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Discovering and Recovering the Changes in Land Use and Land Cover Using Remote Sensing and GIS (Case Study Heev Village, Alborz Province)

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Abstract

Detecting changes is one of the basic needs in the management and evaluation of natural resources. Modeling the process of land cover changes over time using multi- time data in the GIS environment can act as one of the most important factors in managing the mentioned changes. In order to modeling the process of land cover changes and to investigating the possibility of predicting it in the future, land change modeling (lcm) has been used. Therefore, the Landsat TM5 analyzer data of Heev village in Alborz province for the years 1985T 2000 and 2011 were analyzed. Next, using the maximum similarity method, land cover maps of each image for the mentioned years, was extracted and categorized into five layers of vegetation, city, asphalt, barren lands (soil) and rocks and cliffs. The extracted accuracy evaluation coefficients (overall accuracy and kappa coefficient) indicate the high accuracy of this classification method. The analysis of the results obtained from the studies conducted on the two periods of 1985-2000 and 2000-2011 shows an increase in urban construction with a decrease in vegetation, and even in some areas, the disappearance of vegetation, while the village is expanding towards the mountainside. Using the combination of Markov model and automatic cell maps land use prediction maps for the next 16 years were obtained, while the kappa coefficient was used to determine the prediction compliance, and comparing them with the actual map.

***Keywords**:* LCM, Markov Chain, Automated Cells, Kappa Coefficient

1. Introduction

Human history shows the devastating effects of increasing population growth and, consequently, unprecedented urban growth, industrialization, expansion of agricultural lands, and land use change. Land use change in turn, can lead to soil degradation and increased erosion (Hashimoto et al., 2002). Land use has always been one of the most important factors through which humans have affected their environment and historically, the most important change in land, those of which human beings have made, is the deforestation and changing them into agricultural lands and settlements (Lausch and Herzog,

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2002). In Iran and all over the world several studies have been conducted in the field of land use change, in most of which the impact of human development on environmental degradation has been confirmed. Among them, we can mention the studies of Prabaharan et al. (Prabaharan et al. 2010) and Janek et al. (Zhang et al., 2015), who have emphasized on the importance of the issue of change by influential human factors and its destructive consequences in the field of natural resources. Principled land use management requires accurate and timely information in the form of a map. Considering the widespread and unprincipled changes in land use, including the destruction of natural resources in recent years, it becomes really important to study the land cover changes over time, using satellite imagery. On the other hand, the reproducibility and up-to-datedness of satellite data along with their ability to cover large areas has led to their increasing use. during the recent years, due to the good efficiency of satellite data and the capabilities of Geographical systems, the study of land use changes, its modeling and forecasting them for the future has received a great deal of attention from researchers. In addition, monitoring of land use changes related to ecology, deforestation, urbanization, sustainable management of natural resources, identification and modeling of the effects of climate change is also done with the help of these images (Quattrochi, Russell-smith, 2003). Moreover, during the recent decades, satellite data has been widely used to provide land cover information such as rescue in forest areas, intensity of agricultural land development and other man-made changes (Shetabi and Ghanbari, 2010: 2). Land surface itself is a complex system, but modeling land use change is also a complex process involving a variety of variables. Subject maps for modeling are usually obtained using remote sensing methods, image processing, and mapping software. In summary, these models are useful tools that complement the human mind's ability to analyze land use change and make more informed decisions (Bakr et al. 2010: 593). The process of recognizing the difference in the state of a phenomenon by observing it at different times is called "change monitoring" (Singh, 1989) In rime detection of changes in land surface characteristics, leads to a better understanding of the relationship between human and natural phenomena, and also performing better management and use of resources. In general, change monitoring involves the use of multidimensional datasets to quantitatively analyse the temporary effects of a phenomenon (Lu, et al., 2004). Using the LCM method, Dawelbaita and Morari detected the changes in the Czech Republic and concluded that 6% of the mixed forests had become broadleaf forests, while, the residential areas have increased about 5.3% (2012). Deserts in the Sudan region were also surveyed using high-resolution satellite imagery and detailed spectral analysis. The results of the study indicate that the use of combined spectral analysis and Landsat images show consistent, accurate and low-cost results for areas at risk (Lamchin, et al, 2016). In order to better manage natural and man-made ecosystems and long-term planning, it is necessary to model land use / land cover changes and predict their changes in the future. In the last two decades, a wide range of land use change / land cover models have been developed to assist in land management and better understanding and evaluating the role of these changes in land system functioning (Mas et al., 2014). Accordingly, the purpose of the current study is to evaluate and predict changes in Heev village in Alborz province, using satellite images and a new integrated model of Markov chain and automated cells.

