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Detecting and predicting vegetation cover changes using sentinel 2 Data (A Case Study: Andika Region)

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Abstract

The earth surface is itself a complex system, and land cover variation is a complex process influenced by the interference of variables. In this study, the data of Sentinel 2 for 2017 and 2016 were processed and classified to study the changes in the Andika area. After discovering vegetation changes between two images over the mentioned time, vegetation increased by 661.74 hectares. Multiple regressions have been used to identify factors affecting vegetation changes. Multiple regressions can explain the relationship between vegetation changes and the factors affecting them. In order to investigate the factors affecting vegetation change, altitude data, distance from the road, distance from residential areas of the village and river were introduced into regression equation. Since this method uses three parameters such as Pseudo-R^2 and Relative Operation Characteristic (ROC), 0.23, and 0.696 values for the above parameters, which indicates that the model is in good agreement. The results of regression analysis show that linear composition of height variable as independent variables in comparison with other parameters has been able to estimate vegetation change. Subsequently, by using two classified pictures of 2017 and 2016, the amount of vegetation changes was calculated, and Markov chain method was used for 2018 forecast changes.

Keywords: NDVI, Sentinel 2, Cellular Automata Markov and logistic regression

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1. Introduction

On a global scale, population growth can be considered as the main reason for changing the land use. Paying attention to the patterns, the trend of landscape changes to understand the dynamics of vegetation, sustainable conservation and assessment of management approaches is necessary. In recent years, much attention has been paid to changes in land cover, land use and vegetation change. Forecasting and modeling of land cover changes, such as urban development, deforestation, etc. are considered as a powerful tool for managing natural resources and monitoring environmental changes. These changes reflect how are human interactions with the environment and its modeling influences large-scale decision-making and planning (Aslani Moghadam, 2012).

Some phenomena and complications of the earth's surface, such as vegetation, have changed over time due to natural or human factors, which affects the ecosystem's condition and performance. Therefore, the need to detect, predict and care for such changes in an ecosystem is of great importance. In addition, acquiring knowledge about vegetation and its effective factors in soil management plays an important role. Today, the production of a detailed vegetation map is one of the most important tools in design and development. It is usually difficult and limited to monitor vegetation on a global or regional scale. Because traditional and old data is collected from small location at different time interval, which differ in terms of type and credit rating (Pettorelli et al., 2005). Remote sensing technology is a very useful tool that can be used to obtain information layers from soil and vegetation (Adamchuk et al., 2004). Features such as providing a broad and integrated view of a region, the ability to repeat, the ease to use information, and the high accuracy of the resulting information and saving time are the features used to examine vegetation. Accordingly, many researchers have used remote sensing data to study vegetation and this technique is suitable for such studies (Pettorelli et al., 2005; Huete and ustin, 2004). The Normalized Difference Vegetation Index (NDVI)has been beneficial in many studies. This indicator is based on the fact that the chlorophyll in the plant can absorb red light and reflect the mesophilic layer of the near-infrared light.

This index is calculated using the NDVI formula (Equation 1) and its value varies between 1+ and -1. The negative values in this index indicate the absence of vegetation (Pettorelli et al., 2005; Adamchuk et al., 2004; Al-Madrasi Al-Husseini, 2013). The value of this indicator is influenced by the factors that awareness of them play an important role in vegetation studies. In this research, multiple regression has been used to identify the factors influencing vegetation changes.

