Global J. Environ. Sci. Manage.,4(3): 263-280, Summer 2018
DOI: 10.22034/gjesm.2018.03.002

ORIGINAL RESEARCH PAPER

Performance comparison of land change modeling techniques for land use projection of arid watersheds

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Received 11 February 2018; revised 19 May 2018; accepted 23 June 2018; available online 1 July 2018

ABSTRACT: The change of land use/land cover has been known as an imperative force in environmental alteration, especially in arid and semi-arid areas. This research was mainly aimed to assess the validity of two major types of land change modeling techniques via a three dimensional approach in Birjand urban watershed located in an arid climatic region of Iran. Thus, a Markovian approach based on two suitability and transition potential mappers, i.e. fuzzy analytic hierarchy process and artificial neural network-multi layer perceptron was used to simulate land use map. Validation metrics, quantity disagreement, allocation disagreement and figure of merit in a three-dimensional space were used to perform model validation. Utilizing the fuzzy-analytic hierarchy process simulation of total landscape in the target point 2015, quantity error, the figure of merit and allocation error were 2%, 18.5% and 8%, respectively. However, Artificial neural network-multi layer perceptron simulation led to a marginal improvement in figure of merit, i.e. 3.25%.

KEYWORDS: *Artificial neural network-multi layer perceptron (ANN-MLP); CA-Markov; Fuzzy-analytic hierarchy process (Fuzzy-AHP); Land use change; Simulation.*

INTRODUCTION

In general, biodiversity, water and radiation equilibriums, release of greenhouse gases, carbon cycling, and livings are impacted by land use alteration. To render environmental management, particularly in relation to sustainable agriculture on arid or semi-arid lands, Land Use and Cover Change (LUCC) studies and their dynamics seem to be vital. There are diverse models according to assembly and use, which have been employed to determine LUCC dynamics (Verburg *et al.,* 2002; Kamusoko *et al.,* 2009; Memarian *et al.,* 2012). Dynamic systems and agent-based approaches are pliable, mechanistic and combined models which project the joined economic, biophysical, and human behavioral practices of land use alteration, spatially and/or temporally (Rounsevell *et al.,* 2012; Hamilton *et al.,* 2015). These models are capable to merge the multilateral quality of sustainability and land use, i.e. non-stationary and non-linear procedures, transformational alteration and multi-scale effects. To project land use change, the agent-based models are broadly utilized with some heading sides of sustainability (Schreinemachers and Berger, 2011; Memarian *et al.,* 2014), and universal change (Guillem *et al.,* 2015). Significance of LUCC models is obvious from the broad range of current modeling tactics and usages (Agarwal *et al.,* 2002; Parker *et al.,* 2003; Verburg *et al.,* 2004; Heistermann *et al.,* 2006; Memarian *et al.,* 2013a; Geographical Sciences Committee, 2014). The efficiency evaluation of LUCC models is very challenging because they are essentially various and have their own expertise and limitations, as highlighted by Verburg *et al.* (2004),

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Note: Discussion period for this manuscript open until October 1, 2018 on GJESM website at the “Show Article”.

Pontius and Chen (2006), and Luo *et al.* (2010). Thomas and Laurence (2006) expressed that Markov chain is one of the most well-known techniques for modeling LUCC utilizing existing trends. It uses transformation from 't−1' to 't' to forecast likelihoods of land use changes for an upcoming date 't+1'. The base of this technique is the likelihood that a specified piece of land will transit from one particular state to another. Cellular automata (CA) is one of the models that aid to assess local activities and consequential effects on overall patterns (Couclelis, 1985; Batty *et al.,* 1997; Engelen *et al.,* 1999). However, CA can be efficiently applied to project the spatial alteration of a system, according to the prespecified transition norms (Torrens, 2006; Adhikari and Southworth, 2012). The Markov approach does not consider the reasons of land use transitions and it is not space-sensitive. By employing the CA approach, CA-Markov unwinds rigid presumptions in relation to the Markov approach and respects both changes over space and time (Agarwal *et al.,* 2002). CA-Markov in contrast to other LUCC models including Geometric modelers (GEOMOD) and the Conversion of Land Use (CLUE) is also able to propose far inclusive simulation (Mas *et al.,* 2007). However, it causes concern in feigning land cover dynamics on a sequential scale because calibration of CA-Markov is performed according to single time span (Paegelow and Olmedo, 2005). Pontius and Malanson (2005) performed a comparison between CA-Markov and GEOMOD looking upon projecting robustness and rightness for various usages in Central Massachusetts, United States of America. They handled a three-stage technique to assess modeling vigor. First of all, calibration process was alienated from the validation process. Next, validity was evaluated at several resolutions. Eventually, calibrated model was paralleled with a model, which was a null one, that was similar to unadulterated perseverance. Their study indicated that the additional complication of three-dimensional contiguity regulation in CA-Markov was not effective. Paegelow and Olmedo (2005) investigated the constraint and potential of futuristic Geographic Information System (GIS)-based LUCC modeling. Their methods were constructed upon the Markov chain for temporal modeling, Multi Objective Land Allocation (MOLA), Multi Criteria Evaluation (MCE), and CA in order to fulfill spatial vicinity on the projected land use scores. The outcomes pointed to three discrete constraints; the first was produced through intricate variation within the land cover classes, the second was conducted utilizing solely two land cover maps for calibration process, and the third was created based on the assumption that MOLA, MCE, and CA had impact on spatial distribution, but not temporal distribution of simulated scores. Urban land use change by CA-Markov and landscape measures was modeled and studied by Araya and Cabral (2010). They realized that CA-Markov performance with Kquantity and Klocation of 83 % and 87 %, respectively, was acceptable. They did not cut apart capability of the model for land use change prediction through a far detailed methodology like three-dimensional technique. The validation of CA-Markov in land use and cover change simulation was scrutinized at Langat Basin, Malaysia by Memarian *et al.* (2012). CA-Markov validation analysis was carried out by means of the validation metrics "allocation disagreement", "quantity disagreement", and "figure of merit" in a three-dimensional space. The quantity error, figure of merit, and allocation error for simulating total landscape utilizing the 1990-1997 calibration statistics were 3.53%, 5.62% and 6.13%, in order. In this study area, CA-Markov displayed inadequate validity for LUCC replication because of uncertainties in the given data, future land use, cover change trends and the model. In this study, land change modeler (LCM) (Eastman, 2014) has been employed as the handled toolbox and an integrated software framework, to investigate and project LUCC, and to validate the simulation results. LCM is performed in the IDRISI software (Tewolde and Cabral, 2011), where only thematic raster maps with the similar land use classes registered in the same successive norm can be an input to carry out the LUCC analysis (Roy *et al.,* 2014). By using LCM, there is a premier perception of the elements of the land use systems and necessary factors to program and implement the strategy and it can also forecast multiple land covers under different management scenarios and the imaginable future change (Costanza and Ruth, 1998; Ahmed and Ahmed, 2012). Primarily, LCM is on the basis of CA-Markov that assesses land use/cover alterations between two spells, measures the changes, and depicts the results with different charts and maps. Afterward, based on relative transition potential maps it anticipates future Land Use and Land Cover (LULC) maps (Roy *et al.,* 2014) relying on multi-layer perceptron (MLP) neural network or Logistic Regression (Perez-Vega *et al.,* 2012). A scheme termed as "multi-layer perceptron Markov chain (MLP_Markov)" model was introduced by Mishra *et al.* (2014) to simulate future land use and land cover maps in 2025 and 2035 according to the available information. Mas *et al.* (2014) assessed four program packages, i.e. DINAMICA CLUE, CA_MARKOV and LCM as inductive pattern-based manners to model LUCC. In order to evaluate the transition potential, CA_MARKOV and CLUE use suitability maps and LCM and DINAMICA outline the likelihood of land use transitions. The land cover map in Dhaka city was projected using the techniques termed as "Stochastic Markov (St_Markov)", "Cellular Automata Markov (CA_Markov)" and Multi Layer Perceptron Markov (Ahmed and Ahmed, 2012). Based on the findings, the MLP_Markov model showed the highest appropriateness, evaluated through a three map contrast approach, for the prediction of the 2019 land cover map. Arid regions have completely different and complex dynamics of land use and land cover change, as compared to other climatic areas. Thus, their LULC simulation needs to be assessed and compared by different techniques to propose a suitable approach. Therefore, this work was aimed to evaluate the capability of two main techniques of transition potential mapper (Fuzzy-AHP and MLP) in simulating the LULC of Birjand urban watershed based on a Markovian approach using a three dimensional validation technique. This study is innovative in terms of comparing the mentioned methods and the type of validation technique used. The study has been carried out in Birjand urban watershed in 2017.

