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Original Article

Integration of Neural Network, Markov Chain and CA Markov Models to Simulate Land Use Change Region of Behbahan

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Abstract

Purpose- Land is the place of earthly natural ecosystem functionality that has been used by humans in multiple methods. Land-use change (LUC) simulation is the most important method for researching LUC, which leads to some environmental issues such as the decreasing supply of forestry products and increasing levels of greenhouse gas emissions. Therefore, the present study aims at (i) using the Landsat imagery to prepare land use-cover (LULC) maps for 2000 and 2014; (ii) assessing Land use changes based on land change modeler (LCM) for the period from 2000 to 2014, and (iii) predicting the plausible land cover pattern in the region of Behbahan, using an algorithm based on ANN for 2028.

Design/methodology/approach- A hybrid model consisting of a neural network model, Markov chain (MC), and cellular automata (CA Markov) was designed to improve the performance of the standard network model. The modeling of transfer power is done by multilayer Perceptron of an artificial neural network and six variables. The change allocated to each use and the forecasting is computed by Markov chain and CA Markov. Operation model calibration and verification of land use data at two points were conducted in 2000 and 2014.

Findings- Modeling results indicate that the model validation phase has a good ability to predict land-use change on the horizon is 14 years old (2028). The comparison between modeling map and map related to 2013 shows that residential area and agricultural land continue to their growth trend so that residential area will be increased from 3157 hectares in 2014 to 4180 hectares in 2028 and it has 2% growth that has been 2% from 2000 to 2014. The results of this study can provide a suitable perspective for planners to manage land use regarding land-use changes in the past, present, and future. They are also can be used for development assessment projects, the cumulative effects assessment, and the vulnerable and sensitive zone recognition.

Keywords- Change Detection, Neural Network, Markov Chain, CA Markov, Behbehan County.

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1. Introduction

The land is the place of earthly natural ecosystem functionality that has been used by humans in multiple methods (Mohammadyari, et al., 2020). Land-use change (LUC) simulation is the most important method for researching LUC, which leads to some environmental issues such as the decreasing supply of forestry products and increasing levels of greenhouse gas emissions (Macedo et al., 2013). So, land-use change has attracted the attention of managers and planners who are engaged in the issues related to sustainable urban and environmental development (Mohamed & Worku, 2020). LUC is a complex process (Irwin & Geoghegan, 2001; Lambin et al., 2006), and modeling these systems is challenging. It is well known that the drivers of LUC operate across a variety of spatial-temporal scales in a nonlinear way (Veldkamp & Lambin, 2001) and thus nonlinear tools are needed to simulate these dynamics. The type of land use and the land covering is the result of mutual relation between social-cultural factors and land potential power. In other words, changing land use and the cover is the beginning of the dynamic exploitation of natural resources by human beings to manage their needs (Oñate-Valdivieso & Sendra, 2010). The consequences of this phenomenon are economic, social, and environmental on local, zonal, and global scales (Koomen et al., 2007). Koomen Remote sensing satellites are the most common data source for recognizing, quantifying, manifesting, and mapping land-use changes patterns (Abd El-Kawy, 2011). Therefore, the manifestation and modeling of land-use changes can offer suitable recognition of these changes by remote sensing data in a GIS environment (Mendoza, 2011; Bakr, 2010). Land Change Modeler can revolutionize the analysis and investigation of land cover changes and predicting land-use changes (Schulz et al., 2010). In this modeling, the most important assumption is that the nature of development and changes remain the same during time and past changes can predict future changes based on a historical scenario. The ecosystem can be guided to the desired path by predicting land-use changes and adopting effective managerial policies (Jensen, 2007). Land cover models are widely used for the analysis and prediction of land-use change (Bonilla-Bedoya et al., 2020; Mohammad & Worku, 2020; Silva et al., 2020; Dadashpoor et al., 2019; Sun et al., 2018; Huilei et al., 2017; Tripathi & Mozmder, 2014; Yang et al., 2014; Pijanowski et al., 2014; Arsanjani et al., 2013; Ma et al., 2017; Perez-Vega et al., 2012; Shahidul Islam & Ahmed, 2011). Among these studies, Mohammad and Worku (2020), simulating the dynamics of land cover using cellular automata and the Markov chain approach in Addis Ababa and its suburbs. The research employed a hybrid Cellular Automata, Markov chain, and multi-criteria analytical hierarchy process modeling approach. The result shows the rapid growth of built-up, which accounts for 3.7% in 2005, 5.7% in 2011, and 7.0% in 2015. Moreover, Silva et al. (2020), modeled the land cover change based on an artificial neural network for a semiarid river basin in northeastern Brazil. The results showed that for 2035, an increase in the herbaceous and shrub vegetation class and a decrease in the area occupied by tree-shrub vegetation are predicted. The study aimed to indicate the land cover alterations in the region of Behbahan between 2000 and 2014 to understand the future land use scenario (2028) of the area through integrating remote sensing and advanced GIS techniques with the ANN model, Markov chain, and CA Markov.

The paper is structured as follows. Section 1 presents the study site in Behbahan, the database, and the data preparation process. The two-section briefly introduces the methodology of neural network modeling to determine essential driving forces of sprawl, Markov chain, and CA model. Section 3 discusses the outcomes of the implemented approach, and finally, the paper concludes with a summary and some suggestions for future works.

2. Research Methodology

2.1 Geographical Scope of the Research

The studied region is between 50 degrees and 91 minutes longitude to 50 degrees and 25 minutes eastern, 30 degrees and 45 minutes latitude to north 30 degrees and 32 minutes in zone 39 that the highest altitude is 1380.93 meters and the lowest 267.14. The highest slope is 69.87 and the lowest slope is 1%, the minimum annual temperature is 18.1 c° and the maximum annual temperature is 32.37 °c. The space of area is 615.6 square kilometers and the regional climate is dry based on the Domarten method. A threedimensional map of the region is provided by Surfer11 software (Figure 1).

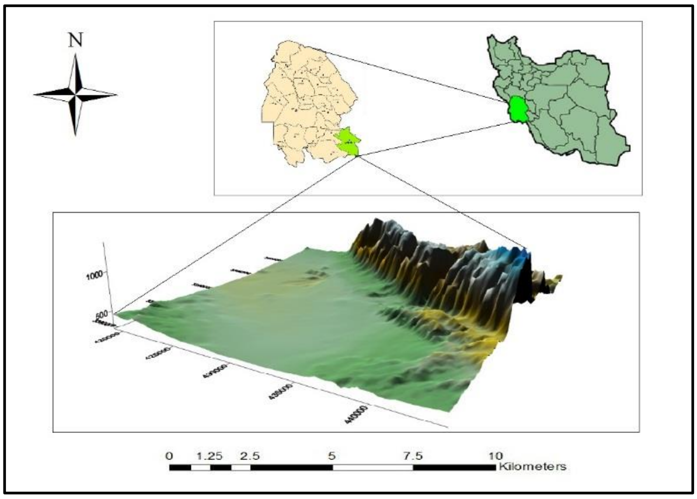

Figure 1. Location of the study region, Behbahan, Iran

2.2. Methodology

The type of this research is the application and data collection is done in two forms: library and mensuration. It is also used ArcGIS 10, Google EARTH, Surfer11, IDRISI Tiga, and ENNVI 4.8 software.