2. Methodology

2.1. Scope of the Study

Heev is a village in the central district of Savojbolagh county, Alborz province, Iran; It is located in the south of Taleghan town. This region is located in the coordinates: 361 ′ 441 ″ N, 50 ° 38′45 ″ E, 36.02806 ° N and 50.64583 ° W. Its altitude is 1497 meters above sea level. According to the census, the population of the village in 2016 was 8697 people. Heev, which is 2,000 years old, is located near the Alborz Mountains and has grown more than nearby villages due to its proximity to commuting centers. the village injoys the beautiful views of the Alborz Mountains hillside. In the not so distant past, the majority of people were engaged in mining and the most important mineral product of this village is coal. During the last four decades, with the establishment and operation of Abik and Fakhre Iran Cement

Factories around the Heev, most of the residents either worked in these factories or got to work in the affiliated guilds. The climate of Heev is a local steppeand the rainfall is very little. The average annual temperature is 13.4 ° C and the average rainfall is 273 mm (Figure 1).

Figure 1. The area of the study area

2.2. Data Analysis

In a current study, the images from the Landsat TM5 analyzer related to the dates 05/05/1985, 30/05/2000 and 16/07/2011 have been used. Satellite data which were prepared in Geo TIFF format, have been categorized into seven spectral bands, while, band 6 was omitted due to its high spatial resolution. The images used with the L1T correction level (including systematic radiometric correction, geometric correction using ground control points, as well as topographic displacement correction error) were obtained from www.earthexplorer.usgs.gov. Table 1 shows the specifications of the analyzer and the images employing road maps, uses and immovability of buildings. The ENVI 4.8, IDRISI and ARCGIS10.1 software were used for the processing and reconstruction of the data, modeling and getting output, while the Maximum Likelihood method was used for classification of land uses and also creating the LCM model for prediction of changes. After preparing the map on land use, the changes that occurred during the study periods were also detected and evaluated. At this point, the LCM model was used in IDRISI software. The changes include net reductions, increases, and net changes in each land use, as well as their transition from one use to another.

Table 1. The specification of the images used in the research

Correction level	Gregorian date	the date in the solar calendar	Based on	Sensors
L1T	05/05/1985	16/02/1364	ZONE39_UTM- WGS84	TM5
L1T	30/05/2000	10/03/1379	ZONE39_UTM- WGS84	TM5
L1T	16/07/2011	25/04/1390	ZONE39_UTM- WGS84	TM5

3. Methodology

The overall procedure of the study, after preparing satellite images and performing preprocessing, processing and post-processing on them, includes preparing maps on land use, detecting and preparing change maps in the selection of models and sub-models, and preparing land cover prediction maps respectively, which are given in the flowchart below (Figure 2).