MATERIALS AND METHODS

Study area

Birjand urban watershed is placed between 57° 57' to 59° 40' east longitude and 31° 20' to 33° 31' north latitude (Fig. 1). This area, with an average altitude of 1500 m, is placed within the dry climatic region in which average precipitation based on a 30 year statistical records is 154 mm. The Birjand urban watershed is topographically divided into two distinct regions, i.e. the mountainous area in upstream and flat plain in downstream (Velayati and Tavasoli, 1993). The study area is mostly covered by poor rangelands which are mainly occupied by the species Artemisia sieberi and Artemisia aucheri (Zarei *et al.,* 2010). The city of Birjand had a population of 187000 people at the time of the last official census in 2013. It is a fast-growing city, thus becoming one of the major centers in the East of Iran (Donyavi *et al.,* 2014).

Data set

In order to analyze and interpret the satellite images, they were sorted and categorized. Landsat images, as one of the most utilized satellite images, are extensively considered for mapping and planning

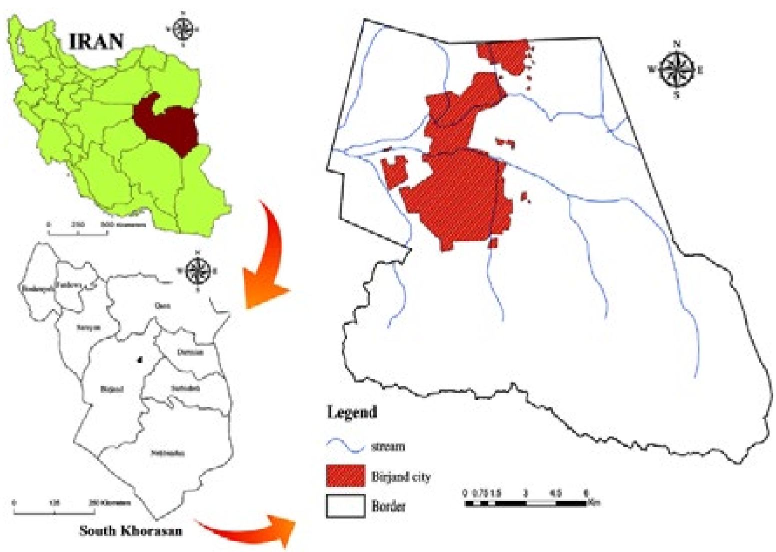

Fig. 1: Geographic location of the study area

studies due to their spectral, spatial and temporal resolution (Sadidy *et al.,* 2009). The sensors Thematic Mapper (TM), Operational Land Imager (OLI), and Enhanced Thematic Mapper + (ETM^+) were utilized to supply Landsat images of the years 1987, 2009 and 2015 as the source to map land use/cover classes in this study. The images were projected to universal transverse mercator (UTM), Zone 40 N with a datum of world geodetic system (WGS). The resolution merge using forward-reverse principal component transforms (Chavez *et al.,* 1991) was performed to produce a color image with high resolution. Dark subtraction technique (Memarian *et al.,* 2013b; Chavez, 1988) was employed for atmospheric scattering correction on the whole scene. In this work, based on the available land use maps and field investigations, four land use/cover categories, i.e. residential, irrigated agriculture, rainfed agriculture, and rangeland were identified. Each image was individually categorized using maximum likelihood classifier (MLC) with the overall accuracies higher than 95%. The computational structure of this study was illustrated in Fig. 2.

CA-Markov

X(t) (A random process) is considered as a Markov process in case that for any instant in time, $t_1<t_2< \cdots <t_n<t_{n+1}$ (Markov, 1971). In Markov process, future is not dependent of the past; it means that future of a random process does not depend on where it is now or how it got there (Miller and Childers, 2004; Memarian *et al.*, 2012). A Markov chain with the states {x1, x2, x3, ⋯} is defined as *X*[k]. The likelihood of change from condition i to condition j in 1 time moment is as Eq. 1,

$$p_{i,j} = P_r(X[k+1] = j|X[k] = i) \tag{1}$$

In a Markov chain with a limited number of conditions, such as n, the Transition Probability Matrix (TPM) is demarcated as Eq. 2 (Miller and Childers, 2004; Memarian *et al.,* 2012):

$$\begin{bmatrix} P_{1,1} & P_{1,2} & \cdots & P_{1,n} \\ P_{2,1} & P_{2,2} & \cdots & P_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n,1} & P_{n,2} & \cdots & P_{n,n} \end{bmatrix} \tag{2}$$

