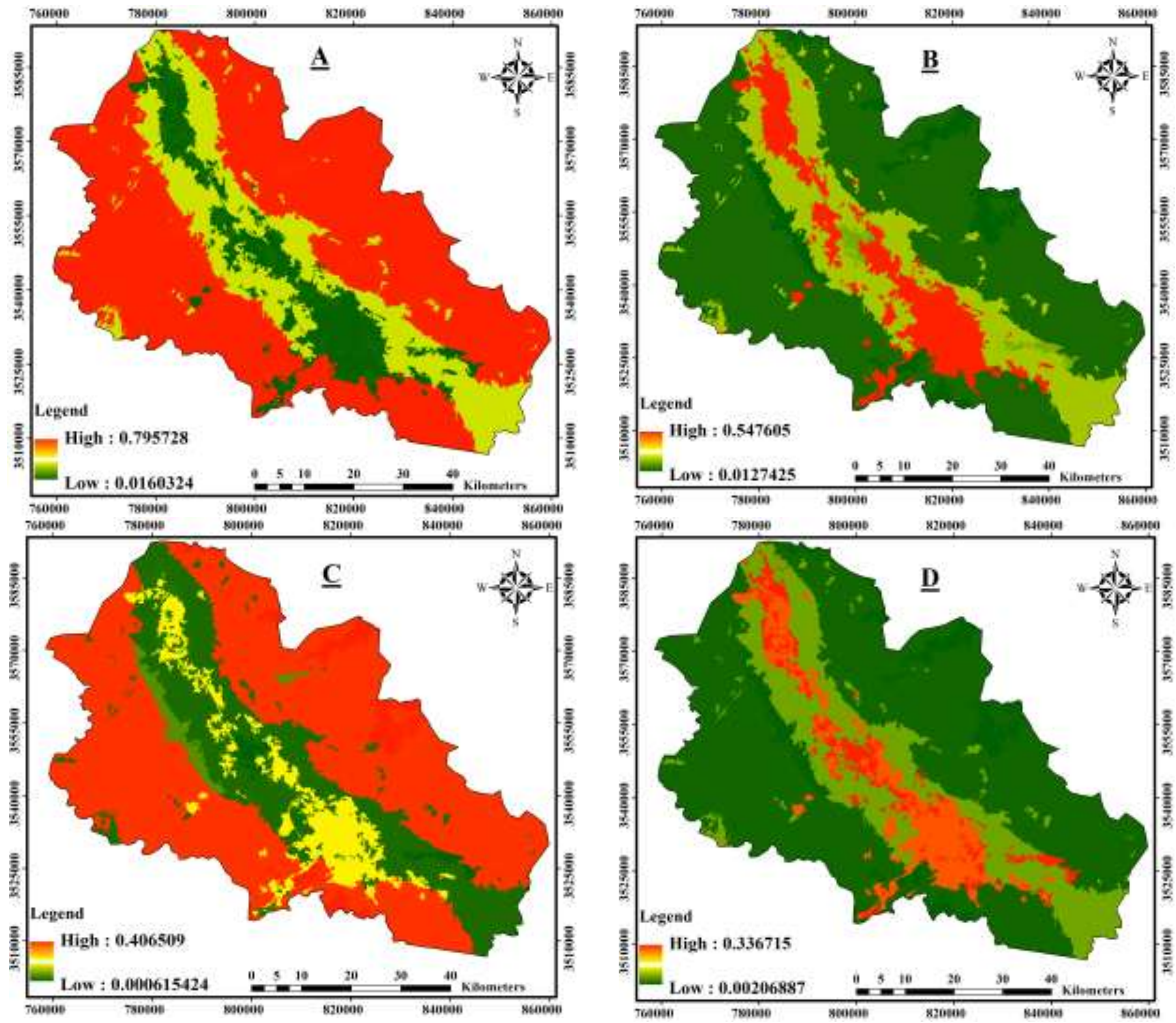


Figure 5: Map obtained from the CA-Markov validation for 2010

If we consider the trend of future changes as equivalent to the current changes, the probability matrix obtained from the maps of 2010 and 2016 is calculated using the Markov chain to simulate changes in the next 14 years (2030) (Table 6). In addition, Fig. 6 shows the map derived from the prediction by the Markov chain for each of the land pattern.