Land use map preparation- Landsat satellite images were used for providing land use maps relating to 2000 and 2014 (Table 1).

Table 1. Specification of satellite images

WRS Row	WRS Patch	Number bands	SIZE Pixels	SENSOR	SPACECRAFT	DATEACQUIRED
39	164	8	28.5	ETM^{+}	Landsat-7	2000.01.24
39	164	11	30	OLI	Landsat-8	2014.01.22

In this research, images were used with real colorful combinations for obvious representation of some special phenomenon relating to research purposes. The combination of band 3 infrared, band 2 with green color, band1 with blue color, or 321 RGB models are used for ETM sensor images creation, and for OLI sensors 432 combinations are used. First of all, geometrical, atmospheric correction and early pro processing are done on all used images several times. Then, the supervisory classification method is used for classification. In this controlled classification, the first step is the introduction of a region of intersect for each land cover class. Didactic samples are defined by visual interpretations on colorful combination images and by topography maps provided by the Topography Organization of Iran. In this process, the normal differential vegetation index (NDVI) is used for green coverage classification so that the vegetarian cover is separated from others easily and the sampling is done with more accuracy. The numbers of classes are selected according to images from available maps, the condition of the region, and the class required for land coverage maps, and six gained separation classes are: 1. residential area, 2. agricultural land, 3. Water, 4. forests, 5. grasslands, 6. bare lands. After didactic samples are determined, satellite images are classified. In this research, the Maximum Likelihood algorithm (Schulz et al., 2010) and AVI, MNF index is used to make a classification. Image classification is one of the main components in data collection that is achieved through the study of the relationship between spectral effects and classes or different classes (Oommen, 2008). The process of images classification is a conversion of data to comprehensible information (Mountrakis et al., 2011). Then, a mode filter is done on classification results so that images are simplified and small parts are removed (Nahuelhual et al., 2012).

Classification accuracy assessment- To ensure the accuracy of an extracted map from satellite images, its accuracy should be evaluated (Lillesand & Kiefer, 2000). The accuracy of classification represents the confidence level of the extracted map and refers to the adjusting level between remote sensing data and source information (Dewan & Yamaguchi, 2009). Evaluating the accuracy of classified maps is done by specifying 200 points for 2014 images by random stratified sampling in the region and the real land use is compared to them by Garmin 62S GPS. Kappa coefficient is calculated. Kappa shows the accuracy of the map. Amounts between 0 to 100 percent show a specific level for this classification and negative amounts show bad results. Kappa coefficient is above 90 percent which shows the high accuracy of prepared maps. Evaluating the maps prepared in 2000 is done by visual interpretations and a controlled spot in a land that has not changed during a time (Schulz et al., 2010).

Changes display- The changes display of land use is an essential tool for environmental analysis, planning, and management. In this research, land use maps relating to 2000, 2014 are entered into the LCM model for analysis and area changes detection. Land change modeler is software to create constant ecological development and it is planned and constructed to identify the increase in land changes and obvious need for biodiversity analysis. It is in IDRISI software and it is also available as an application for Arc GIS. Land change modeler gives a tool to investigate and do the empirical evaluation and modeling of land-use change and its effects on biological variations with the help of the modeler (Eastman, 2006).

Variable election- The variables used for the model are the digital elevation model, slope, distance from residential areas, distance from agricultural lands, distance from roads, and evidence likelihood map. Cramer correlation coefficient is used to determine a correlation between independent variables and dependent variables. This correlation coefficient compares independent variables with subjective classification from land use map (evidence likelihood) (Eastman, 2006). Variables used in this research are used in most of the studies related to land-use change modeling. Euclidian distance analysis is used for providing maps relating to distance from residential are agricultural land and distance from the road. All of the above variables are quantitative. Map relating to transmission from all use to agricultural land and map relating to transmission from agricultural to all uses are produced for land coverage quantitative variables and they are transformed to quantitative variables model input by evidence likelihood deformation and land coverage map in the early year (Eastman, 2006).

Potential modeling of land-use change by the artificial neural network of multilayer Perceptron- In this section of modeling, transformation power from one use (such as a forest) to another use (such as agriculture) becomes a model according to explaining variables (such as slope, nearness to the road) that is each pixel of the image has how much potential to change from one user to another. The output of this section will be a transformation power map for each variable (for example from forest use to agricultural land). Cramer V coefficient is calculated which shows the amount of relationship between variables and land cover. Six sub-models (agricultural to residential, forest to grassland, grassland to agricultural, grassland to arid land, arid land to residential and arid land to agricultural) and six variables (quantitative variable in agricultural sub-model, digital model of altitude, distance from agricultural lands, distance from residential areas, distance from road and slope) are selected to modeling of the possibility of occurrences in each transformation by multilayer Perceptron neural networks (Pijanowski et al., 2002; Chuvieco, 2002).

Markov chain model- The MC model is a stochastic process model that describes how likely one state is to change to another state. It has a key-descriptive tool, which is the transition probability matrix. The MC model is defined as a set of states where a process begins in one of the states and moves consecutively from one state to another; each move is defined as a step (Zhang et al., 2010). In the MC model, two distinct land use maps at different time points should exist, and then it is possible to calculate the probabilities of transition between these time steps. The analysis of the Markov chain is suitable for use changes and land coverage and it's useful when changes aren't easily describable. Markov chain is the collection of random values whose possibility in a given time depends on the numbers in the past (Fan et al. 2008). In this research, the change allocation to each use was calculated by the Markov chain (Haibo et al., 2011; Coppedge et al., 2007; Wu et al., 2006).

CA-Markov model- CA-Markov model incorporates the theories of the Markov chain and Cellular Automata (CA) and is commonly used in predicting LUC (Sang et al., 2011). CA has strong capabilities in simulating the spatiotemporal characteristics of complex systems and can be used to simulate unexpected behaviors of complex systems that cannot be represented by specific equations. Markov chain is commonly used for predicting geographical characteristics lacking after-effect events. When LUC is predicted by the Markov chain, land use is regarded as a stochastic process and different land-use types as the states of a chain (Cabral & Zamyatin, 2009; Clancy et al., 2010). Implementation of the CA-Markov model can be described by the following 3 steps:

1. Calculated transition area matrix using Markov Chain analysis is used to predict the transition area matrix of LUC. At first, the original transition probability matrix (denoted by P) of land use type should be obtained from two former land use maps. Then, according to the non-aftereffect of Markov, the transition probability matrix for target simulation periods can be predicted according to Eq. (1).

$$P(N) = P(N-1) \times P \quad (1)$$

where P(N) is the state probability of any time, and P(N−1) is the preliminary state probability. Having a transition probability matrix, the transition area matrix can be easily obtained, which is performed by Eq. (2).

$$A = \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1n} \\ A_{21} & A_{22} & \dots & A_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix} \quad (2)$$

where A is the transition area matrix, A_{ij} is the sum of areas from its land-use class to the i^{th} land use to the j^{th} class during the years from start point to target simulation periods; and n is the number of land-use types. This process can be achieved by utilizing the MARKOV mod in the IDRISI Andes, which is a raster-based spatial analysis software developed by Clark Labs at Clark University. With IDRISI Andes, you can explore, predict, and model impacts on land cover change with the innovative Land Change Modeler facility.