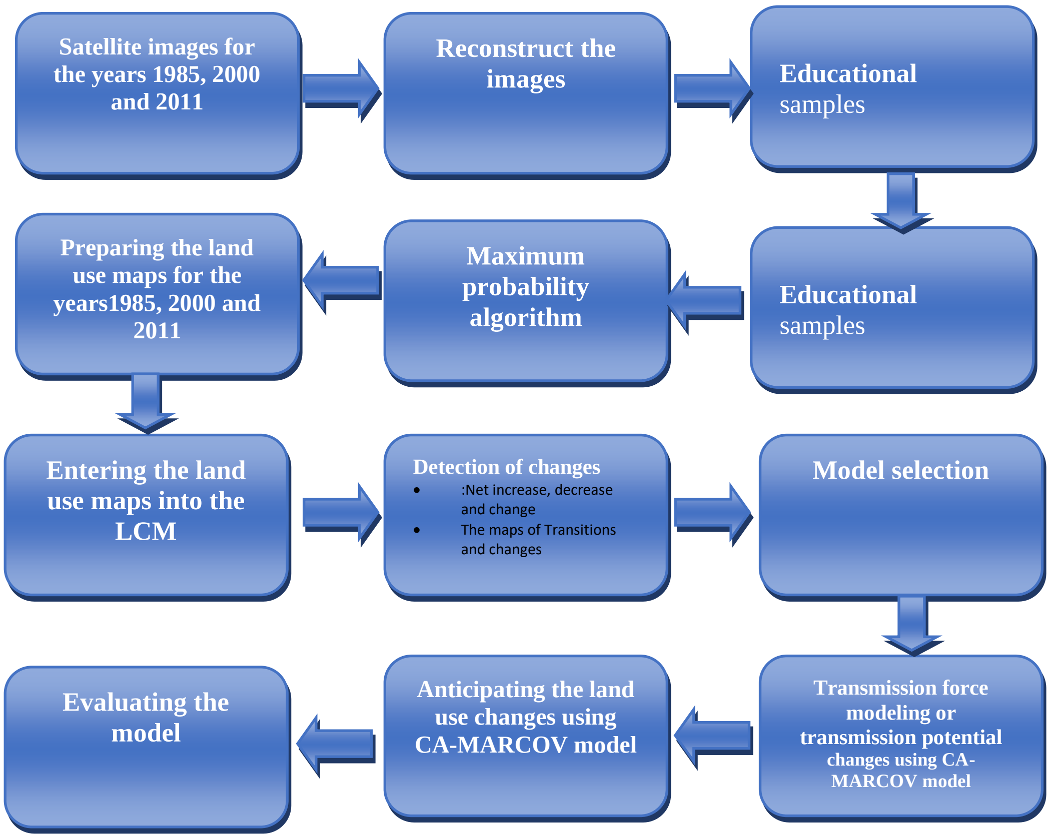


Figure 2. Flowchart

3.1. Evaluation of Image Quality

The data were examined for any geometric and radiometric errors, before any analyzing or processing. the data were collected at L1T level (including systematic radiometric correction, geometric correction using ground control points, and topographic displacement correction error); In order to prevent errors, the data of all three times were examined in terms of radiometric errors such as corrosion, by displaying individual bands as well as different color combinations on the computer screen and by enlarging different parts of these images. In order to study the geometric condition of the images and also to ensure the appropriateness of the geometry of them, the vector layers of roads and waterways were extracted from digital maps and placed on satellite images (Arkhi,2014).

3.2. Classification of Satellite Images and Preparation of Maps on Land Use

As the separation and identification of phenomena in terms of color gives better results, false color images were used. Bands 741 are the best false color mode. These images help visualize the types of land uses in the area. To prepare the Land cover maps, the supervised classification method was used. By recognizing the area, using topographic maps and images from Google Earth, five layers of vegetation, city, asphalt, barren lands (soil) and the rock and cliff were extracted for the three years of 1985, 2000, 2016 (An average of 10 control points has been considered for each use). Moreover, the maximum probability algorithm was used to classify the images. Given that the maximum probability algorithm is considered as one of the most accurate common methods for base pixel classification, (Perma and Shatai, 2010: 231), the algorithm was used to classify the data, while all three time periods were classified the land cover map was prepared for them. Since the validity of each map prepared from the images depends on its accuracy, the accuracy of the map was calculated according to the overall accuracy and kappa coefficient.

3.3. Detection of Changes Using Land Change Modeler

Detection of land use change is an essential tool for environmental analysis, planning and management. Land change modeler is software for sustainable ecological development that is designed and built to identify the urgent and growing problem of land change and biodiversity conservation analytical needs. It is available as an Ancillary tool within the IDRISI software system. It is also available as an Ancillary for ARCGIS software. Land change modeler provides a tool, by use of which you can evaluate and experimentally model land use change and its impact on species habitat and biodiversity (Arkhi,2014).As the model requires two first and last classified maps (2000-2005) as input; therefore, the maps are entered into the LCM model of Terrset software. In the change analysis section, the gain and losses of each class and the net changes were prepared and analyzed in the form of diagrams, change maps, map of areas with persistence (stable) and transition from each class to land cover classes (Vaclavik and Rogan, 2009: 56). Next, in the modeling stage, the transition force from on use to another (e.g., green space to the urban) was modeled according to the explanatory variables, which includes: the distance from residential region, the distance from the road and the distance from existing uses in here. This means checking the capability of each pixel of the image to change from one user to another. The output of this part of the map will be the force capability for each change. The process was repeated for the second period (2000-2016) and the relevant maps and diagrams were prepared.

3.4. Markov Chain Model

The founder of this method is Andrei Androvich Markov, a great Russian statistician and mathematician who used this method in 1905 to describe the principle of cycloidal motion as a series of chain experiments (Ghahraman, 2004). Makov chain is a good tool for modeling land use and land cover changes, and it can be used when changes in landscapes are not easily descriptive. The Markov chain includes a set of random values whose probability in a given time interval depends on the value of numbers in the past (Fan et al., 2007). The model which is usually used to predict the geographical changes without any secondary effect, it has now become an important forecasting method in geographical research (Sang et al, 2011). Markov chain describes land use change from one period to another and uses it as a basis for mapping future changes. This is done by developing a probability transition matrix of land use change from time 1 to time 2, which will be used as a basis for mapping future time periods (Mahini et al, 2011)Based on the conditional probability, the relationship between the prediction of changes in land use in Markov model is calculated using the following equation (Sang et al. 2011).