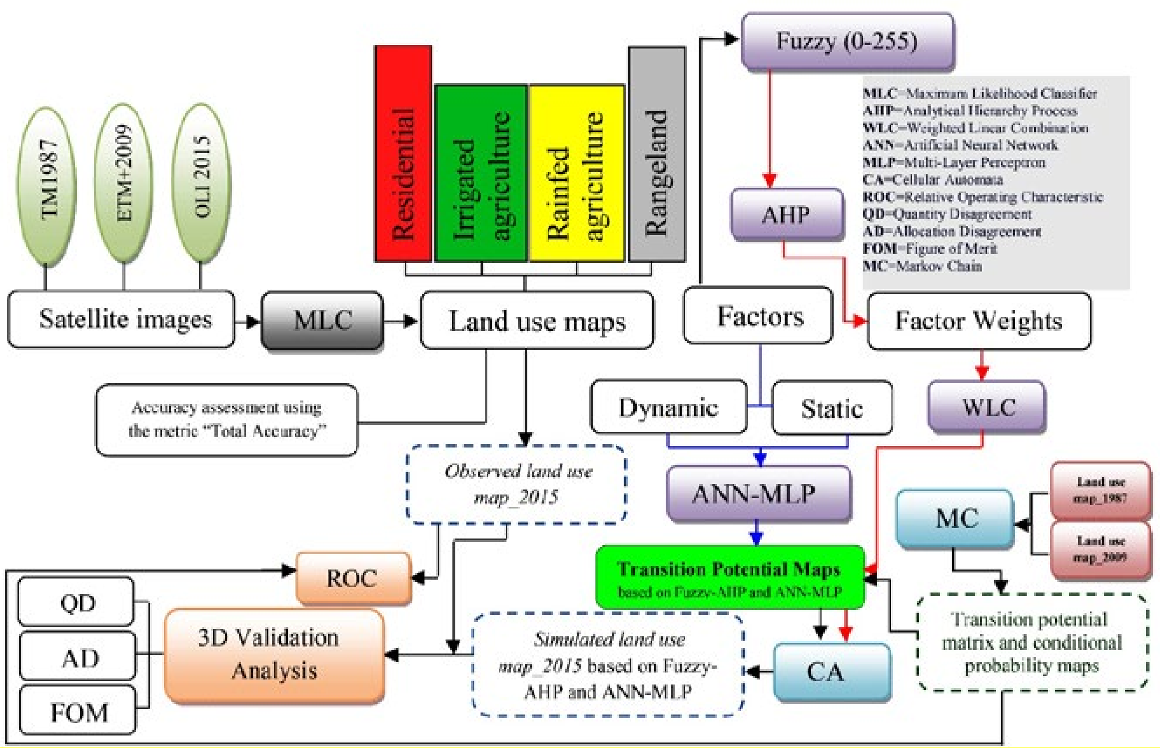

Fig. 2: Computational framework of the study

The Markov process is driven based on the transition probability matrix according to the land use maps in two different times. Then the quantity of land use transition should be geographically positioned using the contiguity filter and cellular automata. CA-Markov in IDRISI includes cellular automata and Markov chain analysis (Araya and Cabral, 2010; Memarian *et al.,* 2012). Cellular automata consider the dynamics of alteration occasions that rooted in contiguity idea. According to this idea, the areas nearer to existing regions with a similar category are far probable to transit to other category. A cellular automaton as a cellular substance changes its state in view of its previous condition based on a Markov transition regulation and contiguous neighbors (Eastman, 2009). In this work, the following 5×5 neighborhood filter was employed in CA process:

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

Land change modeler (LCM)

The LCM applies back-propagation neural network, logistic regression or similarity-weighted instance-based machine learning tool (SimWeight) in transition potential mapping (Eastman, 2009).

Change Prediction Process in LCM

1) Change analysis: This analysis can be fulfilled utilizing two land cover maps with similar legends (Eastman, 2009). In this work, LUCC analysis was performed between the pairs of land uses in 1987 and 2009.

2) Transition potential modeling: In this step, the transitions are assembled into a set of sub-models by the users and then the potential vigor of descriptive drivers is discovered (Eastman, 2009). The time-dependent drivers are dynamic and recalculated over time, whereas static factors designate sides of basic capability for the change under deliberation, and are timely constant (Mishra *et al.,* 2014). The MLP neural network, logistic regression, or a SimWeight approach are employed for transition modeling. MLP as a general design applied in Artificial Neural Network (ANN) was employed in this work. The most popular training method for MLP is back-propagation algorithm (Rumelhart *et al.,* 1986). Generally, the MLP is an organization of interrelated layers of artificial neurons, hidden, input and output layers. Neurons in the first layer normally transmit weighted statistics and accidentally chosen bias using the hidden layers, when a neural set is organized with data through the input layer. The output answer is made at the node utilizing a function of transfer, when the net summation at a hidden node is defined (Kuo *et al.,* 2007; Kim and Gilley, 2008; Memarian *et al.,* 2013c). The MLP network training is carried out using error adjustment learning, that indicates that the favorable response for the system must be recognized (Memarian and Balasundram, 2012; Graupe, 2013; Principe *et al.,* 2015). This process, as the back-propagation algorithm, is loaded into the momentum learning (Memarian and Balasundram, 2012; Memarian *et al.,* 2013c). In this work, based on the trial and error analysis, 8 and 4 neurons were defined on input and hidden layers, respectively for land use transitions to irrigated agriculture and rainfed agriculture. However, for land use transitions to the residential category, 7 and 4 neurons were determined on input and hidden layers, respectively. The momentum factor and sigmoid constant were set at 0.5 and 1, respectively. The 50% of sample size per class was determined for MLP training and the rest for testing. The metrics Root Mean Square (RMS) error, accuracy rate, and skill measure were used to test the power of MLP in transition potential mapping. The skill score represents the difference between the calculated accuracy using the validation data and expected accuracy if one were to randomly guess at the class memberships of the validation pixels. This measure varies from -1 to +1 with a skill of 0 indicating random chance (Eastman, 2014). Table 1 shows the accuracy rate and skill measure for different transition sub-models computed through MLP simulation. Based on Table 1, it can be revealed that the best accuracy rates and skill measures were obtained through rangeland and residential change simulations which supports the validation results presented in Table 6.

3) Change prediction: In the final stage of land change modeling, LCM can project a future plan for a preordained future time through the historical rates of transition, imported from Markov chain analysis and the transition potential model (Eastman, 2014).

Modelling

Before all else, six calibration periods, i.e. 1987-2001, 1987- 2004, 1987-2009, 2001-2004, 2001-2009 and 2004-2009 were noticed and reported simulation records were put under pre-analysis regarding goodness of fit. Based on the obtained results, 1987-2009 period was far able to project the upcoming alterations of land; thus the calibration data within the interval 1987-2001 was utilized to elicit TPM in this work. In order to extract suitability maps according to the Fuzzy-AHP method, two kinds of criteria (factors and constraints) were employed to identify the proper lands for future transition. Parameter maps were regulated into a suitability continual scale from 0 (least suitability) to 255 (highest suitability) (Fig. 3) utilizing Fuzzy method. Fuzzy theory, as a supplement to the classical Boolean theory, was presented by Zadeh (1965). The linear membership function was utilized to re-extend factor maps into a range of 0 to 255. Analytic Hierarchy Process (AHP) was arranged on proficient judgment to determine significance scales by pair wise contrasts (Saaty, 2008). AHP was utilized to calculate the weights of active elements in suitability mapping. According to the AHP method, comparisons are rendered considering a definite judgment scale that displays how far an element overcomes another for a particular quality. However, there is a likelihood of judgment inconsistency (Saaty, 2008; Memarian *et al.,* 2012). The judgments may be too uneven to be dependable if the consistency index (CI) exceeds 0.1. The Consistency Ratio (CR) of zero signifies that the decisions are completely consistent (Coyle, 2004; Memarian *et al.,* 2015).