2. Generated transition potential maps

Transition potential maps are the simulation foundation of the Markov-CA model; they are used to control the spatial distribution of land use. At the earliest stage, transition potential maps are generated from the transition probability matrix, which is calculated using Markov Chain. For this type of transition potential maps, patches of a land-use type would transit to other land use classes with the same probabilities. Recently, several studies have attempted to incorporate natural and socioeconomic data (such as slope, elevation, distance to the nearest road, population density, and GDP per capita) to generated transition potential maps. These attempts have helped to improve the simulation accuracy of the Markov-CA model.

3. Simulated land-use change (LUC) using CA model

Simulated LUC using the CA model, provides a spatial framework. Deciding iteration times, integrating transition area matrix and transition potential maps as the local transition rule of CA, land use map in the future could be simulated. The local transition rule of the Markov-CA model can be performed by Eq. (3).

if Sj = max(S1, S1, . . ., Sn) and Areaij < Aij T then Ci → Cj (3)

where Sj is the potential of a patch transit to the j^{th} land-use class; Area is the total area from land-use class I to land-use class j in the current iteration; T is iteration times; Ci is the i^{th} land-use class.

3. Research Findings

The classification of images by maximum likelihood classification shows six land use classes in the study area. Figure 2 shows land use maps relating to 2000 and 2014 and their area are shown in Table 2; Kappa coefficient is 94.35 for 2014 and 93.53 for 2000. Moreover, the overall kappa coefficient for 2000 and 2014 maps, 0.95 and 0.97 respectively, were acceptable results.

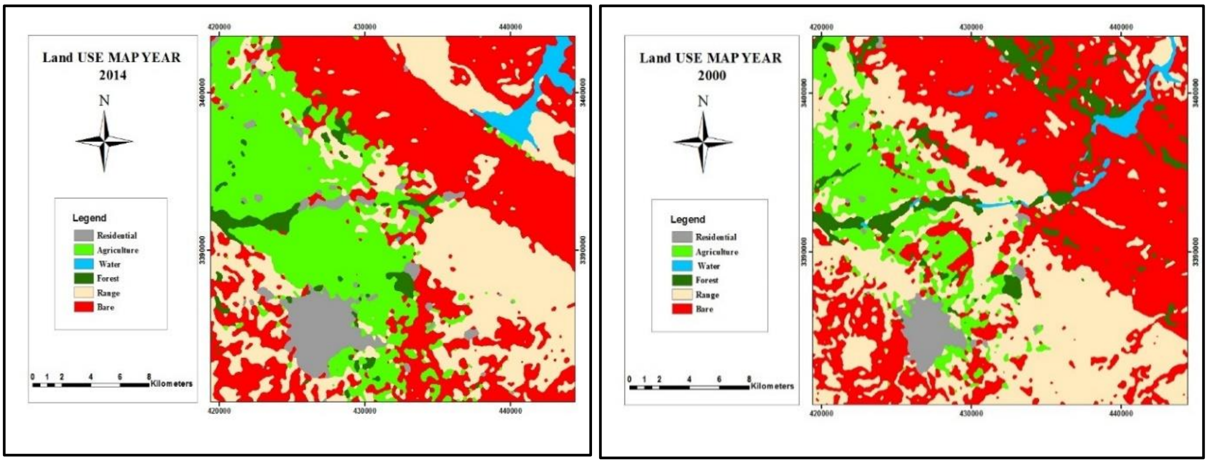

Figure 2. Land use map
(Source: Right: 2000, Left: 2014)

Table 2. User area targeted in the region

Land uses	The year 2000		The year 2014	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Residentia	16.596	3	31.5783	5
Agriculture	69.9444	11	150.3045	24
Water	8.5329	1	11.4093	2
forest	36.5499	6	15.7329	3
Rangeland	220.0572	36	174.4533	28
Bare	264.456	43	232.1217	38
Total	615.6	100	615.6	100

The result of changes display shows the area was under many changes of land use during 2000 to 2014. These changes include decreases, increases, and mere changes for each class and transformation from one class to another class. The most decrease includes grasslands destruction and their transformation to other uses. In this research, according to changes display results, six sub-models are considered for transformation power modeling by multilayer Perceptron artificial neural network. Sub-models are agricultural to the residential, forest to grasslands, grasslands to agriculture, grasslands to arid land, bare land to residential, and arid land to agriculture. After selecting sub-models, six variables are selected according to regional characteristics. Studying Cramer correlation coefficient, variables whose correlation coefficients are more than 0.1 are selected for modeling (Table 3).

Table 3. Overall Cramer's Results

Independent Variables	Overall Cramer's
DEM	0.1391
Slope	0.1099
Distance *Residential*	0.1228
Distance *Agriculture*	0.1296
Distance Road	0.1125
Evidence Likelihood	0.249

According to independent variables and sub-models, transformation potential maps are drawn for every sub-model by multilayer Perceptron neural networks (Figure 3).