$$S\,(T+1) = pij * s\,(t) \qquad (1)$$

Where, s (t) and s (t + 1) are the states of the system at time t and t + 1, and the pij matrix is the probability of transition in a state, which is calculated by the following equation:

$$p_{ij} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix}$$

$$\left(0 \le p_{ij} < 1 \; and \; \sum_{j=1}^{N} P_{ij} = 1. \; (i.j = 1.2. \ldots .n)\right) \tag{2}$$

Generally, whenever the Markov chain is used, the changes are shown based on a probabilistic method and by considering the effect of time on the changes (image cells), while, the amount of the related changes in the considered period of time are also calculated.

3.5. Automated Cell Model (CA2)

In this model, space is defined as a network whose squares is called cell each. The automated cells are updated simultaneously, in discrete times, according to the local law. The value of each cell is determined based on the values of neighboring cells and the cell itself. The automated cell model can be obtained from the following equation (Sang et al., 2011).

$$S\ (t, t + 1) = f\ (s\ (T), N) \tag{3}$$

Where; s is a finite and distinct set of cellular states, N is the cellular context, t, t + 1 represents different times, and f is the rule for transition in cellular states in local space.

3.6. Integrated Markov Chain Model with Automated Cells

By implementing the Markov Chain Model, several images are created. The images, which are obtained from the transition probability matrix, have the ability to calculate the probability of each land cover creation or change in the future. Although, the calculated probabilities for each transition are very accurate, but there is no information about the spatial distribution of the uses. Therefore, Markov's random model lacks any spatial dependency information. in contrast, the automated network has the ability to change its status based on the lawful application of the new status, which indicates the current status in accordance to the previous status and the status of its neighbors. The CA filter is also used to develop a weighting factor (spatial proximity) to change the status of cells based on the status of its neighbors. As a result, to solve the problems of these two methods, the combined CA-MARKOV method is used(Mahini et al,2011).

3.7. Verification and Predictive Validity

The Kappa Index is one of the most well-known statistical parameters for expressing the accuracy of produced drawings. The agreement Kappa index (KIA) which is known as standard kappa in here, is used for overall accuracy between two reference and comparison maps. To determine the validity of the prediction, the agreement Kappa index was used. The closer the index is to the number (or closer to 100 in percentage terms), the greater the validity of the prediction model.

$$K = \frac{\sum_{i=1}^{T} Xii - \sum_{i=1}^{T}(Xi^{+} \times X^{+}i)}{N^{2} - \sum_{i=1}^{T}(Xi^{+} \times X^{+}i)} \tag{4}$$

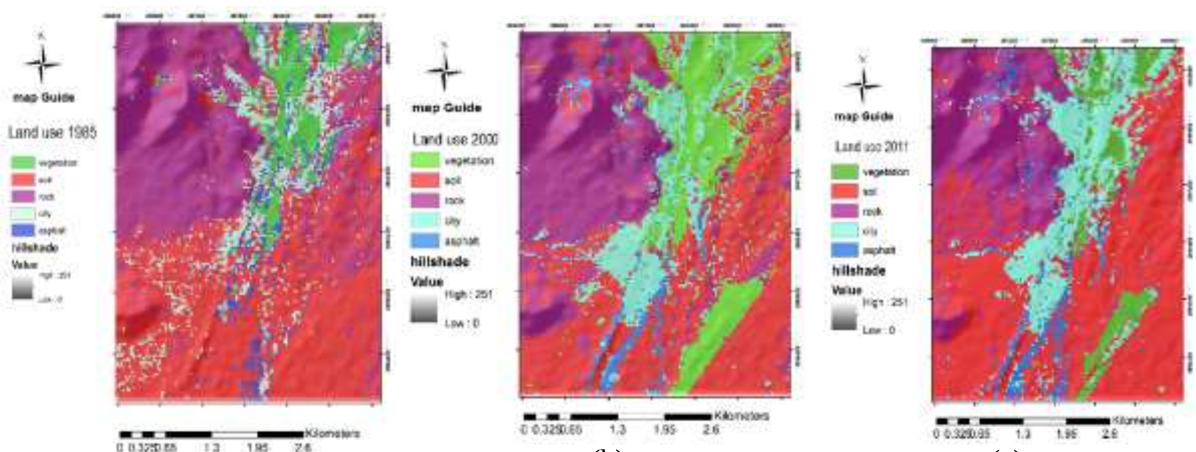
Where: T is the number of rows of the error matrix, xii is the number of observations in the row i and column, xi + is the sum of the row arrays other than the principal diameter arrays, xi + is the sum of the total column arrays other than the main diameter arrays, is the total number of cells in the matrix (Cangalton, 1991).