The factors presented in Table 2 were pooled using Weighted Linear Combination (WLC) technique (Alizadeh *et al.,* 2013; Tajbakhsh *et al.,* 2016) to extract transition suitability maps (Fig. 3). In this study, 27 sub-models as static or dynamic were fed into the LCM. The factors like proximity to road and proximity to existing land uses were introduced as dynamic factors. To measure a quantitative relationship among effective factors on land use change, Cramer's V can be employed. The Cramer's V value gives a Chi square (χ^2) based degree of association (Liebetrau, 1983). A high Cramer's V confirms if the possible

Table 1: Accuracy rate and skill measure for different transition sub-models in MLP approach

Transition sub-model	Accuracy rate (%)	Skill measure
Irrigated agriculture to rainfed agriculture	65	0.29
Irrigated agriculture to rangeland	57	0.13
Irrigated agriculture to residential	65	0.31
Rainfed agriculture to irrigated agriculture	63	0.26
Rainfed agriculture to rangeland	50	0.15
Rainfed agriculture to residential	84	0.68
Rainfed to irrigated agriculture	65	0.30
Rangeland to rainfed agriculture	77	0.53
Rangeland to residential	83	0.66
Residential to irrigated agriculture	92	0.84
Residential to rainfed agriculture	86	0.71
Residential to rangeland	55	0.18

Table 2: Form of fuzzy membership function, eigenvectors of weight (values in italic) and AHP consistency ratio for each land use class

Parameter \ Land use	Residential	Irrigated agriculture	Rainfed agriculture	Rangeland
Proximity to urban patches	LMD – 0.37			LMI – 0.07
Proximity to villages	LMD – 0.21	LMD – 0.06	LMD – 0.08	LMD – 0.09
Slope	LMD – 0.08	LMD – 0.08	LMD – 0.10	LMI – 0.22
Proximity to water resources	LMD – *0.13*	LMD – 0.22	LMI – *0.04*	LMD – 0.05
Land economic value	LMI – *0.13*			
Proximity to road	LMD – *0.09*			LMD – 0.04
Proximity to agricultural lands		LMD – 0.16	LMI – *0.21*	
Soil condition		LMI – 0.11	LMI – *0.14*	LMI – 0.13
Land suitability for agriculture		LMI – 0.34	LMI – *0.39*	
Population density		LMI – 0.03	LMI – *0.05*	
Range condition				LMI – 0.38
Consistency Ratio	0.012	0.025	0.028	0.023

Note: LMI: Linear membership function-Monotonically Increasing, LMD: Linear membership function-Monotonically Decreasing descriptive value of the variable is worthy, although it may not make sure a robust efficiency as it does not consider the mathematical necessities of the modeling procedure utilized and the connection complications (Eastman, 2014). Therefore, to choose right land transitions in each sub-model, an examination of the sensitivity based on skill measure was conducted using MLP. The difference in skill delivers information on the influence of that variable. Fig. 4 depicts different transition potential maps extracted via the MLP.

Validation

According to the calibration period of 1987-2009, the land use map in 2015 was employed for validation analysis of the model. The difference between projected map and real map was assessed through the disagreement parameters (Pontius *et al.,* 2011; Pontius and Millones, 2011; Memarian *et al.,* 2012). Quantification error (quantity disagreement) happens when number of pixels of a category in the projected map is dissimilar to number of cells of a similar category in the observed map. Similarly, location error (allocation disagreement) happens if position of a category in the projected map differs from position of that category in the observed map (Pontius *et al.,* 2011). Pontius and Millones (2011) offered the methods in which these validation measures are calculated based on them. This approach

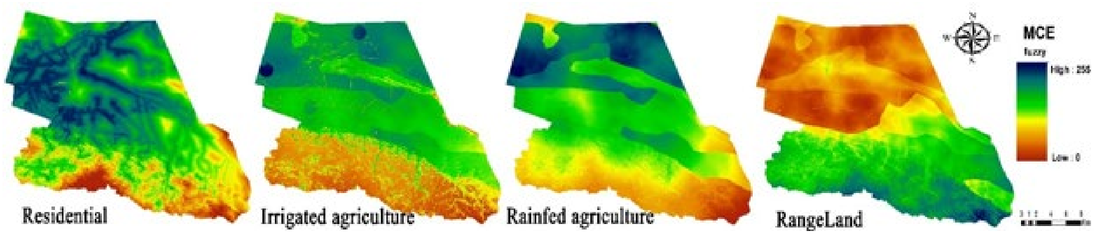

Fig. 3: Transition suitability maps for different land uses produced via MCE

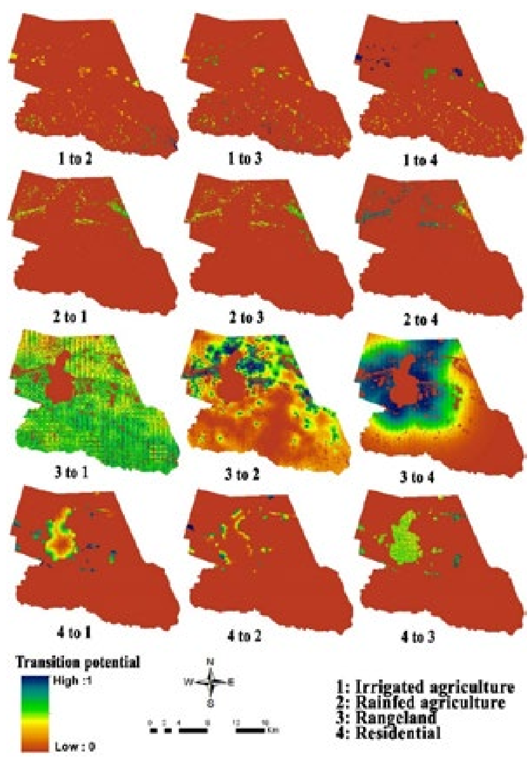

Fig. 4: Transition potential maps for different land uses generated through MLP

was employed and explained in detail by Memarian *et al.* (2012) and Memarian *et al.* (2013b).

Disagreement components

The Table 3 is considered as the reference for extraction of disagreement indices. J denotes the number of classes and number of strata in a typical stratified sampling scheme. Each class in the simulated map is signed by i, which extends from 1 to J. The number of cells in each stratum is defined by Ni. Each observation is documented based on its class in the simulated map (i) and observed map (j). The number of these records is summed as the record nij in row i and column j of the contingency matrix. Proportion of the study area (Pij) with the class i in the simulated map and the class j in the observed map is calculated using the Eq. 3 (Pontius and Millones 2011; Memarian *et al.*, 2012; Memarian *et al.*, 2013b):

$$p_{ij} = \left(\frac{n_{ij}}{\sum_{j=1}^{J} n_{ij}}\right)\left(\frac{N_i}{\sum_{i=1}^{J} N_i}\right) \tag{3}$$

Quantity disagreement (qg) for a desired class g is computed via the Eq. 4.

$$q_g = \left|\left(\sum_{i=1}^{J} p_{ig}\right) - \left(\sum_{j=1}^{J} p_{gj}\right)\right| \tag{4}$$

Total quantity disagreement (Q) which includes all J classes is calculated through Eq. 5.

$$Q = \frac{\sum_{g=1}^{J} q_g}{2} \tag{5}$$

The Eq. 6 calculates allocation disagreement (ag) for a desired class g. The omission of class g is described by the first argument within minimum function, while the next argument is the commission of class g.

$$a_g = 2\min\left[\left(\sum_{i=1}^{J} p_{ig}\right) - p_{gg}, \left(\sum_{j=1}^{J} p_{gj}\right) - p_{gg}\right] \tag{6}$$

The total allocation disagreement (A1) is calculated via the Eq. 7.