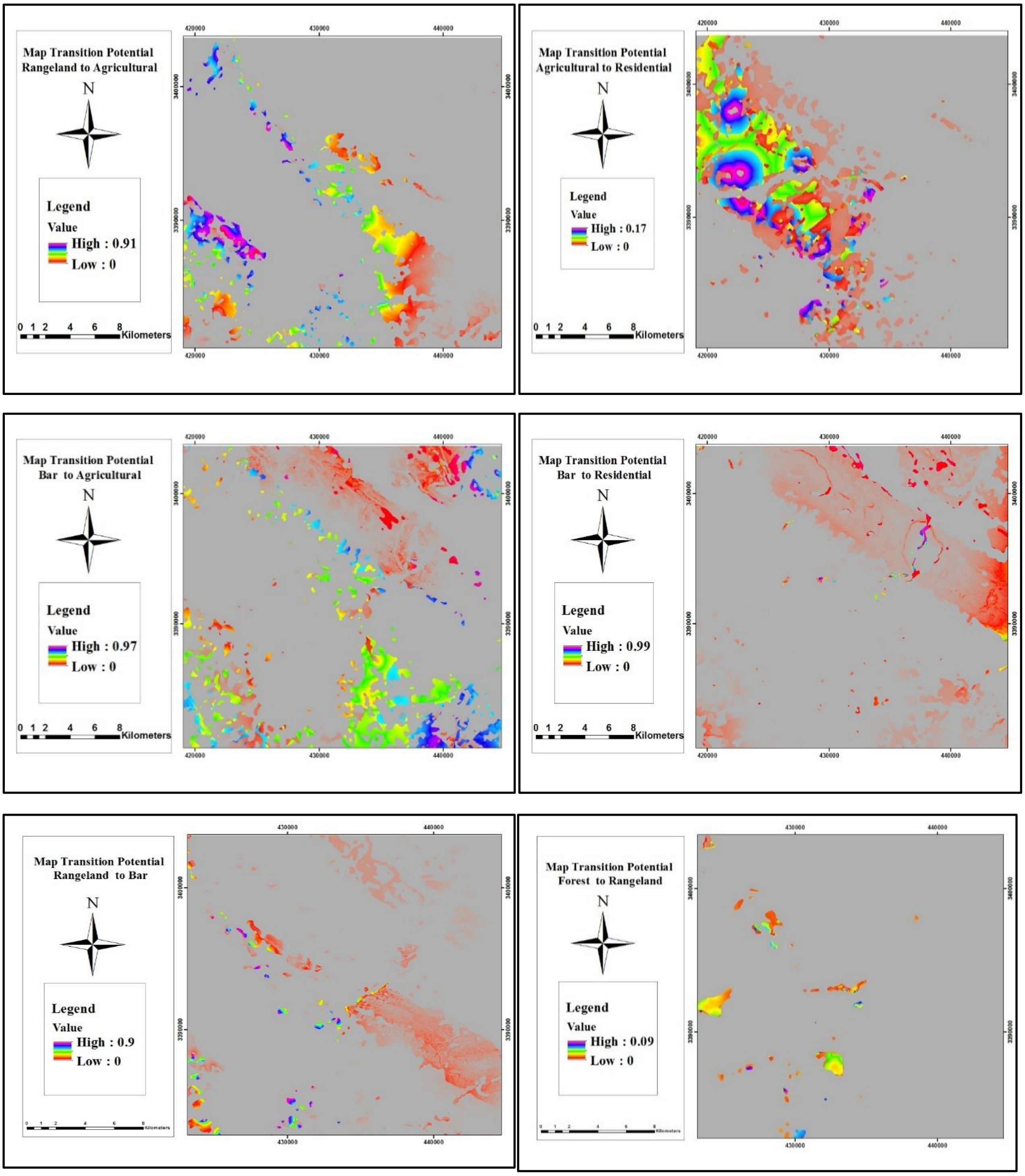

Figure 3. Maps of the potential transmission models

Three accuracy assessment factors, training error, and test error are determined for modeling transformation power modeling (Table 4).

Finally, the amount of each use change is predicted by the Markov chain, and land use maps relating to 2028 are drawn in the LCM model by the multilayer Perceptron neural networks method (Figure 4 and Table 5).

Table 4. Accuracy assessment of artificial neural network

Accuracy rate	Testing RMS	Training RMS
84.35	0.1493	**0.1457**

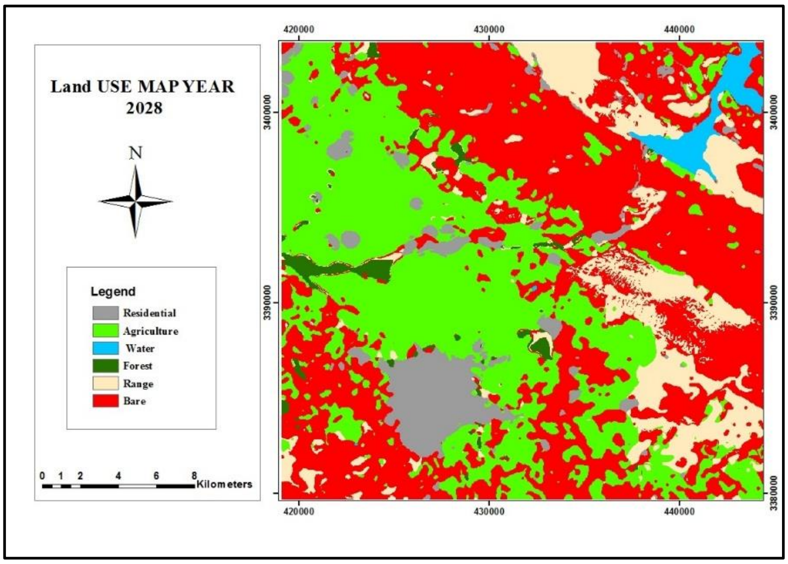

Figure 4. Land use map predicted 2028 (MARKOV chain)

Table 5. User area map modeling (MARKOV chain)

Land uses 2028	Area (km^2)	Area (%)
Residentia	41.8086	7
Agriculture	210.3687	34
Water	11.4093	2
forest	9.3636	2
Rangeland	76.1544	12
Bare	266.4954	43
Total	615.6	100

The possibility of transformation each use to other users is represented by the probability matrix (Table 6).

The transformed area matrix registers the number of cells which are expected in changing from one kind of land coverage to other kinds in the future (Table 7).

Table 6. Transition probability matrix

Land uses	Residential	Agriculture	Water	forest	Rangeland	Bare
Residential	0.9057	0.0287	0.0012	0.0182	0.0033	0.0429
Agriculture	0.0417	0.9019	0	0.0213	0.0179	0.0172
Water	0.0159	0.0277	0.6205	0.0590	0.1587	0.1191
forest	0.1043	0.1312	0.2033	0.2033	0.4049	0.1359
Rangeland	0.0257	0.2890	0.0113	0.0151	0.3479	0.3110
Bare	0.0171	0.0686	0.0109	0.0101	0.3042	0.5891

Table 7. Matrix transferred area

Land uses	Residential	Agriculture	Water	forest	Rangeland	Bare
Residentia	31778	1009	41	639	116	1504
Agriculture	6960	150626	0	3559	2985	2875
Water	202	352	7866	747	2000	1510
forest	1823	2293	356	3554	7079	2376
Rangeland	4977	56012	2183	2935	67440	60290
Bare	4408	17690	2803	2617	78450	151945

This matrix is drawn by multiplying each column from the transformation probability matrix with land use cells relating to it in the second picture (Eastman, 2006). After running Markov, the CA-MARKOV transfer area has tables, maps transfer potential derived from the neural network methods and land use map is the second year of preparation (Figure 5).