4. Results and Discussion

In a current study, in order to prepare the map on land use of the region, the images from the Landsat5 were used in the ENVI software by means of supervised classification of the maximum likelihood method. Figure 3 shows the maps on land use for the three mentioned years. Accordingly, the study area was divided into 5 land uses; including: vegetation, city, asphalt, barren lands (soil) and rocks and cliffs, and finally, the maps were examined in terms of overall accuracy and kappa coefficient. Table 2, shows the results from the examination of the maps accuracy. It indicates the acceptable accuracy of the prepared maps.

Table 2. The results from the examination of the maps accuracy

Year 2011	Year 2000	Year 1985	
94.84	96.62	94.24	Overall accuracy
0.925	0.950	0.898	Kappa Coefficient



(b) (c)

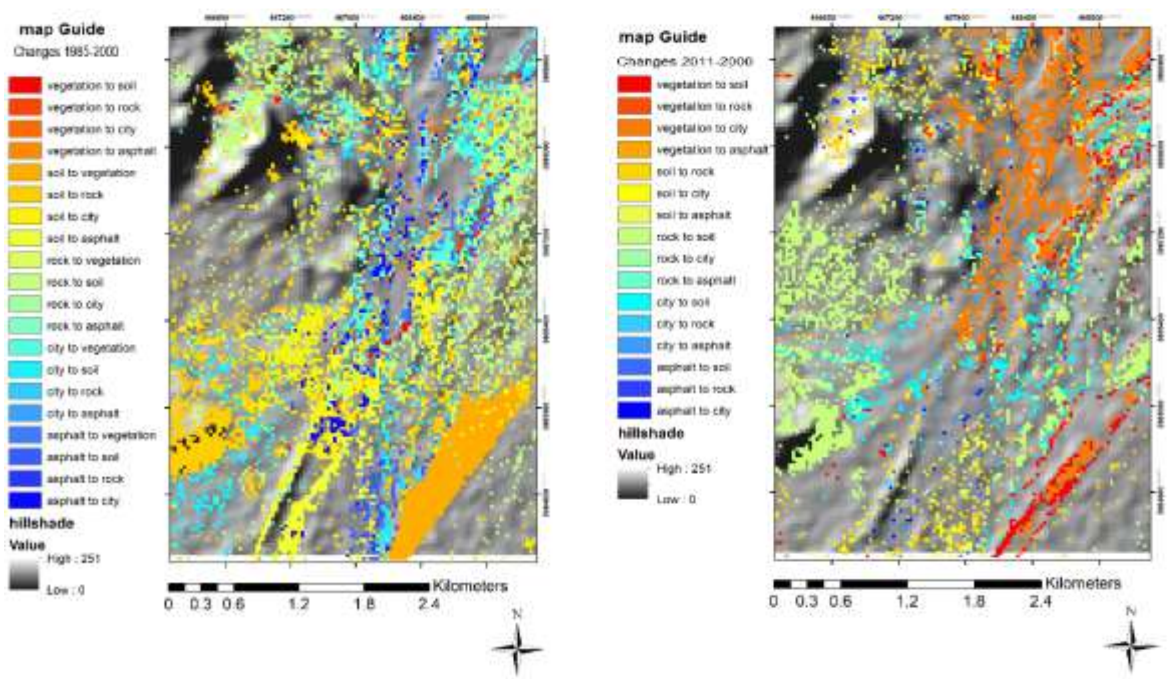
(a)

Figure 3. Classified image (a) 1985 (b) 2000 (c) 2011

After preparing the map on land use, the changes that occurred during the study periods were detected and evaluated. At this stage the LCM model is used in IDRISI software. These changes include net reductions, increases and net changes for each land use and also the transition from one land use to another (Figure 3). According to the results for the years 1985- 2000, due to the cultivation of areas outside the city, the vegetation had increased, while the amount of the barren land (soil) has decreased. Also, during this period, the city area has increased, which is accompanied by a decrease in rock use (i.e., the city has advanced towards the hillside). But, in terms of Asphalt land use, no results were obtained, due to the presence of mixed pixels in the urban area. The decline of the rock has been due to the direction of urban growth towards the hillside and the increase of barren lands (soil) can be due to rock erosion during these 16 years or incorrect classification due to the presence of mixed pixels.