$$A1 = \frac{\sum_{g=1}^{J} a_g}{2} \tag{7}$$

The proportion of agreement (C1) is computed through Eq. 8.

$$C1 = \sum_{j=1}^{J} p_{jj} \tag{8}$$

According to the Eq. 9, total disagreement (D1) is a summation of total quantity disagreement and total allocation disagreement.

$$D1 = 1 - C1 = Q + A1 \tag{9}$$

Figure of merit (FOM)

Intersection of witnessed change and simulated alteration divided by union of the observed change and replicated change will estimate another validation metric, defined as the figure of merit (FOM). FOM sorts from 0 (no intersection between observed and simulated changes) to 100 % (complete intersection between observed and simulated changes) as Eq. 10.

$$\text{Figure of Merit} = B / (A+B+C+D) \tag{10}$$

Where, *A* is extent of error owing to the observed change projected as persistence; *B* is area of correct owing to the observed change projected as change; *C* is zone of error because of the observed change projected as per change to incorrect class; and *D* is area of error because of the observed persistence projected as change (Pontius *et al.*, 2008; Memarian *et al.*, 2012).

Relative operating characteristic (ROC)

On the basis of comparison of the simulated map with the observed map; ROC is a summary statistic extended from several two-by-two adjacency tables.

Table 3: Layout of projected population matrix (Pontius and Millones 2011)

		Observed				Simulated total
		j = 1	j = 2	…	j = J	
Simulated	i = 1	P11	P12		P1J	$\sum_{j=1}^{J} p_{1j}$
	i = 2	P21	P22		P2J	$\sum_{j=1}^{J} p_{2j}$
	…					
	i = J	PJ1	PJ2		PJJ	$\sum_{j=1}^{J} p_{Jj}$
	Observed total	$\sum_{i=1}^{J} p_{i1}$	$\sum_{i=1}^{J} p_{i2}$		$\sum_{i=1}^{J} p_{iJ}$	1

If a pixel of a desired category in the projected image locates on the similar category in the observed image, it fills a record in contingency table as “true positive”, if not that pixel will be registered as “false positive” (Pontius and Schneider, 2001; Eastman, 2015). According to this concept, ROC chart is depicted by plotting a point for each threshold with true positives percentage on vertical axis and false positives percentage on horizontal axis (Pontius and Schneider, 2001; Eastman, 2014). Based on the trapezoidal instruction, ROC uses integral calculus to estimate the Area Under Curve (AUC). In ROC curve, diagonal line originates from an input image with the values’ locations which are randomly assigned (AUC=0.50). The AUC with a range of 0.90-1.00 is classified as excellent, and the AUC with a range of 0.5-0.6 is placed within the fail category (Tape, 2006). There are also three other categories between these two classes: good (AUC = 0.8-0.9), fair (AUC = 0.7-0.8), and poor (AUC = 0.6-0.7).

RESULTS AND DISCUSSION

In this work, calibration was performed according to the transitions in land uses during the period 1987-2009 (Fig. 5 and Table 4).

Change detection analysis of land uses during the period 1987-2015 established that land use alterations were synchronized with the expansion of urban patches which continuously led to the acreage reduction of rangelands surrounding the city. Since 1987 to 2015, residential area has been increased over 14 km^2 (112% increase), meanwhile, rangelands experienced an acreage reduction of 19 km^2 (8% decrease). During this period, irrigated and rainfed agriculture acreages have increased by 0.82 and 4.5 Km^2, i.e. 8.7% and 160% increase, respectively. According to Table 4, the change trends of residential and rangeland categories have the same slope (around 60 ha.yr^{-1}) but in reverse order. During the period 1987-2009, with the expansion of rainfed agriculture, the acreage of irrigated agriculture has not changed significantly. However, from 2009

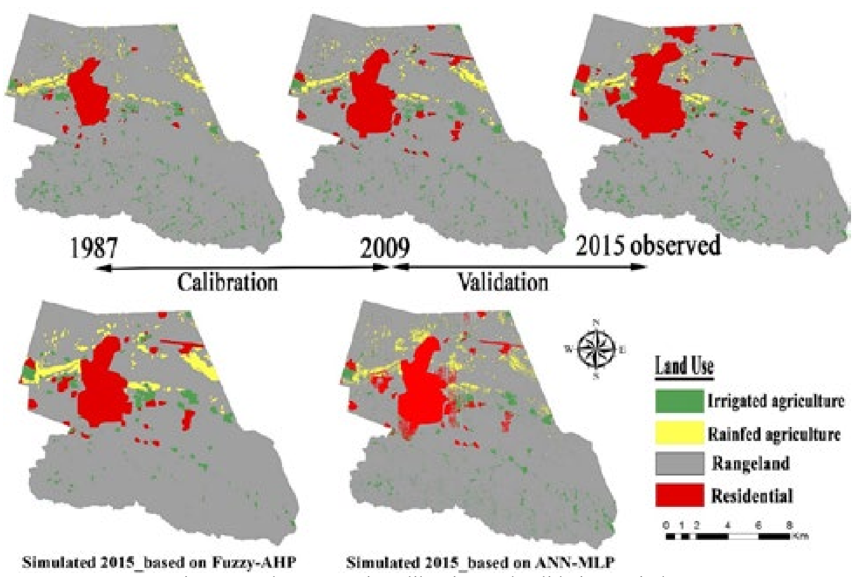

Fig. 5: Land use maps in calibration and validation periods

Table 4: Land use acreage (Km2) in different dates

Land use	1987	2009	2015	Change trend
Residential	13.19	24.05	28.89	
Irrigated agriculture	9.43	9.15	10.25	
Rainfed agriculture	2.83	8.28	7.38	
Rangeland	237.60	227.60	218.20	

onwards an increase of 18 ha in irrigated agricultural lands can be observed. Markov chain products transition matrix (Table 5) through examining two land use maps of two different times, i.e. 1987 and 2009. This matrix was utilized to project the land use map for the goal point 2025. Based on TPM (Table 5), the greatest land use changes happened in irrigated agricultural lands. The transition probability of the residential category to the same category is higher than the transition to other categories, which reflects the expansion of the residential context. In TPM, apart from the transition probabilities of similar land uses together, the transition probabilities of irrigated and rainfed agriculture to rangeland, i.e. 0.3179 and 0.3133 respectively, are the highest probabilities. The transition probability of rangeland to rainfed agriculture is higher than the transition to other categories. However, some land use transitions in TPM seem to be really mismatched. For example, the transition of residential lands to agriculture or rangeland seems unreasonable which can arise from the errors or uncertainties in land use classification based on satellite imagery (Memarian *et al.,* 2012).