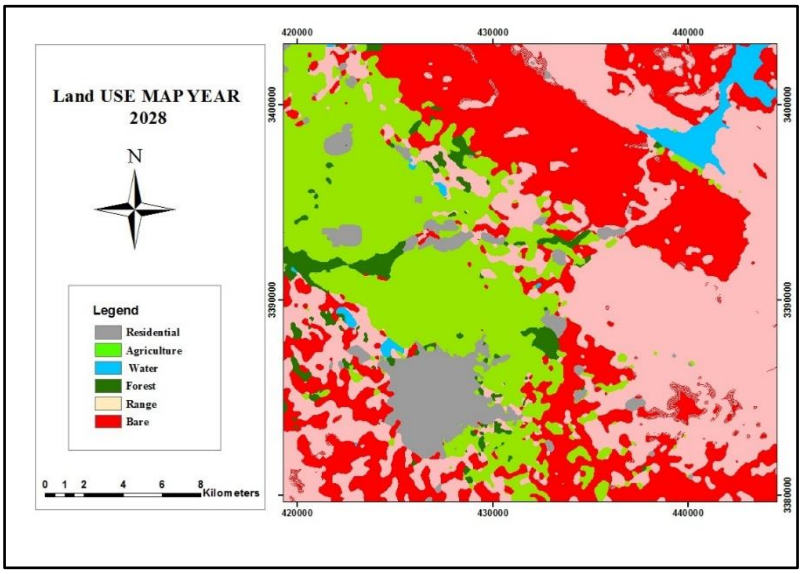

Figure 5. Land use map predicted 2028 (CA-MARKOV)

Table 8. User area map modeling (CA-MARKOV)

Land uses 2028	Area (km^2)	Area (%)
Residential	38.584	7
Agriculture	149.656	24
Water	12.965	2
forest	16.981	3
Rangeland	204.896	33
Bare	192.518	31
Total	615.6	100

4. Discussion and Conclusion

After the two methods produce maps with CA-MARKOV modeling and Markov chain prediction, results were compared with the 2014 land use map. According to two different approaches for modeling, results showed that it map Was predicted by Markov- Chain is closer to reality. So, to create a future scenario in the year 2028, forecast maps with the Markov model were chosen.

In this research, a land change modeler is used for land-use changes modeling in the Behbahan region. The results of land-use changes from 2000 to 2014 show that these changes have occurred in the vast area. Among of studied uses, the most increase happens in the area related to agricultural, residential, and water use, and most of the increase in the area is related to agricultural use (8036.01 hectares). The decrease occurred in the grassland, drier land, and forest use and most of the decrease occurred in the area related to grassland use (4560.39 hectares). The decrease in grassland area and its conversion to other uses include 6233 hectares from grasslands to agriculture, 1199 hectares to dried land, 1146 hectares to a forest, and 599 hectares to the residential area. The comparison between the modeling map and map related to 2013 shows that residential area and agricultural land continue to their growth trend so that residential area will be increased from 3157 hectares in 2014 to 4180 hectares in 2028.

An interesting point is that the number of villages does not increase during these 14 years but the extension of village area will be increased and agricultural land decreases from 15030 hectares to 2103.6 hectares. The growth percentage of this use land had been 10% from 2000 to 2014 but it will be changeless from 2014 to 2028. The dried land area also will increase 5% more than in 2013. Water zone space will be changeless during these 14 years. The decreasing process will probably occur in the water district and Maroun dam in the future decades. Unfortunately, not only destruction process of grasslands and forests is not avoided but also it is followed with more pace than in the past. Grassland had been 17445 hectares in 2014 but it is 7615 on the modeling map. 637 hectares will be decreased from forest area that it is the warring issue and management activities should be done for maintaining forests so that the problems such as flood, soil erosion, increasing of greenhouse gases, and loss of biodiversity are avoided. The decrease also happens in grassland and forests. The compactness of population centers in Behbahan and changing natural views to urban ones are the greatest changes in this city. It is expected that this process will continue with more pace in the future and the increase in agricultural lands confirms this point. About the decrease in grassland areas, it can be said that the growth of population in villages and the need for food made the villagers change grasslands to agricultural lands. On the other hand, another reason for grassland destruction is the excessive livestock grazing that changes vegetation coverage composition and ranchers destruct and changes forest coverage by grazing livestock from young trees, twig trees, livestock born construction, fuel, and household consumption.

The results of this study (increasing residential areas and decreasing forests and grasslands) are in line with the results of Mohammad and Worku (2020), Silva et al. (2020), Dadashpoor et al. (2019), and Sun et al. (2018). Moreover, the result of transformation power modeling assessment by the artificial neural network shows high accuracy. In many studies (Mohammad & Worku, 2020; Silva et al., 2020; and Perez-Vega et al., 2012), the accuracy of this method has been mentioned. Results of this study show that population growth and urban expansion are the main factors of use changes which are in line with the results of Caldas et al. (2010) and Joorabian Shoshtari et al. (2012). The population of this region has increased from 163032 in 1375 to 180593 in 2016 (www.amar.org.ir). The results of the Cramer correlation coefficient show that the most important independent variable explaining Behbahan city changes sequence are: quantitative variable in the agricultural model, digital elevation model, distance from agricultural land, distance from a residential area, and distance from road and slope. These variables are selected in many studies like Gholamalifard et al. (2013) and Schulz et al. (2010).

This paper tried to demonstrate that this hybrid technique (neural network–Markov–CA) offers certain advantages compared with traditional techniques. Firstly, this approach is capable of considering and integrating environmental and socioeconomic factors, which are not considered in current CA models, SLEUTH (Clarke et al., 1997; Yang & Lo, 2002; Dietzel & Clarke, 2006). Secondly, any spatial factor can be imported to this approach to measure its influence on urban sprawl and, accordingly, can be rejected after statistical assessment. Finally, the mentioned approach was tested and verified in two steps: (i) while the approach was being developed (the model calibration process) and (ii) through the comparison of the actual map and the simulated map of 2006, which was generated to verify the outcome of the approach. Whereas the validation of the current LUCC models is still weak (Pontius & Spencer, 2005), it is not feasible to validate the certainty of the simulated maps for the future. Thus, the only possible way to verify the model was to validate it at the most recent time, and following the assurance of the model's performance, future land use maps could be simulated more confidently.

This research is the presentation of an empirical model between a dependent variable (the amount of land-use change) and independent variables. According to the existence of non-linear relationships among variables, an artificial neural network has been used. The development and changes in nature will be the same during a time and it is the most important hypothesis in this modeling. In the other words, the last changes can predict future changes based on a historical scenario. The results of this study can provide a suitable perspective for planners to manage land use concerning land-use changes in the past, present, and future. They are also can be used for development assessment projects, the cumulative effects assessment, and the vulnerable and sensitive zone recognition. Finally, the results of this research can be used for performing projects relating to decreasing destruction effects, deforestation, and forest destruction in that the main purpose is decreasing greenhouse gases and maintaining biodiversity.