$$\text{Normalized Vegetation Index} = (TM4-TM3)/(TM4+TM3) \quad (1)$$

One of the tools used by planners to control the process of changing forests cover is regression relations, given that environmental science deals with various phenomena. Therefore, in regression issues, multiple regressions are of great importance (Bihamta and Zare Chahui, 2011). Multiple linear regressions are available to analyze the relationship between multiple variables. In multiple linear regressions there is an assumption of the existence of linear relationship between dependent variables and independent variables (Salman Mahini et al., 2012). Using remote sensing data and linear regression equation in GIS environment provides a better understanding of how to change forest cover and determine the effecting factors. Jafarzadeh and Arkhi (2012), simulated destruction in the northern forests of Ilam, they aimed to predict the spatial distribution of deforestation and the identification of its effective factors in the northern forests of Ilam province. In order to estimate the spatial distribution of deforestation, the logistic regression method was used for modeling. Modeling results showed that deforestation is the most commonly found phenomenon in discrete forest coverages and in areas near forest and non-forest boundaries (Miranda et al., 2012). Modeling regions are susceptible to forest cover changes using logistic regression in the rain forest of northern Mexico. The results showed that forests in the study area are highly susceptible to degradation and change in utilization, which is a major factor in increasing the population and unnecessary use of forest resources in the region. The study of land cover change in Isfahan area was carried out during the years 1987 to 1998 (Safiyanian, 2009). The results indicated that the ground level of agriculture has undergone significant changes. In another study in Isfahan, population growth has been the main factor in reducing vegetation cover and increasing residential utilization (Zairi Amirani and Safiyanian, 2010). In the country, limited research has been done on coastal land changes. In a study of land change in Aslouyeh coastal area shows that under the influence of land changes, the erosion and sediment of the area have changed dramatically (Na'imi Nezam et al., 2010). Also, remote sensing is an appropriate tool for monitoring coastal land changes (Ghazalfali and Alawafanah, 2010). A variety of studies have been done to simulate coating changes using the CA-Markov model. These include studies in the prediction of the land cover situation in Isfahan (Fallahtakar et al., 2009) simulation of land cover changes in the Gorganroud area, (Sheikh Goodarzi et al., 2013) and the study of vegetation changes (Chang et al., 2006; López et al., 2001; Sang et al., 2011).

Therefore, considering the importance of the study of vegetation changes, as well as the determination of coordinated and integrated planning for sustainable use of land resources, the present research intends to study the trend of vegetation changes over environmental factors by determining the land cover changes in the Andika city, using satellite data and the time trend of vegetation changes using the logistic regression.

The distinction between the present study and previous study in this model, while identifying the positive or negative effects of each variable on the presence and absence of effective factors, can identify variables that have a greater effect on the behavior of vegetation changes (Sensitization). The present study intends to use the satellite data to model landslide changes in the Andika city, and to prepare spatial distribution of changes map and to fit the Logistic regression model to investigate the vegetation change and map the probability of vegetation change in the study area. The general objective of this research is to identify the factors affecting vegetation change and predict vegetation changes in the forested area of Indica in northern Khuzestan province.

2. Materials and Methods

2.1. Realm of research

Andika is located between 49 degrees and 53 minutes to 49 degrees and 52 minutes east longitude from Prime Meridian (Greenwich) and 31 degrees and 43 minutes to 32 degrees and 39 minutes north latitude from the equator in the eastern part of Khuzestan province. The area of the Andika city is 2336 km^2 and the altitude of the sea level is approximately 800 meters. The elevation is between 400 and 3000 meters above sea level. The average temperature is 50°C in July, and the average temperature is 6°C in January and the average annual precipitation is 400 mm in the form of rain and hail; and snow in the highlands of the region. The amberthermic curve shows that the region has no rainfall since late spring to early autumn (Figure 1).

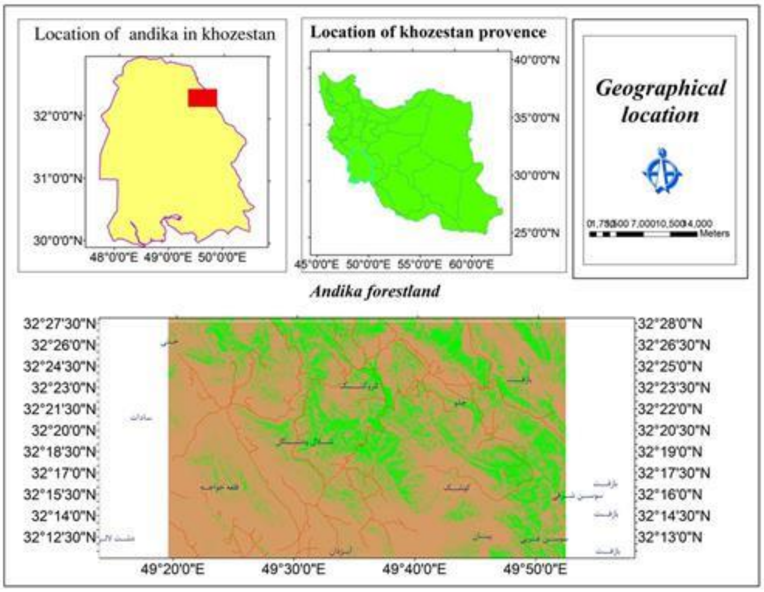

Figure 1. Geographical location of the study area

2.2. Research Method

Land changes have been studied for many years. However, the advent of satellite imagery and land-based techniques has opened a new dimension to review and evaluate land change patterns (Matsushita et al., 2007). Geographic information system and remote sensing data can be used as a tool for analysis and provide accurate results (Aronov, 2013). The multivariate feature of satellite imagery for assessing changes is widely been used in environmental review, land cover change assessments, forest surveys, and urban studies which plays an important role in many areas of application (Zebiri and Majd, 2001).