The model validation traditionally recourses to the comparison between simulated and observed maps (Van Vliet *et al.,* 2009). The credibility of the results is always doubtful, particularly when the model simulates a future plan on the basis of disturbed variables (Mishra *et al.,* 2014). To analysis the model validation, a technique has been used to compare three maps, i.e. a reference map in time 1, a reference map in time 2 and a projection map in time 2. In this study, the 2009 reference map, the 2015 reference map and the simulated map in 2015 (according to MLP and Fuzzy-AHP transition potential mapping) have been utilized. The three map comparison for each modeling claim estimates the accuracy of a prediction which is inferable from land use persistence against land use alteration. According to this validation approach, it is permitted to differentiate between the correct pixels due to persistence or due to change (Pontius *et al.,* 2008). According to error analysis presented in Tables 6 and 7, transition simulation of the rainfed agriculture category

Table 5: Transition probability matrix for LUCC modeling based on the 1987-2009 calibration period

	Irrigated agriculture	Rainfed agriculture	Rangeland	Residential
Irrigated agriculture	0.6765	0.0013	0.3179	0.0043
Rainfed agriculture	0.0639	0.6216	0.3133	0.0012
Rangeland	0.0111	0.0138	0.9653	0.0097
Residential	0.0144	0.0001	0.0153	0.9703

Table 6: Validation metrics for each land use class and total landscape using three-dimensional approach

Category	Gain (omission)		Persistence		Loss (commission)		Quantity Error		Allocation error		FOM	
	% of study area											
	MLP	Fuzzy-AHP	MLP	Fuzzy-AHP	MLP	Fuzzy -AHP	MLP	Fuzzy-AHP	MLP	Fuzzy-AHP	MLP	Fuzzy-AHP
Irrigated agriculture	1	1	3	1	6	2	2	2	2	2	30	31
Rainfed agriculture	2	2	0	1	0	2	1	1	2	3	9	7
Rangeland	6	5	82	82	5	4	1	1	10	9	88	89
Residential	3	2	3	6	1	1	2	2	2	2	49	51
Total	12	10	88	90	12	9	2	2	8	8	19.10	18.5

Table 7: Validation results for simulation of total landscape via three-dimensional technique

Component	Proportion (%)	
	MLP	Fuzzy-AHP
Persistence simulated correctly	87.71	88.05
Persistence simulated as change	2.89	2.54
Change simulated as change to wrong category	0.46	0.43
Change simulated correctly	2.34	2.22
Change simulated as persistence	6.61	6.76
Total	100	100
Simulated Change	5.69	5.18
Observed Change	9.41	9.41

in both techniques led to the lowest figure of merit (9% based on MLP and 7% based on Fuzzy-AHP). This could be due to the transit nature of this category. Land use transition in rainfed agriculture is very dependent on the quantity and the distribution of rainfall during a year. In a year with a low amount of rainfall, rainfed agricultural lands are covered by scrub. Farover, in the study region, due to the proximity of some rainfed agricultural lands to urban/rural patches, land conversion and cultivation for establishing the ownership is one of the factors affecting rangeland transition to low-yielding rainfed agriculture. This tendency of land transition in closer regions to urban patches is the first step of the speculation process, which unfortunately is a thoughtful environmental difficult for developing cities in Iran (Tajbakhsh *et al.,* 2016). According to Table 6, simulation of rangeland led to the highest figure of merit as 88% and 89% based on MLP and Fuzzy-AHP approaches, respectively. This could have arisen from a high proportion of persistence in this category, i.e. 82%. Due to the complexity and the rules governing rainfed agriculture transitions, the persistence amount in rainfed agricultural lands in both Fuzzy-AHP and MLP approaches is very low. In both simulations, quantity errors were similar in all categories. However, Fuzzy-AHP approach led to a higher allocation error in rainfed agriculture, i.e. 3% as compared with that by MLP, i.e. 2%. Furtherfar, rangeland change simulation by Fuzzy-AHP could result in a lower allocation error (9%), in comparison with that by MLP (10%). There was a similarity between quantity error and allocation

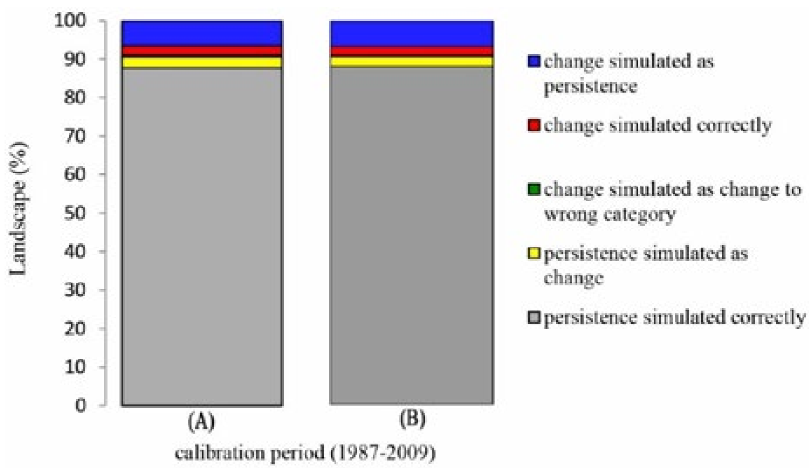

Fig. 6: Agreement and disagreement components in Fuzzy-AHP (A) and MLP (B) simulations

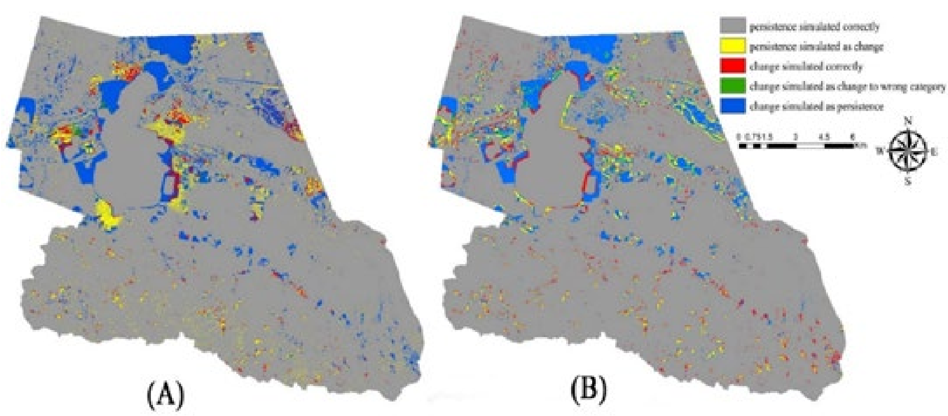

Fig. 7: Map of agreement and disagreement components in Fuzzy-AHP (A) and MLP (B) simulations

error in simulation of irrigated agriculture and residential regions. This confirms that simulation of irrigated agriculture and residential regions is effected by both kinds of errors. However, in the projection of rainfed agriculture and rangelands, allocation error was remarkably greater than the quantity error. In this work, transition inconsistency between calibration and validation periods mostly impacted the simulation of agriculture lands. The total figures of merit in MLP and Fuzzy-AHP simulations were 19.10% and 18.50%, respectively. In both simulations, total quantity error (2%) and total allocation error (8%) were similar. As presented in Table 7, simulated change is sum of "persistence simulated as change", "change simulated as change to wrong category" and "change simulated correctly." Observed change is sum of "change simulated as change to wrong category", "change simulated correctly" and "change simulated as persistence". According to Figs. 6 and 7 and Table 7, the component "change simulated correctly" in MLP simulation was 2.34% which was higher than this component in Fuzzy-AHP simulation, i.e. 2.22%. Furtherfar, the component "change simulated as persistence" in MLP simulation was calculated to be 6.61% which was lower than this component in Fuzzy-AHP simulation, i.e. 6.76%. However, in both simulations the component "change simulated as persistence" was significantly high, which could have originated from the high transition rates of land uses especially after 2009. Based on the obtained results, MLP resulted in a higher "simulated change" (5.69%), as compared with that by Fuzzy-AHP (5.18%). This condition, led to a higher FOM by MLP, i.e. 19.1% in comparison with that index by Fuzzy-AHP, i.e. 18.5%. However, in both simulations, because of a high proportion of "persistence simulated as change", observed change (9.41%) was greater than simulated change, i.e. 5.69% and 5.18% in MLP and Fuzzy-AHP simulations, respectively (Table 7, Figs. 6-7).