Table 6: Probability matrix of land use change in the statistical period 2016-2030 using the 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



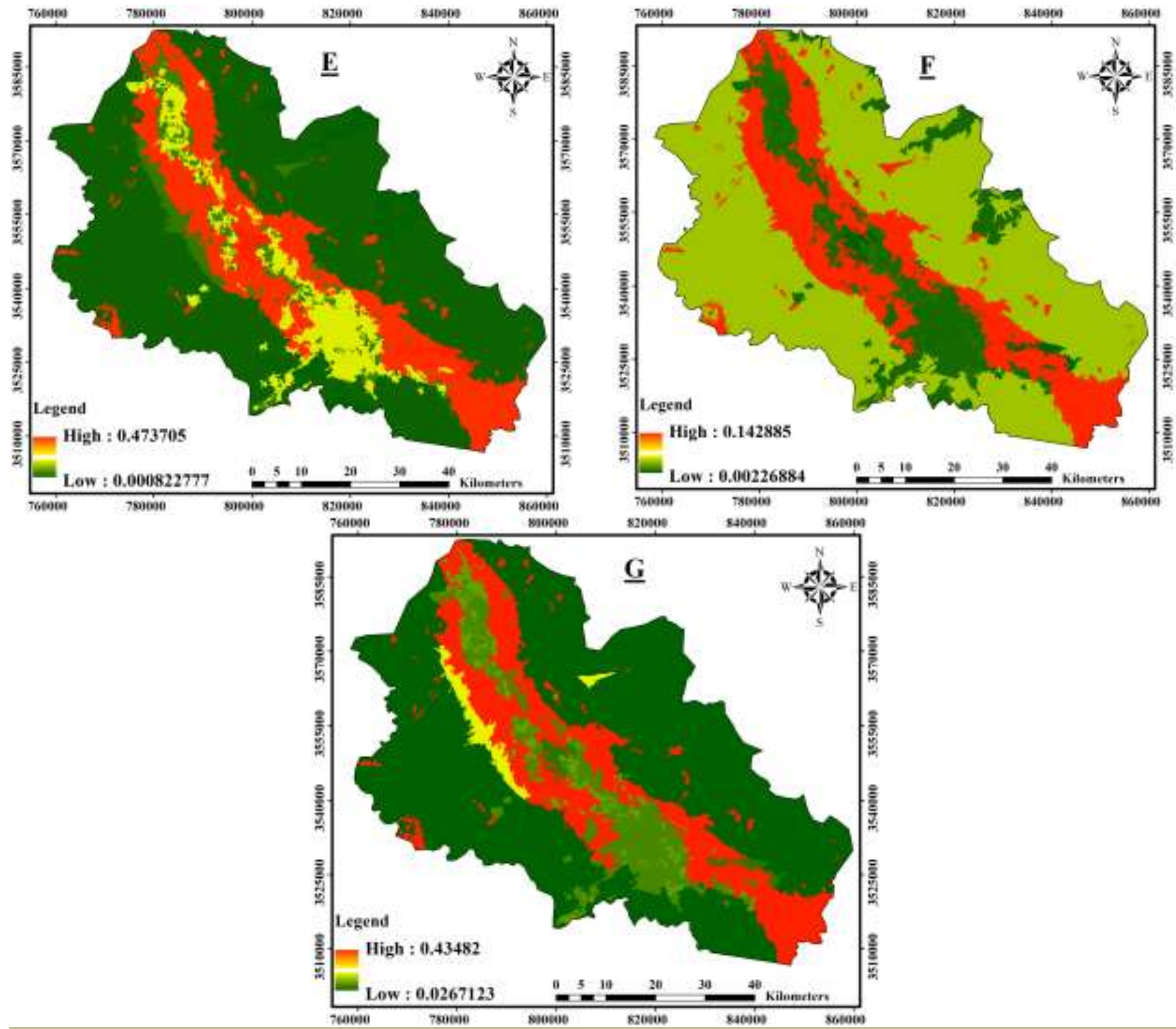


Figure 6: Prediction maps of the land use for the year 2030 (A: Afforestation; B: Agriculture land and garden; C: Barren land; D: Poor rangeland; E: Residential land; F: Rocky land; G: Sand dune)

The model of CA-Markov was used to prepare the simulation map of 2030. The simulation map of the YazdArdakan plain for 2030 and change the area of each land use from 1986 to 2030 as shown in Fig. 7 and Fig. 8, respectively. Based on the area obtained from each use in 2030 compared to 2016, the areas of afforestation use, agricultural land and gardens, residential land and sand dune are increasing, and the barren land and poor rangeland are declining. Accordingly, in 2030 compared to 2016, the area of afforestation, agricultural land and gardens, residential lands and sand dunes increased approximately 544, 7365, 11398 and 2681 ha, respectively, and the area of the barren land and poor rangeland decreased approximately 139921 and 8099 ha, respectively. Rocky lands are also almost constant.