In this research, in order to achieve quantitative and qualitative changes in vegetation changes in the Andika region, the normalized difference index data (an indicator based on the band ratio) was extracted from Sentinel satellite images of 2016 and 2017. This index is calculated using the formula (equation 1) and its value varies between numbers +1 and -1. Negative values in this index indicate the absence of vegetation (Aslani Moghadam, 2012; Almodaresi Al-Husseini, 2015). In this study, in order to study vegetation changes as an associated variable and digital elevation data from the sea level, distance from the road, distance from residential areas of the village and river as effective parameters in vegetation change process as independent variables in establishing multiple linear regression. The regression equation shows each of the independent variables and the constant coefficient. The constant coefficient represents the value of the dependent variable at the time when all independent variables have zero values. Regression coefficients show the effect of each independent variable on the dependent variable. R represents the multiple correlation coefficients between dependent variables and independent variables. R^2 indicates the variability of the dependent variable based on all independent variables. Using the determination coefficient, it is determined how much is variable variation dependent on the independent variable. Several methods for analyzing the time series of images, such as principal components analysis, wavelet analysis, Fourier analysis, are proposed. These methods allow the change process to be interpreted only between two periods (e.g. between years or stages of growth), which makes analysis dependent on the choice of these courses. Additionally, changing the time series that occurs with seasonal variations of temperature and rainfall, the techniques of detecting changes focuses on minimizing seasonal variations over a particular period in a year. In order to predict forest area changes, the CA-Markov model was used. Markov chain analysis describes land-use changes from one period to another and uses them as a basis for mapping future changes. CA-Markov is an important issue in Markov's analysis and there is no spatial element in this modeling (Mahdavi et al., 2015).

In fact, the Markov model focuses on quantity in predicting land changes. The spatial parameters in this model are weak and different types of land cover variations are not recognized in spatial patterns (Sang et al., 2011). The automated CA network will be used to add the location element to the model. CA has the capability to locate spatially-temporal dynamics in combination with sophisticated spatial systems, with a good location-based detection capability. The CA-Markov model combines the ability of Markov and CA which is well-suited for predicting spatial and temporal series. Thus, the CA-Markov model provides a better simulation of spatial and temporal patterns of land cover variations in a given amount and location (Sang et al., 2011). In this study, the CA-Markov model integrated with the Idrisi program was used to simulate forest cover change.

Several software applications have been used in this research. Among them are: 1. ENVI4.8 and SNAP software for geo-referencing images and production of vegetation map and classification. 2. EDRISI software for applying the LCM model, mapping the vegetation changes, preparation of independent variables, and also studying the potential of vegetation change due to independent factors. 3. ArcGIS10.2 for cutting the area.

3. Results

3.1. Change detection

The discovery of changes has been one of the major applications of measuring sensitivity. With the repetition of the remote sensing data of different times, it is possible to detect and verify the dynamic variable phenomena in the environment. Identifying an appropriate method for detecting changes in the region to generate good results is a crucial element in detecting changes (Matsushita et al., 2007). In this study, NDVI method was used to detect the vegetation changes.

Image 2 has latitude of 290 km and a precision of 10 meters. First, two geometric corrections were made for 2016 and 2017, and then the desired range was clipped, used to cut a layer of a vector in the ENVI4.8 software. Then, NDVI from the desired areas was created and classified for each image (Figure 2).

The NDVI value varies between +1 and -1. The negative values in this index indicate water and values from 0 to 0.2 are the soil classes (the first class is from -1 to 0.2 which means the vegetation is absent) and the values of 0.2 to 1 are attributed to the vegetation class. The classification results showed that in 2016, the total surface area of the region was about 35884.78 hectares covered by vegetation, while in 2017 vegetation class were about 35223.04 hectares (Table 1).