Table 2. Area of uses in terms of hectares

Use	Year 1985	Year 2000	Year 2011
Vegetation	135.54	284.46	121.14
City	200.34	236.88	316.35
Asphalt	70.92	85.32	86.58
Rock	715.57	951.96	509.49
Barren (Soil)	909.99	799.83	100.89



(a) (b)

Figure 4. Change maps for the years: (a) 1985-2000 and (b) 2000-2011

A combination of Markov chain model and automated cells was used to predict land use changes. The Markov chain is based on two land use maps, obtained from satellite images and transition probability matrix, the results of which are shown in Table 3. Accordingly, the land use condition and their changes for the year 2000, completely depend on the results from the previous 15-year period. Fallowing, a change probability map was prepared for the second 11 years ending in 2011, while, the distance from residential areas, roads, existing uses had been considered as the influential human factors in the occurrence of changes. To prepare each of the human characteristic maps, 1: 25000 prepared topographic maps were used, while, they have changed into a raster structure to be suitable for being used in spatial analysis. By entering these maps along with probability maps obtained from the Markov model, into the CA-MARKOV model, the 2011 forecast map was obtained and compared to Real map obtained from satellite images of 2016. After satellite image processing, classification and finally prediction it is time for the important stage of accuracy assessment.

Table 3. Transition probability matrix for the period 1985-2000

User	Vegetation	City	Asphalt	Rock	Barren (soil)
Vegetation	0.724	0.153	0.002	0.037	0.082
City	0.284	0.263	0.018	0.110	0.324
Asphalt	0368	0.269	0.022	0.042	0.297
Rock	0.030	0.056	0.021	0.511	0.380
Barren (soil)	0.123	0.150	0.048	0.236	0.441

According to Tables 3 and 4, which show the matrix of change percentage, during the 15-year period of 1985 to 2000, the vegetation use was the most stable one (Table 3), so that about 72% of which remained unchanged during this period due to urban growth while the most dramatic changes in land use are related to the urban context with a change of about 15%. Rock, barren lands, and asphalt are in the next categories among which, the rocks have the most progress towards barren lands. Moreover, during the period 2000- 2011(Table 4) vegetation continues to decline in favor of urban growth.

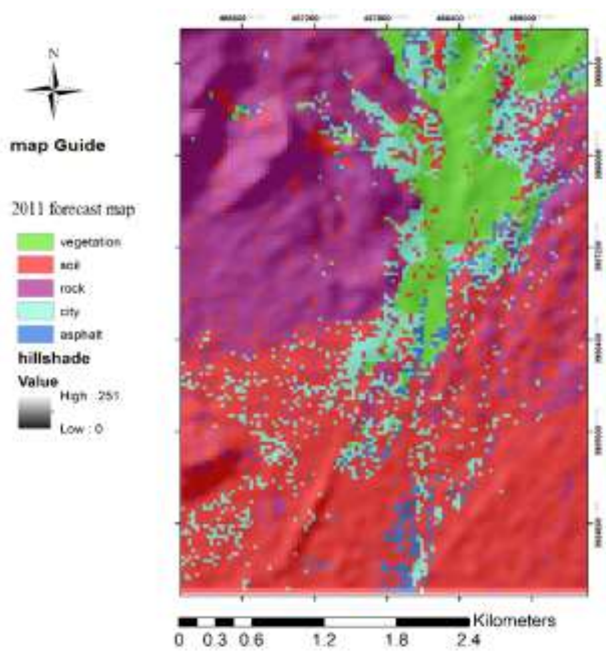


Figure 5. Forecast map for 2011

In the model validation section, the most important types of kappa including: standard kappa, kappa location, kappa for quantity and kappa for lack of information. The K Standard, K location, K strata and Kno are examined. K Standard method compares the observed relative accuracy to the expected relative accuracy based on chance. In this way, the total accuracy is also expressed as a percentage, indicating the degree of agreement and concordance of the two images. Considering the correspondence of the results from land use analysis with reality, the standard kappa for the modeling and land use map obtained from the satellite image of 2011 showed the number 0.37. Then, a forecast map was constructed for the next 17 years (Figure 6). The process was performed according to the ca-Markov model according to the changes, occurred in the period 2000-2011. The results were presented in transition probability matrix, and according to the Table 4, the greatest land use change belongs to the vegetation of the region, 55% of which has been destroyed and changed into the urban area. On the other hand, about 15% of it has changed into the barren lands (soil) and only 27% of the region's vegetation will remain unchanged for the next 16 years. The highest level of stability belongs to the barren land uses with about 74 percentage.