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References

1. Abd El-Kawy, O. R. (2011). Land use and land cover change detection in the western Nile delta of Egypt using sensing data. *Applied Geography, 31, 2* 483-494. https://doi.org/10.1016/j.apgeog.2010.10.012
2. Arsanjani, J. J., Helbich, M., Kainz, W., & Darvishi Boloorani, A. (2013). Integration of logistic regression, Markov chain, and cellular automata models to simulate urban expansion. *International Journal of Applied Earth Observation and Geoinformation, 21*, 265-275. https:// doi.org/ 10.1016/ j.jag.2011.12.014
3. Bakr, N. (2010). Monitoring land cover changes in a newly reclaimed area of Egypt using multitemporal Landsat data. *Applied Geography, 30, 4* 592-605. https://doi.org/10.1016/j.apgeog.2009.10.008
4. Bonilla-Bedoya, S., Mora, A., Vaca, A., Estrella, A., & Ángel Herrera, M. (2020). Modeling the relationship between urban expansion processes and urban forest characteristics: An application to the Metropolitan District of Quito. *Computers, Environment and Urban Systems, 79, 16* 101-120. https://doi.org/10.1016/j.compenvurbsys.2019.101420
5. Cabral, P., & Zamyatin, A. (2009). Markov processes in modeling land use and land cover changes in Sintra-Cascais, Portugal. *Dyna*, *76*(158), 191-198. http://www.scielo.org.co/scielo.php?pid=S0012-73532009000200018&script=sci_abstract&tlng=pt
6. Caldas, M., Simmons, C., Walker, R., Perz, S., Aldrich, S., Pereira, R., Leite, F. & Arima, E. (2010). Settlement Formation and Land Cover and Land Use Change: A Case Study in the Brazilian Amazon. *Journal of American Latin Geography, 9, 1* 125-144. https://doi.org/10.1353/lag.0.0066
7. Chuvieco, E. (2002). Teledetección ambiental: La observación de la Tierra desde eespacio. Editorial Ariel. Barcelona, España. ISBN**:** 84-344-8047.
8. Clancy, D., Tanner, J. E., McWilliam, S., & Spencer, M. (2010). Quantifying parameter uncertainty in a coral reef model using Metropolis-Coupled Markov Chain Monte Carlo. *Ecological Modelling*, *221*(10), 1337-1347. https://doi.org/10.1016/j.ecolmodel.2010.02.001
9. Clarke, K. C., Hoppen, S., & Gaydos, L. (1997). A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and planning B: Planning and design*, *24*(2), 247-261. https://doi.org/10.1068%2Fb240247
10. Coppedge, B. R., Engle, D. M., & Fuhlendorf, S. D. (2007). Markov models of land cover dynamics in a southern Great Plains grassland region. *Landscape Ecology 22, 9* 1383-1393. https://doi.org/ 10.1007/s10980-007-9116-4
11. Dadashpoor, H., & Salarian, F. (2019). Urban sprawl on natural lands: Analyzing and predicting the trend of land-use changes and sprawl in Mazandaran city region, Iran. *Environment, Development, and Sustainability, 22, 2* 593–614 (2020). https://doi.org/10.1007/s10668-018-0211-2
12. Dewan, A. M., & Yamaguchi, Y. (2009). Land use and land cover change in Greater Dhaka, Bangladesh: Using remote sensing to promote sustainable urbanization. *Applied Geography, 29,3* 390–401. https://doi.org/10.1016/j.apgeog.2008.12.005.
13. Dietzel, C., & Clarke, K. (2006). The effect of disaggregating land use categories in cellular automata during model calibration and forecasting. *Computers, Environment and Urban Systems, 30*(1), 78-101. https://doi.org/10.1016/j.compenvurbsys.2005.04.001
14. Eastman, J. R. (2006). *IDRISI Andes. Guide to GIS and Image Processing*. Worcester: Clark Labs, Clark University.
15. Fan, F., Wang, Y., & Wang, Z. (2008). Temporal and spatial change detecting (1998–2003) and predicting of land use and land cover in Core corridor of Pearl River Delta (China) by using TM and ETM$^+$ images. *Environmental Monitoring Assessment, 137, 3,* 127-147. https://doi.org/10.1007/s10661-007-9734-y

16.Gholamalifard, M., Joorabian Shooshtari, Sh., Hosseini Kahnuj, S.M., & Mirzaei, M. (2013). Modeling land-use changes using LCM coast of the province in GIS environment. *Journal of ecological, 38, 4* 109-124. (In Persian). Doi: 10.22059/jes.2013.29867
17.Haibo, Y., Longjiang, D., Hengliang, G., & Jie, Z. (2011). Tai'an land uses Analysis and Prediction Based on RS and Markov Model. *Procedia Environmental Sciences, 10,* 2625–2630. https://doi.org/10.1016/ j.proenv.2011.09.408
18.Huilei, L., Jian, P., Yanxu, L., & Yina, H. (2017). Urbanization impact on landscape patterns in Beijing City, China: A spatial heterogeneity perspective. *Ecological Indicators 82*, 2 50–60. https://doi.org/ 10.1016/ j.ecolind.2017.06.032
19.Irwin, E. G., & Geoghegan, J. (2001). Theory, data, and methods: developing spatially explicit economic models of land use change. *Agriculture, Ecosystems & Environment*, *85*(1-3), 7-24. https://doi.org/10.1016/S0167-8809(01)00200-6.
20.Jensen, J.R. (2007). An Earth Resource Perspective. Pearson Prentice Hall, Remote Sensing of The Environment, 17, 350-355.
21.Joorabian Shooshtari, Sh. (2012). Monitoring land cover change, degradation, and restoration of the Hyrcanian Forests in Northern Iran (1977–2010). *International Journal of Environmental Sciences, 3, 3* 1038-1056. [In Persian]
22.Koomen, E., Stillwell, J., Bakema, A. & Scholten, H.J. (2007). Modeling Land-use Change, Progress, and Applications. Netherlands, Springer, 6, 225-228.
23.Lambin, E. F., Geist, H., & Rindfuss, R. R. (2006). Introduction: local processes with global impacts. In *Land-use and land-cover change* (pp. 1-8). Springer, Berlin, Heidelberg.
24.Lillesand, T., & Kiefer, R.W. (2000). *Remote sensing and image interpretation*. New York: John Wiley and Sons.
25.Ma, L., Li, M., Ma, X., Cheng, L., Du, P., & Liu, Y. (2017). A review of supervised object-based land-cover image classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *130*, 277-293. https://doi.org/10.1016/j.isprsjprs.2017.06.001
26.Macedo, C. F., Pani, P., Cardoso, V., & Crispino, L. C. (2013). Into the lair: gravitational-wave signatures of dark matter. *The Astrophysical Journal*, *774*(1), 48. https://doi.org/10.1088/0004-637X/774/1/48
27.Mendoza, M. E. (2011). Analyzing land cover and land-use change processes at watershed level: A multitemporal study in the Lake Cuitzeo Watershed, Mexico (1975-2003). *Applied Geography, 31, 1* 237-250. https://doi.org/10.1016/j.apgeog.2010.05.010
28.Mohammad, A., Worku, H., (2020). Simulating urban land use and cover dynamics using cellular automata and Markov chain approach in Addis Ababa and the surrounding. *Urban Climate*, (31), 100545. https://doi.org/10.1016/j.uclim.2019.100545
29.Mohammadyari, F., Mirsanjari, M. M., Suziedelyte Visockiene, J., & Zarandian, A. (2020). Evaluation of change in land usage and land cover in Karaj, Iran. Environmental engineering. Paper presented at 11th International Conference. Vilnius Gediminas Technical University. Lithuania. DOI: 10.3846/enviro.2020.649
30.Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing, 66, 3* 247–259. https:// doi.org/ 10.1016/ j.isprsjprs. 2010.11.001
31.Mozumder, Ch., & Tripathi, N.K. (2014). Geospatial scenario-based modeling of urban and agricultural intrusions in Ramsar wetland Deepor Beel in Northeast India using a multi-layer perceptron neural network. *International Journal of Applied Earth Observation and Geoinformation*, 32, 92-104. https://doi.org/10.1016/j.jag.2014.03.002
32.Nahuelhual, L., Carmona, A., Lara, A., Echeverría, C., & González, M.E. (2012). Land-cover change to forest plantations: Proximate Causes and implications for the landscape in south-central Chile. *Landscape and Urban Planning*, *107, 1* 12-20. https://doi.org/10.1016/j.landurbplan.2012.04.006
33.Oñate-Valdivieso, F., & Sendra, J. B. (2010). Application of GIS and Remote Sensing Techniques in Generation of Land Use Scenarios for Hydrological Modeling. *Journal of Hydrology 395*, (3-4), 256-263. https://doi.org/10.1016/j.jhydrol.2010.10.033
34.Oommen, T. (2008). An objective analysis of Support Vector Machine-based classification for remote