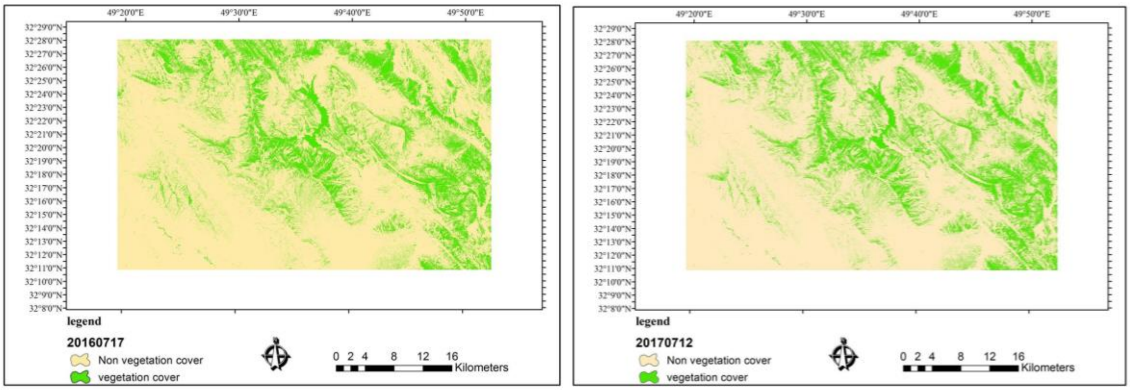

Figure 2. Classification of vegetation in the Andika region

Table 1. Changes in vegetation cover in 2016-2017

User classes	Non vegetation cover	vegetation cover	Total
Area of 2016 (Hectare)	128489.42	35884.78	164374.2
Area of 2017 (Hectare)	129151.16	35223.04	164374.2
Level of changes (Hectare)	661.74	-661.74	
Percentage change versus total	0.402581	0.40258	

The results of the comparison between the two maps indicates that 661.74 hectares of vegetation areas have been reduced. The change is shown in Figure 3 and the changes in the vegetation cover are shown in Figure 4.

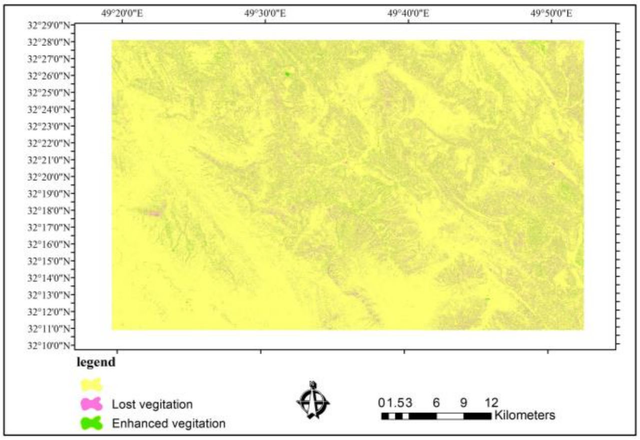

Figure 3. Map of vegetation changes in the Andika region

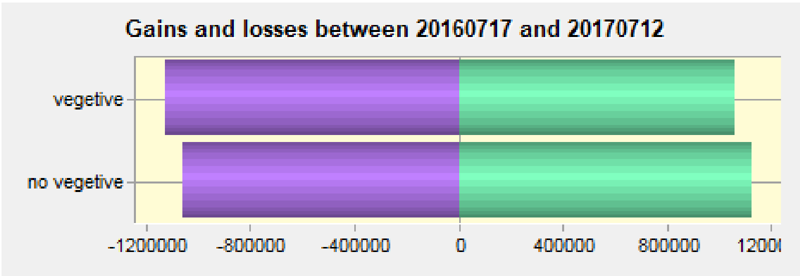

Figure 4. Vegetation changes in the Andika region between 2017 and 2016

Table 2. Variation in vegetation cover between 2016-2016

User classes	Changes (Hectare)
Non vegetation cover to vegetation cover	10604.48
Vegetation to the Non vegetation cover	11266.22
Total	21870.7

The study area with an area of 2187.7 hectares has been observed which shows that 11266.22 hectares of the vegetation cover area has been destroyed and 10604.48 hectares of land has changed to vegetation.

3.2. Multiple regressions

Empirical estimation methods, using statistical techniques, models the relationship between the forest cover reduction and the influencing factors. Logistic regression is one of the experimental models that fit the probabilistic model between forest cover reduction (as dependent variable) and its effective factors (as an independent variable). Based on this model, one can explain the relationship between variables, estimate the relative importance of index variables and map (Kamyab et al., 2010).