Table 4. Transition probability matrix for the period 2000-2011

User	Vegetation	City	Asphalt	Rock	Barren (soil)
Vegetation	0.272	0.550	0	0.016	0.015
City	0	0.560	0.048	0.011	0.350
Asphalt	0	0.102	0.702	0.172	0.022
Rock	0	0.012	0.016	0.546	0.425
Barren (soil)	0	0.042	0.058	0.152	0.763

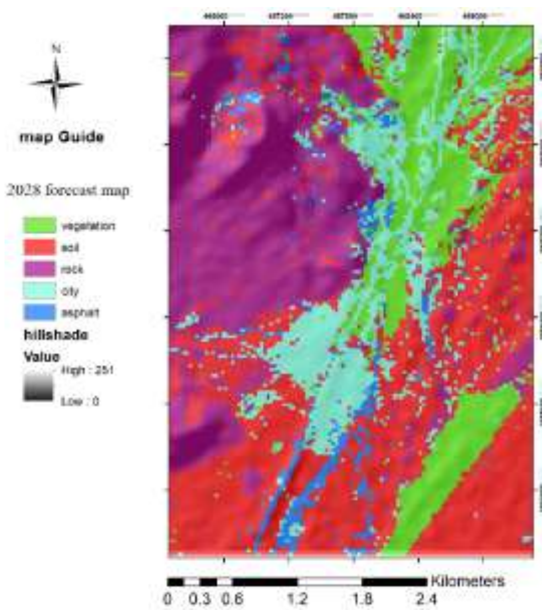


Figure 6. Forecast map for 2028

5. Conclusion

One of the prerequisites for optimal land use is knowledge of land use pattern and its changes over time. Principled exploitation of natural resources requires patterns and models of the region to not only comply with the guidelines of ecological models, but to consider the sustainable exploitation. As a result, it is very efficient to know the type and percentage of land use and also the extent of their changes in natural resources and other sectors. Also, as a management parameter, it can help planners of different executive departments in comprehensive management and development. It was found that in this study, it was found that vegetation has decreased in favor of urban growth and on the other hand, the use of the urban area and barren lands has increased as a result of the vegetation increase, while the decrease in rangeland has environmental consequences such as dust, severe soil erosion, floods, Loss of groundwater and other source of water. It is necessary to examine the general aspects of the matter before any change of land use. Increasing the level of public awareness and managers' attention to maintaining green space and rangeland besides effective management practices can reduce the process of degradation in the study area. Moreover, detecting the land changes occurred around the study area can help the planners and regional managers to identify effective factors and adopt optimal management methods in the process of sustainable development. The three-year management basis was used to better manage natural ecosystems over the next 17 years. The results of radiometric quality study and geometric control of images indicated that the images for the considered 3 years are of good quality and do not have any known radiometric errors. Also, the classification of images using maximum likelihood classification showed that there are five land use classes including: vegetation, city, asphalt, barren lands (soil) and rock and cliffs. in order to evaluate the validation, the prepared maps were compared to the Earth reality maps and the error matrix results were presented in a form of table. The overall accuracy for the classified maps of 1985, 2000 and 2011 was 94.94%, 94.62%, 96.84%, respectively, and shows the high accuracy of the maximum similarity method for classification. From the interpretation of land use maps prepared by the supervised classification method, it was found that the supervised classification method in separating the types of land cover and land use obtains appropriate results and easily separates the types of land use (Yaghmaeian NaderiKhorasgani, and Givi, 2011). Among the different algorithms used for the classification, the maximum probability algorithm was selected as the best algorithm; which has higher accuracy and precision, according to the results from the research of (Yaghmaeian, NaderiKhorasgani, and Givi, 2011; Kevin et al., 2010) and also the results of the current study.

References

Arkhi, S. (2014). Predicting the trend of spatial land use change using LCM model in GIS environment (Case study: Sarableh area). *Iranian Journal of Forests and Rangelands Protection, 12*(1), 1-19.

Salman Mahini, A,. ZareGarizi, A., Saaduddin, A., & Sheikh Vahed, B. (2011). Spatio-temporal simulation of forest area changes in ChehelChay watershed of Golestan province using an integrated model of automatic cells and Markov chain. *Iranian Forest and Poplar Research, 2*, 273-285.

Bakr, N., Weindorf, D. C., Bahnassy, M. H., Marei, S. M., & El-Badawi, M. M. (2010). Monitoring land cover changes in a newly reclaimed area of Egypt using Multitemporal Landsat data. *Applied Geography, 30*(4), 592-605.

Congalton, R. G.(1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment, 42*, 35-37. Doi:http://dx.doi.org/10.1016/0034-4257(91)90048-B

Dawelbaita. F., Morari. (2012). Monitoring desertification in a Savannah region in Sudan using Landsat images and spectral mixture analysis. *Journal of Arid Environments, 80*, 45-55. Doi:http://dx.doi.org/10.1016/j.jaridenv.2011.12.011

Eastman, J. R. (2006). *IDRISI Andes. Guide to GIS and Image Processing*. Clark Labs, Clark University, Worcester, MA.