sensing. *Mathematical Geosciences, 40, 3* 409–424. https://doi.org/10.1007/s11004-008-9156-6

35. Perez-Vega, A., Mas, J., & Ligmann-Zielinska, A. (2012). Comparing two approaches to land use/cover change modeling and their implications for the assessment of biodiversity loss in a deciduous tropical forest. *Environmental Modelling & Software, 29,* 11-23. https://doi.org/10.1016/j.envsoft.2011.09.011
36. Pijanowski, B. C., Brown, D. G., Shellito, B. A., & Manik, G. A. (2002). Using Neural Networks and GIS to Forecast Land Use Changes: a Land Transformation Model. *Journal Computers Environment Urban Systems, 26, 6* 553-575. https://doi.org/10.1016/S0198-9715(01)00015-1
37. Pijanowski, B. C., Tayyebi, A., Doucette, J., Pekin, B. K., Braun, D., & Plourde, J. (2014). A big data urban growth simulation at a national scale: configuring the GIS and neural network based land transformation model to run in a high performance computing (HPC) environment. *Environmental Modelling & Software*, *51*, 250-268. https://doi.org/10.1016/j.envsoft.2013.09.015
38. Pontius Jr, R. G., & Spencer, J. (2005). Uncertainty in extrapolations of predictive land-change models. *Environment and Planning B: Planning and design*, *32*(2), 211-230. https://doi.org/10.1068%2Fb31152
39. 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*(3-4), 938-943. https://doi.org/10.1016/j.mcm.2010.11.019
40. Schulz, J. J., Cayuela, L., Echeverria, C., Salas, J., & Rey, Benayas, J.M. (2010). Monitoring Land Cover Change of the Dryland Forest Landscape of Central Chile (1975 - 2008), Applied Geography, 30, 436-447. https://doi.org/10.1016/j.apgeog.2009.12.003
41. Shahidul Islam, M., & Ahmed, R. (2011). Land-use change prediction in Dhaka city using GIS-aided Markov Chain modeling. *Life Earth Science, 6,* 81-89. https://doi.org/ 10.3329/jles.v6i0.9726
42. Silva, L. P., Xavier, A., Silva, R. M., Santos, G. (2020). Modeling land cover change based on an artificial neural network for a semiarid river basin in northeastern Brazil. *Global Ecology and Conservation, 21, 2* 1-13. https://doi.org/10.1016/ j.gecco.2019-00811.
43. Sun, X., Crittenden, J. C., Li, F., Lu, Z., & Dou, X. (2018). Urban expansion simulation and the Spatio-temporal changes of ecosystem services, a case study in Atlanta Metropolitan area, USA. *Science of the Total Environment, 622–623,* 974–987. https://doi.org/10.1016/j.scitotenv.2017.12.062
44. Veldkamp, A., & Lambin, E. F. (2001). Predicting land-use change. *Agriculture, Ecosystems & Environment*, 85(1–3), 1-6. https://doi.org/10.1016/S0167-8809(01)00199-2.
45. Wu, Q., Li, H. Q., Wang, J., Paulussen, Y., He, M., Wang, B., Wang, H., & Wang, Z. (2006). Monitoring and predicting land-use change in Beijing. *Landscape and Urban Plan. 78, 4* 322-333. https:// doi.org/ 10.1016/ j.landurbplan.2005.10.002
46. Yang, X., & Lo, C. P. (2002). Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta, Georgia metropolitan area. *International Journal of Remote Sensing*, *23*(9), 1775-1798. https://doi.org/10.1080/01431160110075802
47. Yang, X., Zheng, X. Q. & Chen, R. (2014). A land-use change model: Integrating landscape pattern indexes and Markov-CA. *Ecological Modelling, 283,* 10 1-7. https://doi.org/10.1016/ j.ecolmodel.2014.03.011
48. Zhang, X., & Shu, C. W. (2010). On positivity-preserving high order discontinuous Galerkin schemes for compressible Euler equations on rectangular meshes. *Journal of Computational Physics, 229*(23), 8918-8934. https://doi.org/10.1016/j.jcp.2010.08.016

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Original Article

تلفیق مدل‌های شبکه عصبی مصنوعی، Markov chain و CA Markov برای شبیه سازی تغییرات کاربری زمین منطقه بهبهان

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چکیده مبسوط

۱. مقدمه

زمین مکانی از عملکرد اکوسیستم طبیعی است که توسط انسان به روش‌های مختلف استفاده شده است. شبیه سازی تغییر کاربری زمین مهمترین روش برای تحقیق در مورد تغییر کاربری زمین است که منجر به تعدادی از مسائل زیست‌محیطی مانند کاهش عرضه محصولات جنگل و افزایش سطح انتشار گازهای گلخانه‌ای می‌شود. بنابراین ، تغییر کاربری اراضی مورد توجه مدیران و برنامه ریزانی قرار گرفته است که درگیر موضوعات مربوط بـه توسـعه پایـدار شهری و مسائل محیط‌زیستی هستند. نوع کاربری اراضی و پوشش سرزمین درواقع نتیجهٔ روابط متقابل عوامل اجتماعی - فرهنگی و توان بالقوهٔ سرزمین می باشد. به عبارت دیگر، تغییرات کاربری اراضی و پوشش سرزمین آغاز بهره برداری‌های پویای انسان از منابع طبیعی جهت رفع نیازهایش است. وقوع این پدیده پیامدهای اقتصادی، اجتماعی و زیست محیطـی در مقیـاس محلـی، ناحیه‌ای و جهانی به همراه خواهد داشت. ماهواره‌های سـنجش از دور رایـج ترین منبع داده برای تشخیص، کمی‌سازی و نقشه‌سازی الگوهـای تغییـرات کاربری اراضی هستند. بنابراین آشکارسازی و مدل‌سـازی تغییـرات کـاربری اراضی با استفاده از داده‌های سنجش از دور در محیط GIS می‌تواند شناخت مناسبی از چگونگی این تغییرات ارائه دهد.