After determining the location and extent of vegetation changes, multiple linear regressions assume a linear relationship between dependent and independent variables. With a number of independent variables, the linear multiple regression equation will be (Relationship 2). In logistic regression, the null hypothesis is that the probability of obtaining a certain value of a nominal variable in relation to a measured variable is not, or indeed, the linear gradient that expresses the relationship between the measurement variable and the probability of a nominal variable is zero. Logistic regression is followed by an equation that predicts the value of the variable Y for each value of the X variable. Here, the dependent variable Y is not directly measured; instead the probability of obtaining a certain value of it is investigated. This probability is between zero and one variable, although this value cannot be directly entered in the regression (Shojaeai et al., 2017).

$$Y= a+b1\ x1 +b2\ x2 +\ldots+bn\ xn \qquad (2)$$

In the process of modeling with the logistic regression that is done in the Idrisi software, a map will eventually result in a model showing the potential for vegetation changes for 2016 and 2017. A file that contains information on modeling results, the weight of independent variables and indicators for assessing the logistic regression model are presented along with the output map of the model (Figure 5).

3.3. Assessing the logistic regression

Recently, the developing world has experienced unprecedented growth in urban areas which has a significant impact on land use intensification. Therefore, modeling and predicting changes for planning natural resource conservation advocates is crucial for setting up a sustainable development strategy, whose main goal is to identify the factors and the process of changes (Kamyabet al., 2010). Indicators for evaluation of logistic regression model the ROC index is expressed numerically between 0-1 which is obtained from the ROC curve When there is a perfect match between the actual map and the map from the model. The ROC index is equal to one and The value of 0.5 for this indicator expresses the randomness of the positions and shows that the value of the cells in the prediction map is created in the form of random positions (Mirza'i Zadeh et al., 2016). The use of the Pseudo-R2 index in the logistic regression model for the fit test of the model was confirmed by McFadden 1973 Domnick and McFadden 1975 and Clarke and Hawking 1986 (Mesgari and Ranjbar, 2003; Domencich and McFadden, 1975; Clark and Hosking, 1986). According to the study, the Pseudo-R2 acceptable rate for verifying the satisfaction of the model ranges from 0.2-0.4 (Mirza'i Zadeh et al., 2016).

logit (lcm Train Non vegetation cover to vegetation) = -1.6322+1.489921 *contour - 0.354199*road- 1.626083*river - 0.434008*village (3)

The Distance from urban and rural residential areas and also the distance from the road and the river were considered as independent variables. Then, the linear multiple regression relationship between vegetation changes was established as a dependent variable with the above parameters, which is shown in Table 3. Regression coefficients show the effect of each independent variable on the dependent variable.

Table 3. Multiple Regression Model Linear Results

Adjusted Odds Ratio	ROC	Chi-square	Pseudo R-square	B4x4	B3x3	B2x2	B1x1	A	Y
1.4797	0.696	5402.3866	0.23	-0.434008	-1.626083	-0.354199	1.489921	-1.6322	Y1
				Village	River	Road	Height	y-intercept	Vegetation changes

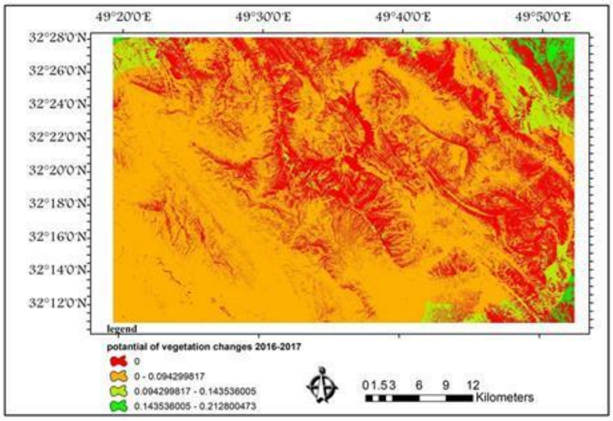

Figure 5. Output map of Logistic Regression Model (Potential of non-vegetation cover conversion to vegetation)

Since this method uses three parameters such as Pseudo-R^2, ROC, there is a value of 0.23, 0.696 obtained for the above parameters that represents the good fit of the resulting model with reality (Almodaresi Al-Husseini, 2015). Using the coefficient of determination, it is determined how much is change dependent on the independent variable. According to the coefficient determined with a probability of 0.696, vegetation cover per hectare has been created by independent variables. It can be said that the error rate of 10% indicates that the probability of the model error is 49969.7 hectares. The ROC value for the present study was 0.696. This statistic is an appropriate statistic for assessing the validity of the model and can be used to compare the actualized image. Value 1 represents the complete spatial agreement and value of 50% represents a low agreement of the model with reality (Salman Mahini et al., 2012).