Fan, F., Wang, Q., & Wang, Y. (2007). Land use and land cover change in Guangzhou, Chaina, from 1998 based on land sat TM/ETM+ imagery. *Sensors*. Doi:https://doi.org/10.3390/s7071323

Ghanbari, F., & Shetabi, Sh. (2010). Investigating the trend of forest surface changes using aerial photographs and ASTER images (Case study: forests on the southern and southwestern outskirts of Gorgan). *Journal of Wood and Forest Science and Technology Research, 17*(4), 1-18.

Ghahraman, J. (2004). Application of Markov chains in human resource planning (a practical approach for human resource managers in social organizations). *Administrative Transformation, 43-44*, 75-93.

Hashimoto, M., Nose, T., & Muriguchi, Y. (2002). Wood products: potential carbon sequestration and impact on net carbon emissions of industrialized countries. *Environmental Science & Policy, 5*, 183-193.

Kevin O'Donnell, T., Goyne, K. W., Miles, R. J., Baffaut, C., Anderson., S. H., & Sudduth, K. A. (2010). Identification and quantification of soil redoximorphic features by digital image processing. *Geoderma, 157*, 86–96.

Lamchin, M., Lee, J. Y., Lee, K., Lee, Y., Kim, M., Lim, H., Choi, H., & Kim, S. (2016). Assessment of landcover change and desertification using remote sensing technology in a local region of Mongolia.

Advances in space research, 57, 64-77. Doi: https://doi.org/10.1016/j.asr.2015,10,006

Lausch, A., & Herzog, F. (2002). Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution and interpretability. *Ecological indicator, 2*(1-2), 3-15.

Lu, D., Mausel, P., Brondizio, E., & Moran, E. (2004). Change detection techniques. *International Journal of Remote Sensing*, *25*, 2365-2401.

Mas, J., Kolb, F., Paegelow, M., Camacho Olmedo, M., & Houet, T. (2014). Inductive pattern-based land use/cover change models: a comparison of four software packages. *Journal of Environmental Modelling and Software, 51*(13), 94-111.

Perma, R., & Shetabi, Sh. (2010). Investigation of the possibility of preparing diversity and canopy density maps of Zagros forests using ETM + sensor images (Case study of Qalajeh forests of Kermanshah province). *Iranian Forest Journal, 2*(3), 242-231.

Prabaharan, S., Raju, K. S., Lakshumanan, C., & Ramalingam, M. (2010). Remote sensing and GIS applications on change detection study in coastal zone using multi temporal satellite data. *International Journal of Geomatics and Geosciences, 1*(2), 159.

Russell-Smith, J., Yates, C., Edwards, A., Allen, G. E., Cook, G. D., Cooke, P., Craig, R., Heath, B., & Smith, R. (2003). Contemporary fire regimes of northern Australia, 1997–1380: change since Aboriginal occupancy, challenges for sustainable management. *International Journal of Wild land Fire*, *12*, 283-297.

Sang, L., Zhang, C., Yang, J., Zhu, D., & Yun, W. (2011). Simulation of land use spatial pattern of towns and villages based on CA–Markov model. *Mathematical and Computer Modelling, 54*, 938-943. Doi: https://doi.org/10,1016/j.mcm.2010, 11,019

Singh, A. (1989). Digital Change Detection Techniques Using Remotely Sensed Data. *International Journal of Remote Sensing*, *10*, 983-1003. Doi: https://doi.org/10,1080/01431168908903939

Vaclavik, T., & Rogan, J. (2009). Identifying trends in land use/land cover changes in the context of post socialist transformation in Central Europe: A case study of the greater Olomouc region, Czech Republic. *GIS science & Remote Sensing, 46*(1), 54–76.

YaghmaeianMahabadi, N., NaderiKhorasgani, M., & Givi, J. (2011). Percentage of land degradation changes in Ardestan region of Isfahan province in the last three decades using remote sensing technology. *Journal of Agricultural Science and Technology and Natural Resources, Soil Science. 15*(58), 82-71.

Zhang, F., Tiyip, T., Feng, Z., Kung, H. T., Johnson, V., Ding, J., Tashpolat, N., Sawut, M., & Gui, D. (2015). Spatio-Temporal Patterns of Land Use/Cover Changes Over the Past 20 Years in the Middle Reaches of the Tarim River, Xinjiang, China. *Land Degradation & Development*, *26*(3), 284-299.