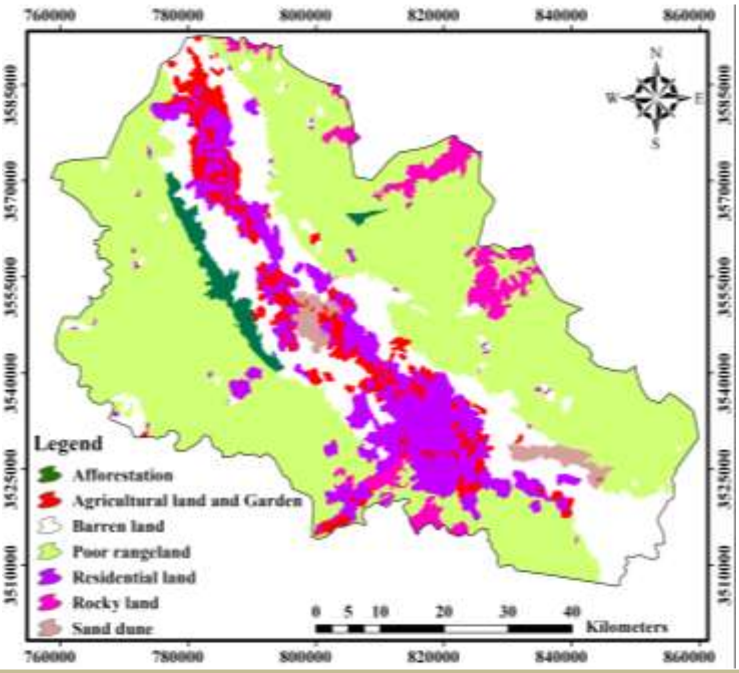
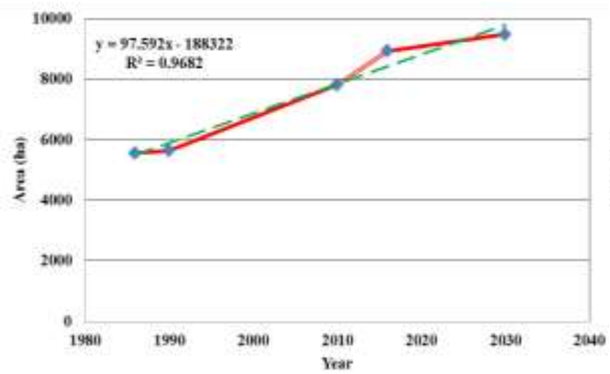
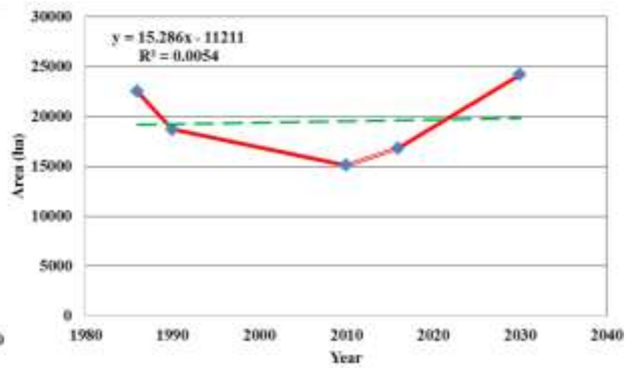


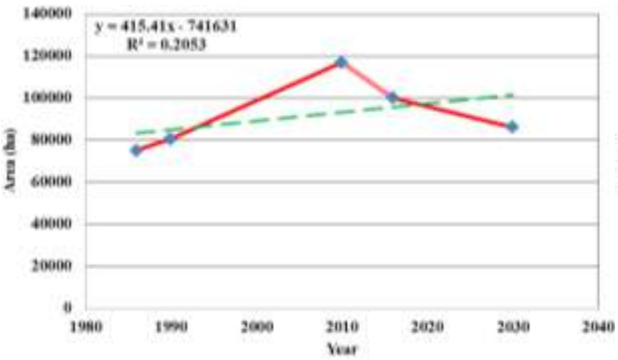
Figure 7: Land use simulation map of 2030 using the CA-Markov model