3.4. Model sensitivity

In order to determine the importance of independent variables, the sensitivity of the model (regression equation of soil changes to vegetation) has been studied. The sensitivity of the multiple linear regression model is such that and after the implementation of the model with a complete data series, the model is restored to the number of independent variables. Now, the difference in each stage is the model of one of the independent variables which is eliminated and the model with the remaining independent variables is performed (Courage and Aniya, 2009). The advantage of this is in sensitizing the variables and discovering the effect of the variables in the final model. After each iteration, the coefficient of model determination is extracted and based on the obtained difference with the complete data series, the independent variable is calculated (Figure 5). The variables of distance from height have a determinant effect on the performance of the model because by deleting these variables, the coefficient index determines a significant decrease (Salman Mahini et al., 2012).

Table 4. Results of the model sensitivity

Deleted independent variable	**Variable coefficient**	**Deleted independent**
Perfect model	0.696	1
Village	0.6299	2
Road	0.5937	3
River	0.6442	4
Height	0.5904	5

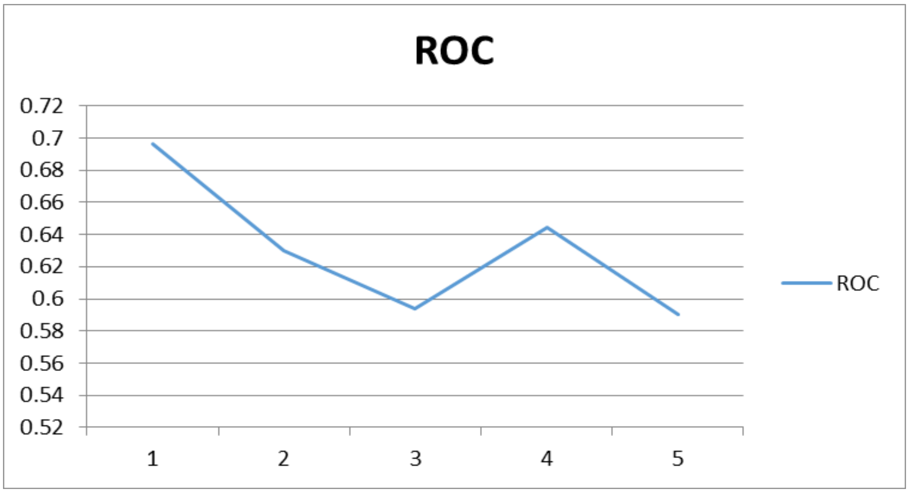

Chart 1. Relationship between ROC and independent variable

With enough information on how to change the city and the process of vegetation change, better plan can be mastered on how to expand the city and vegetation in future. The area of Andika includes a metropolitan area on a hillside and the villages scattered around the city. Since the height is a deterrent factor of urban development, this model does not consider the mountainous areas susceptible to agriculture. Mountain range areas are more agricultural in terms of their location and the greatest potential for changing vegetation is in the bulk. The sensitivity of the model shows that the height of the mountains has the largest effect on vegetation change and oak shoots are mostly concentrated in mountain heights Figure 6.

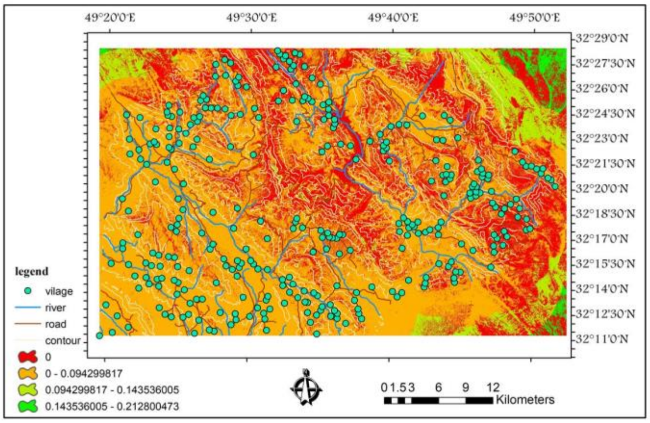

Figure 6. Map of change potential in the Andika region along with factors affecting vegetation change