ROC analysis was performed for the simulation results of CA-Markov, as well (Fig. 8). Results showed that the highest and the lowest AUCs, i.e. 0.90 and 0.68 were obtained for residential and irrigated agriculture change simulations, respectively, which correspondingly establishes excellent and poor performances (Tape, 2006). Rainfed agriculture and rangeland classes with the AUCs of 0.84 and 0.73, respectively confirmed good and fair strength of simulations. The Pierce Skill Score for simulations based on MLP and Fuzzy-AHP was estimated at 0.96 and 0.86, respectively, which indicates an acceptable performance by both approaches in total landscape simulation.

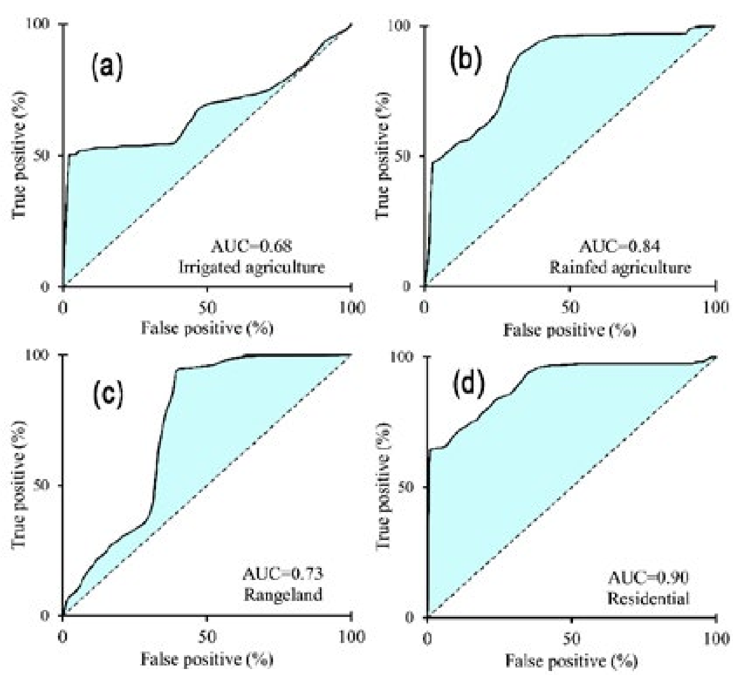

Fig. 8: ROC analysis results for CA-Markov simulation; (a) Irrigated agriculture, (b) Rainfed agriculture, (c) Rangeland, (d) Residential

According to Pontius and Malanson (2005), some LUCC models presume land use transition as simulated precisely utilizing spatial dependence imposed in a proximity statute. Nevertheless, as depicted in Fig. 9, the new patches of rainfed agriculture category do not grow from present patches. As mentioned before, CA-Markov enforces spatial dependency through the contiguity instruction. In this way, CA-Markov would be incapable to precisely project land use transition for rainfed agriculture. Once the major sign of land is perseverance, it is essential that the model emphasizes the most imperative sign of alteration in the landscape. The study have confirmed that the projecting efficiency of CA-Markov is better for situations where it emphases on the main sign and neglects noise (Pontius and Malanson, 2005; Memarian *et al.,* 2012). In this area, there was some noise originating from alterations of small patches, especially in urban and agriculture classes. However, in this work, this noise was not correctly simulated using CA-Markov. The used land use maps were derived from satellite images via supervised classification. The classification of remotely sensed images for extracting thematic maps in general is on the basis of the spatial objects clustering within a spectral extent. However, this means an ability to split the gradual changeability of the Earth's surface into a limited number of separate non-overlapping categories which are considered systematically exclusive and defined. This kind of method is not appropriate in real world due to the continual nature of the ecosystem characteristics. In addition, the utilized image classification approaches and the standard form of data processing may lead to some information loss, as the continual spectral information is summarized into a set of separate categories. This would make a degree of uncertainty in LUCC simulation (Rocchini *et al.,* 2013). As established by Pontius and Neeti (2010) three causes of uncertainty (model, data, and future land alteration processes) impacted the results of this work. Land use maps - in three points of time - were required for calibration and validation processes and time intervals relied on data accessibility. In this work, data shortage and absence of freedom in data assortment led to a few inconsistencies between validation and calibration interims in terms of change intensity. Furtherfar, Memarian *et al.* (2012) established that on the basis of marginal land use alterations over a specified period, CA-Markov cannot run at high performance in precise LUCC simulation. Markov simulations based on MLP and Fuzzy-AHP approaches led to the overall Kappa of 89 % and 90%, respectively. A high proficiency of the model in LUCC simulation can be concluded by these Kappa agreement statistics based on the specified calibration period. However, as proposed by Pontius *et al.* (2011), the outcomes of the three-dimensional validation approach confirmed that these Kappa accuracies typically stemmed from high land persistence during the time (Table 6 and Fig. 6). Hence, Kappa agreement statistics are not capable of quantifying the model power in LUCC simulation. Normally, these Kappa indices make comparison between accuracy and a randomness baseline. However, Pontius and Millones (2011) stated that randomness is an illogical choice for mapping. Furtherfar, some Kappa indices suffer from fundamental hypothetical faults. Consequently, allocation disagreement and quantity disagreement are

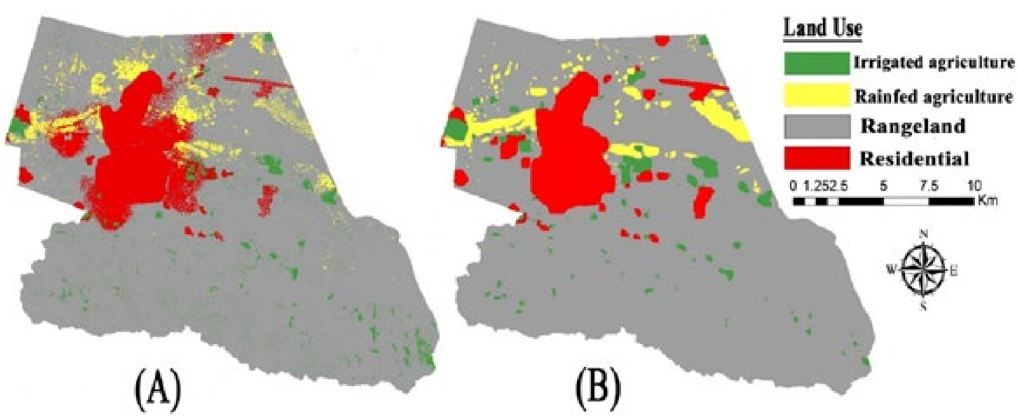

Fig. 9: Markovian LUCC simulation of Birjand plain in 2025 by MLP (A) and Fuzzy-AHP (B) transition potential and suitability mappers