۲. مبانی نظری تحقیق

مدل‌های پوشش زمین به طور گسترده‌ای برای تجزیه و تحلیل و پیش‌بینـی تغییر کاربری زمین استفاده می‌شود. در بین این مـدل‌هـا، مـدل‌سـاز تغییـر سرزمین (Land Change Modeler) می‌تواند انقلابی را در زمینهٔ تجزیه وتحلیل تغییرات پوشش سرزمین و پیش‌بینی تغییرات کاربری اراضی به وجود آورد. مهمترین فرض در این نحوهٔ مدل‌سازی این است که طبیعت توسـعه و تغییرات، طی زمان یکسان خواهد بود و تغییرات گذشته می‌توانند تغییـرات آینده را براساس سناریوی تاریخی پیش‌بینی کنند. با پیش بینی روند تغییرات کاربری اراضی و اتخاذ سیاست‌های مدیریتی مؤثر، می‌توان در راستای هدایت اکوسیستم به سمت مطلوب گـام برداشـت. در ایـن مـدل دو روش زنجیـره مارکوف و اتوماتای سلولی(CA) وجـود دارد. آنـالیز زنجیـره مـارکوف ابـزاری مناسب جهت مدل‌سازی تغییرات کاربری و پوشـش اراضـی اسـت و زمـانی کاربرد دارد که تغییرات موجود در چشم‌اندازها به راحتی قابل توصیف نباشـد. زنجیره مارکف مجموعه‌ای از مقادیر تصادفی است که احتمال آنهـا در فاصـله زمانی داده شده به مقدار اعداد در زمان گذشته وابسته است. همچنین مـدل CA- Markov شامل تئوری هـای زنجیـره مـارکوف و اتوماتـای سـلولی (CA) است و معمولاً در پیش بینی LUC استفاده می‌شود.

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۳. روش تحقیق

این تحقیق از نوع کاربردی و جمع‌آوری اطلاعات به دو شکل کتابخانه‌ای و میدانی (پیمایشی) انجام گرفته است، همچنین از نرم افزارهای ArcGIS 10 ، Google Earth، Surfer11، IDRISI Tiga و ENVI 4.8 استفاده شده است. برای تهیه نقشه کاربری اراضی سال‌های ۱۳۷۸ و ۱۳۹۲ از تصاویر ماهواره لندست استفاده شده است. نقشه‌های کاربری اراضی با روش حداکثر احتمال تهیه شدند. سپس نقشه‌های کاربری اراضی برای تجزیه و تحلیل و آشکارسازی تغییرات منطقه وارد مدل LCM شدند. ۶ زیرمدل (کشاورزی به مسکونی، جنگل به مرتع، مرتع به کشاورزی، مرتع به اراضی لخت، اراضی لخت به مسکونی و اراضی لخت به کشاورزی) و ۶ متغیر (متغیر کیفی در زیر مدل کشاورزی، مدل رقومی ارتفاع، فاصله از اراضی کشاورزی، فاصله از مناطق مسکونی، فاصله از جاده و شیب) برای مدل‌سازی احتمال وقوع در هر انتقال از طریق شبکه‌های عصبی پرسپترون چندلایه انتخاب شد. همچنین پیش‌بینی سناریو آینده با دو روش زنجیره مارکوف و CA- Markov صورت گرفت.

۴. یافته‌های تحقیق

در تحقیق حاضر، از مدل‌ساز تغییر سرزمین برای مدل‌سازی تغییرات کاربری اراضی شهرستان بهبهان استفاده شد. نتایج تغییرات کاربری اراضی در سال-های ۱۳۷۸ تا ۱۳۹۲ نشان می‌دهد این تغییرات در منطقه گسترده بوده است. در بین کاربری‌های بررسی شده کاربری کشاورزی، مسکونی و آب بیشترین افزایش مساحت را به خود اختصاص داده‌اند، که بیشترین افزایش مساحت در کاربری کشاورزی (۸۰۳۶/۰۱ هکتار) می‌باشد. همچنین کاهش مساحت در کاربری مرتع، اراضی لخت و جنگل صورت گرفته که بیشترین کاهش مساحت در کاربری مرتع (۴۵۶۰/۳۹ هکتار) بوده است. کاهش مساحت مرتع و تبدیل آن به کاربری‌های دیگر به ترتیب از بیشترین به کمترین شامل: ۶۲۳۳ هکتار از تغییرات مرتع به کشاورزی، ۱۱۹۹ هکتار از تغییرات مرتع به اراضی لخت، ۱۱۴۶ هکتار از تغییرات مرتع به جنگل و ۵۵۹ هکتار از تغییرات مرتع به مسکونی است.

۵. بحث و نتیجه‌گیری

تحقیق حاضر ارائهٔ مدلی تجربی بین متغیر وابسته (میزان تغییرات کاربری اراضی) و متغیرهای مستقل (توضیح دهندهٔ تغییرات) است. با توجه به وجود روابط غیرخطی بین متغیرها از شبکهٔ عصبی مصنوعی استفاده شده است و شبکه با استفاده از داده‌های سال‌های قبل آموزش دیده است. مهمترین فرض در این نحوه مدل سازی(با توجه ماهیت تجربی) این است که طبیعت توسعه و تغییرات در طی زمان یکسان خواهد بود و یا به عبارتی دیگر تغییرات گذشته می‌توانند تغییرات آینده را بر اساس سناریوی تاریخی پیش‌بینی کنند. نتایج این مطالعه می تواند با توجه به چگونگی تغییرات کاربری اراضی در گذشته، حال و آینده، چشم انداز مناسبی را برای برنامه‌ریزان جهت مدیریت کاربری اراضی فراهم کند. همچنین در پروژه‌های ارزیابی آثار توسعه، ارزیابی آثار تجمعی، شناسایی زون‌های حساس و آسیب پذیر و احیای آنها کاربرد داشته باشد و در پایان با توجه به این که در منطقه مورد مطالعه تاکنون چنین تحقیقی صورت نگرفته لذا نتایج این تحقیق می‌تواند برای اجرای پروژه‌های کاهش آثار تخریب مراتع، جنگل زدایی و تخریب جنگل که هدف اصلی آن کاهش گازهای گلخانه‌ای و حفاظت از تنوع زیستی است قابل استفاده باشد.

کلیدواژه‌ها: تشخیص تغییرات، شبکه عصبی، زنجیره مارکوف، CA مارکوف، شهرستان بهبهان.

تشکر و قدرانی

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