3.5. Predicting Markov chain model changes

There are models of land cover variations, including mathematical and statistical equations, systematic models, randomized models, and automated cell-based models (Sheikh Goodarzi et al., 2013). CA-Markov is a hybrid model of automated cells 4 and Markov system 1. The CA-Markov model is a suitable method for time and space modeling of land covers variations because GIS and remote sensing can be combined with other sciences (Courage and Aniya, 2009). In this regard, remote sensing can be used to prepare a forest plan and monitor spatial and temporal patterns. Satellite images are the best sustainable resource with up-to-date spatial data to estimate deforestation. The Markov chain was presented by a Russian mathematician Andrei A. Markov in 1907. The Markov process is used when the future status of a system can be modeled in general on the basis of the pre-existing state of the system. This method which is now considered as an important method in geographic research, is usually used to predict geographic characteristics with subsequent disruptions (Sang et al., 2011). Markov chain analysis expresses changes in land cover from one period to another, and uses it as the basis for mapping future changes. This work uses the development of a matrix of probability from time one to time two (salman Mahini, et al., 2009). The forecast of land cover changes is calculated as follows:

$$S(t+1) = P_{ij} * S(t) \tag{4}$$

$$Pij = \begin{bmatrix} P11 & P12 & \dots & P1n \\ P21 & P22 & \dots & P2n \\ \dots & \dots. & \dots. & \dots \\ Pn1 & Pn2 & \dots & Pnn \end{bmatrix}$$

$$(O \le Pij < 1 \text{ and } \textstyle\sum nj=1\ Pij = 1 , (i,j = 1,2 , \dots .n)) \quad (5)$$

In the relation s (t) and S (t + 1) are the system states at time t and t + 1, and Pij is the probability change matrix 11.

CA: An automated cell model was first designed in the 1940s by two mathematicians called Olam and Newman (Schatten, 1999). Automatic cells are a discrete dynamical system that mode each cell at time t+1 by the position of neighboring cells at time t and in accordance with predefined rules. As a result, geographic status is more important. The CA model is shown in the following formula:

$$S(t, t+1)= f(s(t),N) \quad (6)$$

S is restrictions and discrete cellular states, N number of cells, t and t + 1 different times and f is the transmission of cell status. The CA model is in fact a raster modeling technique in which the cell's state usually represents the cell's surface (Almeida et al., 2008). These models have features such as spatial location and the ability to integrate with other spatial data. Mathematics can be a tool for studying and modeling complex processes.

An important issue in Markov's analysis is that there is no spatial element in this modeling (salman Mahini, et al., 2009). In fact, the Markov model focuses on quantity in predicting land cover variations. Spatial parameters in this model are poor and do not distinguish different types of land cover changes in spatial patterns (López et al., 2001). CA has the capability to have spatial-temporal detection capabilities in combination with sophisticated spatial systems with proper spatial detection capabilities. The CA-Markov model which combines the ability of Markov and CA, is well-suited for predicting spatial and temporal series. Thus, CA-Markov model provides a better simulation of spatial and temporal patterns of land cover variations in a given amount and location (Sang et al., 2011).

In this study, CA-Markov model was used to simulate forest cover changes. After categorizing the images of 2016 and 2017 and using the automatic cells and Markov chain method, predicting vegetation changes in the Andika forests in 2018 was started. Then, using the automatic cell and Markov chain method, the area of the oak forests for the year 2018 was predicted (Figure 7). After entering the classified images, the area of each classified category can be calculated. After this step, using the Markov chain in the Idrisi software, the matrices of the probability of vegetation changes can be obtained (Table 5). Then, the changes in forest area non vegetation cover is calculated (Table6).