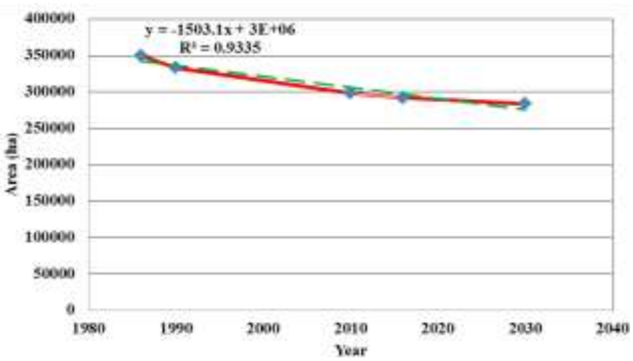
A



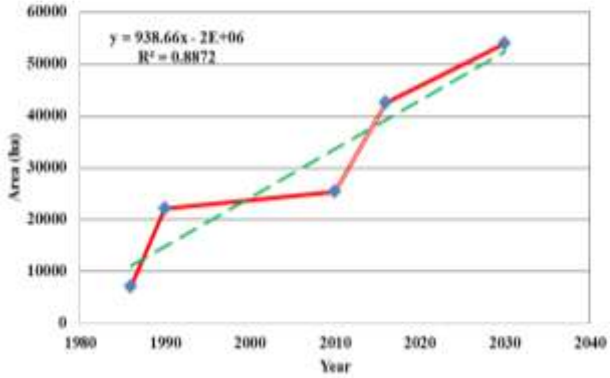
B

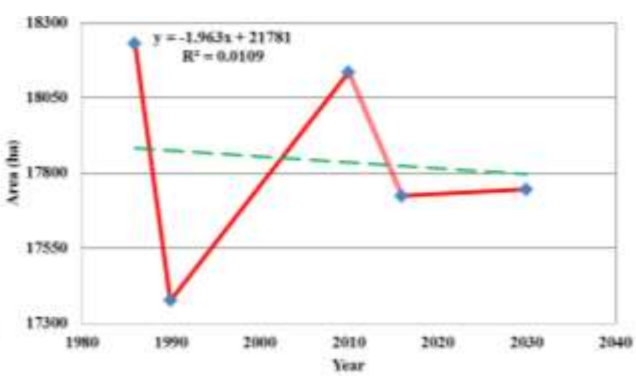


C



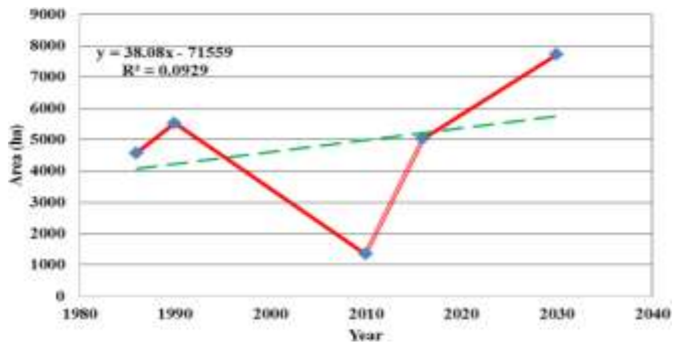
D





E

F



G

Figure 8: The trend of changes in land use patterns from 1986 to 2030 (A: Afforestation B: Agriculture land and garden C: Barren land D: Poor rangeland E: Residential land F: Rocky land G: Sand dune)

4. Discussion

Environmental issues and destruction of natural resources are among the vital reasons for creating risk management and environmental crisis strategies. The increasing destruction of resources in many parts of the world is a serious threat to humanity. Remote sensing and GIS are extremely promising tools for natural resources studies, particularly in the large-scale spatial and temporal variation modeling.

The current study investigates the land use changes in the Yazd-Ardakan plain using the remote sensing data and technique to assess its environmental issues such as land destruction and desertification. The results indicated the high efficiency and reliability of the object-oriented method in extracting the land use map (Kappa coefficient of more than 90% for all years). However, the limitation of selecting the optimal segmentation parameters and the potential error in segmentation is considered the main challenge of this method and somehow an object-oriented method. Errors in the segmentation could result in the error (deletion or addition) in the classification, and therefore, the use of this method will be challenging. The main reasons for the low accuracy of the sand dunes classification in 1986 were the reduced spectral overlapping accuracy and the relative similarity in the land use pattern.