suggested to be employed for accuracy assessment, as a replacement for Kappa statistics (Memarian *et al.,* 2012). Based on the obtained results, there is not a significant difference between the performance strength of LUCC simulations through MLP and Fuzzy-AHP transition potential mappers. However, according to the indices FOM, Pierce Skill Score and the percentage of simulated change, Markov simulation based on MLP approach can be proposed as the recommended technique for LUCC simulation in this study. Using ANN for LUCC simulation has been established in multiple research works (Omrani *et al.,* 2012; Perez-Vega *et al.,* 2012; Camacho Olmedo *et al.,* 2013; Mishra *et al.,* 2014; Qiang and Lam, 2015). As confirmed by Perez-Vega *et al.* (2012) neural networks outputs are capable of conveying the concurrent alteration potential to several land use types far effectively than single likelihoods acquired through the Fuzzy-AHP transition potential mapper. In a study by Camacho Olmedo *et al.* (2013), MLP technique outperformed the MCE-based Markov model in urban growth modeling as the transition potential map for urban growth captured urban alteration far accurately than the suitability map. MCE-based Markov model outperformed MLP model in other categories or transitions as the suitability maps of the categories captured the land use and land change outlines of these classes far accurately. The same condition occurred in our work when the MLP outperformed Fuzzy-AHP for rainfed agriculture and total landscape simulations. However, Fuzzy-AHP approach could outperform MLP for the simulation of other categories.

There are special potentials and constraints for each LUCC model. Thus, a single model is not talented to confine all the crucial processes involved in land use change simulation (Luo *et al.,* 2010). Based on the results of this work and studies of Poelmans and Van Rompaey (2010), Arsanjani *et al.* (2013), and Memarian *et al.* (2012), the following modifications are suggested in order to improve the simulation precision:

- Model urban and residential areas separately using far deterministic criteria
- Compare MLP approach with other deterministic approaches like logistic regression and/or SimWeight for mapping transition potentials
- Integrate far decisive socio-economic variables in LUCC simulation, for instance population growth throughout the simulation period
- Dynamic incorporation of hydro-climatic parameters, drought indices and the influences of climate change scenarios on LUCC simulation

CONCLUSION

Change detection analysis of land uses during the period 1987-2015 established that land use alterations were synchronized with the expansion of urban patches which continuously led to the acreage reduction of rangelands surrounding the city. During this period, irrigated and rainfed agriculture acreages have increased by 8.7% and 160%, respectively. Markov simulations based on MLP and Fuzzy-AHP approaches led to the overall Kappa of 89 % and 90%, respectively. These Kappa metrics determine high competence of the model in LUCC simulation according to the specified calibration period. The outcomes of a three-dimensional validation method established that these Kappa precisions were generally caused from a high amount of land persistence during the time. Thus, error analysis was performed based on the quantity disagreement, allocation disagreement, metrics and figure of merit. Simulation of change in the rainfed agriculture category in both techniques led to the lowest figure of merit (9% based on MLP and 7% based on Fuzzy-AHP). This could be due to the transitory nature of this category, which is impacted by climatic fluctuations and social issues. Owing to relatively high percentage of persistence in the rangeland category, its simulation led to the highest figure of merit as 88% and 89% based on MLP and Fuzzy-AHP approaches, respectively. In this study, projection of agriculture lands was mainly affected by the inconsistency of transition between validation intervals and calibration. The total figure of merit in MLP and Fuzzy-AHP simulations were 19.10% and 18.50%, respectively. MLP resulted in a higher “simulated change” (5.69%), as compared with that by Fuzzy-AHP (5.18%). This condition, led to a higher FOM by MLP, i.e. 19.1% in comparison with that index by Fuzzy-AHP, i.e. 18.5%. However, in both simulations, due to a high proportion of “persistence simulated as change”, observed change (9.41%) was larger than simulated change, i.e. 5.69% and 5.18% in MLP and Fuzzy-AHP simulations, respectively. In this study area, due to the transitions of small patches, especially in urban and agriculture classes, some noises in the map were created during simulation. However, CA-Markov did not project this noise properly. The image classification methodologies and the standard data processing applied, led to the loss of information while the continuous quantitative spectral information was summarized into a set of separate thematic classes. This imposed another source of uncertainty in LUCC simulation. In addition, due to the data shortage and the absence of freedom in data selection, there was an inconsistency between validation intervals and calibration in terms of transition intensity. According to the indices FOM, Pierce Skill Score, and the percentage of simulated change, Markov simulation based on MLP approach can be proposed as the recommended technique for LUCC simulation in this study.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the University of Birjand for valuable supports throughout this research performance.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this manuscript.

ABBREVIATIONS

A	The area of error owing to observed change projected as persistence
A1	Total allocation disagreement
AG	Allocation disagreement
AHP	Analytic hierarchypProcess
ANN	Artificial neural network
ANN-MLP	Artificial neural network-multi layer perceptron
AUC	Area under curve
B	The area of correct owing to observed change projected as change
C	The area of error because of observed change projected as change to incorrect class
C1	Porportion of agreement
CA	Cellular automata
CA_Markov	Cellular automata markov
CI	Consistency Index
CLUE	Conversion of land use
CR	Consistency ratio
D	The area of error because of observed persistence projected as change
D1	Total disagreement
ETM+	Enhanced thematic mapper +
FOM	Figure of merit
Fuzzy-AHP	Fuzzy-analytic hierarchy process
G	Desired class
GEOMOD	Geometric modeler
GIS	Geographic Information System
Ha/yr^{-1}	Hectar per year
I	Class in the simulated map
J	Class in the observed map
Km^2	Kilometer square
LCM	Land change modeler
LMD	Linear membership function-monotonically decreasing
LMI	Linear membership function-monotonically increasing
LUCC	Land use and cover change
LULC	Land use and land cover
m	Meter
MCE	Multi criteria evaluation
MLC	Maximum likelihood classifier
MLP	Multi-layer perceptron
MLP_Markov	Multi-layer perceptron markov chain
mm	Milimeter
MOLA	Multi objective land allocation
Ni	The number of cells in each stratum
OLI	Operational land imager
Pij	Proportion of the study area
Q	Total quantity disagreement
QQ	Quantity disagreement
RMS	Root mean square
ROC	Relative operating characteristic
SimWeight	Similarity-weighted instance-based machine learning tool
St_Markov	Stochastic markov
t	Time
TM	Thematic mapper
TPM	Transition probability matrix
UTM	Universal transverse mercator
WGS	World geodetic system
WLC	Weighted linear combination
X[k]	Markov chain with the states {x1, x2, x3, ⋯}
X(t)	Random process
%	Percent
χ^2	Chi Square

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HOW TO CITE THIS ARTICLE

Tajbakhsh, S.M.; Memarian, H.; Moradi, K.; Aghakhani Afshar, A.H., (2018). Performance comparison of land change modeling techniques for land use projection of arid watersheds.
Global. J. Environ. Sci. Manage., 4(3): 263-280.

DOI: 10.22034/gjesm.2018.04.03.002

url: http://www.gjesm.net/article_31528.html