Table 5. Probability matrix of vegetation changes on the vegetation of the Andika

Vegetation cover	Non vegetation cover	
0.2202	0.7798	Non vegetation cover
0.5831	0.4169	Vegetation cover

Table 6. Changes in the Andika vegetation cover from 2016 to 2018

Year	**2016**	**2017**	**2018**
Non vegetation cover	129151.16	128489.42	115406.05
Vegetation cover	35223.04	35884.78	48968.15

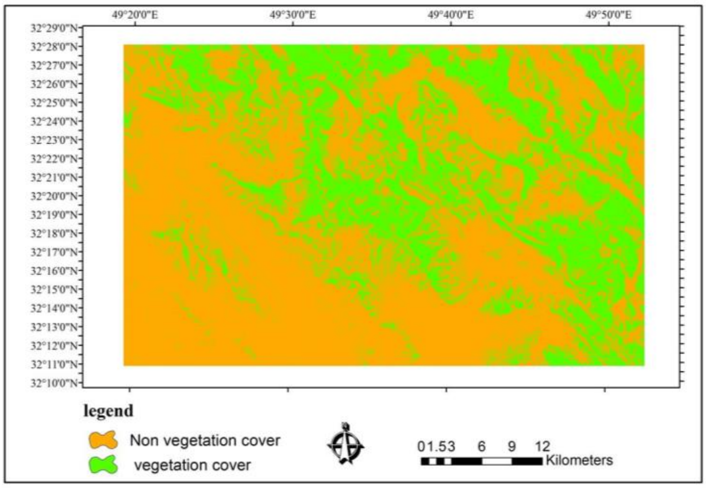

Figure 7. Prediction map of vegetation changes in the Andika region for 2018

4. Discussion

One of the main prerequisites for optimal use of land is the knowledge of land use patterns and changes over time. Principal exploitation of natural resources requires modeling of the region, while observing the instructions of ecological models sustainable development should be taken into consideration.

The results of this study indicate that the integration of remote sensing and GIS techniques is efficient in implementing spatial-temporal variations assessment models to know the type and percentage of land use and the extent of their changes in natural resources and other parts. Planners of different executive sector can assist in comprehensive management and development (Azizi Ghalati et al., 2015).

This research was carried out with the aim of determining the factors affecting vegetation changes in the forest area in Andika county, Khuzestan province. The vegetation of the oak forest is observed at mountain heights and the mountainous nature of the area prevents urban development and also the possibility of provision of welfare facilities for the inhabitants of the villages. Because access to oak forests in the mountains is difficult, residents of the villages do not harm it and the size of the forests has increased over the course of study. The total area is 164374 hectares, and the amount of land cover changes from 2016-2017 was 661.74 hectares.

The effect of four factors, that are the distance from the road, the distance from the rural residential areas, river and altitude from sea level on the amount of vegetation changes was investigated. Linear regression analysis has been used to determine the relationship between the factors mentioned above and increasing vegetation cover. It can be claimed that there is a significant relationship between independent and dependent variables. Outputs of the regression equation show the effect of independent variables on dependent variables. The value of the determination coefficient of 69.6 indicates a huge agreement between the model and reality. The potential map of region changes and independent variables are shown in Figure 5.

The sensitivity of the multiple regression model can be concluded that the height variable has a decisive effect on the performance of the model because by deleting these variables, the index of the coefficient of determination decreases significantly (Salman Mahini et al., 2011). The coefficient of determination decreased from 0.696 to 5904. The highest vegetation cover is at the mountains height around the Andika which are the oak forests. The vegetation cover increased from 35223 hectares to 35884 hectares from 2016 to 2017. The use of automated cells and Markov chain to predict the vegetation changes for 2018 in the area under consideration, estimated an area of vegetation of 48,968 hectares. In other studies, Similar results and could well examine changes at two different times were presented. Land cover changes in the city of Isfahan were carried out by Safiyanan during the years 1987 to 1998. The results indicate that the level of agricultural land has undergone A significant change (Safiyanian, 2009). Also, in another study, population growth has been the main factor in reducing the vegetation cover and increasing residential utilization (Zairi Amirani and Safiyanian, 2010). In a study using logistic regression method, in modeling the spatial pattern of vegetation change probability in Chehel-Chay watershed in Golestan province, the results showed that variables from forest margin, distance to road and distance to the village, the slope of the earth and the distance to the waterways have been considered most relevant in relation to forest cover changes in the catchment area (Zare Garzi et al. 2012). Modeling the forest area changes and the factors affecting it were analyzed using logistic regression model in Waz and Lavij watersheds. Implementation of logistic regression model in two independent discrete and continuous variables, the coefficients obtained from the implementation of the model in a discrete state indicate the probability of 100 meters from the village (Hosseinzadeh et al., 2013).

It is also possible to change the structure of the HNN algorithm, such as how to initialize, how to apply coefficients for different classes depending on compactness and circularity parameters, how to change the averaging method of neurons, how to increase and decrease the values of neurons for each repetition and improved algorithm performance.

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