The increase of the accuracy of the object-oriented algorithm is directly associated with the segmentation parameter and its scale. Determination of segmentation parameters is a user-defined process, which the expounder, based on his knowledge of the region, can perform the image segmentation based on the parameters of shape, texture, and compression coefficient and softness criterion. This has been proven in the literature (Platt & Schoennagel, 2009; Claudia et al., 2007; Collingwood et al., 2009; Blaschke, 2010; Yan, 2003; Gao et al., 2009; Zhaocong et al. 2009).

Comparison of the trend of occurred changes from 1986 to 2016 showed that during the period (1986-2016), the area of agricultural lands and poor rangelands of the region has decreased by 5696 and 579888 ha (1.18 and 1.21%, respectively). While the barren, residential and sand dunes lands have increased by 2419, 35454 and 457 ha (5.16, 7.34 and 0.09%, respectively). In other words, in the course of a 30-year period, most of the changes were related to poor rangeland and residential land. A remarkable point in the region is the implementation of afforestation plan to combat desertification. Afforestation lands have increased from 3367 ha (0.7%) over 30 years. For model validation, the simulated land use map of 2010 was compared to the actual map derived from the satellite image classification of the same year. The obtained Kappa coefficient indicates the high ability of the CA-Markov model (81%) to simulate land use changes in the desert region of the Yazd-Ardakan plain. Based on the obtained matrix results (Tab. 7), it is likely that, at the interval of 2016-2030, 80% of afforestation land, 55% of agricultural lands and gardens, 41% of barren land, 34% of poor rangeland, 47% of residential land and 43% of sand dune will be 93% unchanged. The most important point is the low probability (14%) of rocky lands that remains unchanged. The reason for this issue is the error created in the segmentation in the object-oriented method, which does not segment the rocky lands properly. Furthermore, from 2016 to 2030, the conversion of barren lands to afforestation (55%) and poor rangeland to agricultural lands and gardens (43%) is highly probable.

The reason for decreasing the area of barren and poor rangelands is increasing the amount of agricultural (e.g. rainfed) and residential lands, indicating an increase in the population and human pressure in the studied area. These land uses changes and increasing the human impact on the agricultural and rangeland area are now called tectogenic desertification. The increase of the number of mines in the studied area has created dust and hazes centers. In recent decades, the migration of people from the village to Yazd has increased, and this crisis has doubled the ghetto. The excessive growth of the population and the increasing need for food and new energy sources lead to the unconventional and extreme exploitation of the natural resources of the Yazd-Ardakan plain.

5. Conclusion

The results indicate donor increase and development of residential areas and the conversion of natural habitats such as poor rangeland, agricultural land and garden to urban land. Most of these changes are located in the center of the Yazd-Ardakan plain, with nearly 75 percent of the population density of the province and a significant number of factories and mines in this plain. Furthermore, most ceramic and tile manufacturers of Yazd province are located in the Ardakan-Meybod-Yazd route and provide over 50% of the country's ceramic and tile. The excessive increase in population and the growing need for new sources of food and energy resulted in excessive and unconditional exploitation of natural resources. Undoubtedly, the use of this region accelerated the land use changes and had potential to become a considerable danger for the survivors of the region.

Using the Markov chain and the CA-Markov model in anticipation and providing a prediction map of various land use changes are the important aspects of innovation in this research. It is possible to use the CA-Markov model in future planning using the spatial-possibility map (latitude and longitude) of all pixels of each land use pattern.

The simulated maps in this study can be a suitable guide for managers and planners, especially the part of natural resources. Furthermore, simulated land use maps can be used as a warning system for outcomes and the future effect of land use changes. The results obtained from the study of land use changes trends can be used in land evaluation, environmental studies, and integrated planning and management to use natural resources appropriately and logically, and reduce the destruction of the resources.

Here, the main conclusions that can be derived are:

- The complexities of an area result from the density of land use and the type of similarities between various classes of objects. Trend overall research of segmentation and classification up to the comparison after classification to affect. Thus, designers and local governments need to design new different strategies.
- The optimization selection of segmentation parameters is a critical step in the process of classification of land use that can affect the object-oriented analysis process to achieve the land use map. For this reason, these parameters should be selected with the highest accuracy.
- The overall accuracy of the land use change detection method indicates that the used methodology is strongly influenced by the segmentation process as well as the classification, since the selection of suitable training data will play a fundamental role in categorizing the images, and consequently the direct impact on the classifications comprised to process after classification.

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