ORIGINAL ARTICLE

Spatio-temporal modelling of land use changes by means of CA–Markov model

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Abstract

Cities and their problems in our world today are very important because they can affect the land uses and landscapes around them and make them change. Researchers have been tried to solve these problems using several methods. One way that can be useful in planning is simulation and prediction land use changes according to the parameters that affect changes in land use over the time. In this study, changes in land use of Bojnord city (the capital city of North Khorasan province), were considered and studied. In this regard, the CA–Markov model was used. In this model, suitability maps are the basis of the land use changes transformation. To produce suitability maps in this study, agricultural lands were paid specially attention and suitability of them has been reduced as much as possible in modeling. The land use maps of two different periods of time were used to calibrate the models. To validate the model, the "Validate" method (which is a statistical method to validate models) was used. The calculated kappa coefficients for both models were over 85%. In next step, changes of land use have been simulated until the year of 2050. Examination of the output maps which are obtained by CA–Markov model shows that the most growth in land use is in the built-up areas. In 2050, the built-up areas would grow 5.3% compared to 2009 and in subsequent periods the growth rate would be 3.5% on average.

Keywords Simulation · Markov chain · Multi criteria evaluation · Analytic hierarchy process · Cellular automata

Introduction

Cities in the context of time, such as alive organisms, become bigger and more complex in terms of their physical structure. Subsequent to this physical growth, their socio-economic and cultural development gradually changes. These changes can affect the environment around them and cause them to change and degrade. These changes are influenced by the forces and factors that always affect the physical space of the cities and evolve over time with changes and social and economic progress. This transformation, while imposing a new face and landscape on the physical body of cities, also provides grounds for changes in the content and social structures of the city. In recent years, numerous investigations have been carried out by researchers to solve the problem of uneven urban growth using various methods such as: Nasehi et al. (2019) by CA–Markov model was predicted land uses change in zone 2 Tehran between 2016 and 2032 for 16 years. The results of prediction were shown to increase the built lands and to decrease the open land and green land. Aithal et al. (2018) in their research using CA–Markov model that combined with socioeconomic factors were modeled urban growth in Bangalore-silicon hub of India until 2020. Rabbani et al. (2018) by Shannon's entropy with hierarchical clustering analysis is modeled urban sprawl in Mashhad city in Iran. The results of modelling are shown that urban unplanned sprawl can be cause of increasing informal settlements and crimes and have negative impact on environment and socio-economic parameters. Novin and Khosravi (2017) by emphasis on connective routs networks was modeled land uses change in time period of 2020–2050. Geomode model was used for modelling. The results show the importance of classification of connective routes network

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in urban growth studies. Mitsova et al. (2011) modeled urban growth with an emphasis on natural resources by means of CA–Markov model in cities of Ohio, Cincinnati and Indiana. The CA and particle swarm optimization (PSO) model were combined by Feng et al. (2011) to define new transition rules in CA model by means of the random sampling ability in PSO model. Liu and Phinn (2003) designed fuzzy–CA model to use variants to define CA transition rules in urban growth modeling in Sydney. Hu and Lo (2007) used logistic regression to model urban growth in GIS environment for Atlanta metropolis. Guan et al. (2011) examined and modeled land use changes in Saga city using CA–Markov model. At first, they obtained the rate of changes by means of GIS methods during 1976–2006 and then used natural, social and economic data and information to produce potential maps. Rawat et al. (2013) Considered the rate of land use changes in Ramnagar city located in India by means of remote sensing and geospatial information system techniques and the result of their research implied that agricultural lands and greenbelts were decreased. Dadras et al. (2015) measured the city growth by means of statistical data, Pearson's Chi square distribution method and Shannon's entropy method.

In this research, aerial photos and satellite imagery are used to extract and produce land use maps and several base maps. Then, all the criteria maps are weighted using the AHP method and in the end, the CA–Markov model was used to predict changes in usage.

Studied area

The city of Bojnord is between 37°28′N and 57°20′E and 1010 m above the free water level. Bojnord is located in northern Khorasan province, with an area of about 6700 km² and its center is Bojnord (Fig. 1). It is selected as center of Northern Khorasan since 2004. This city is about the flat and no important natural barriers are urban growth and agricultural lands are affected from this situation. About 300 years ago, the original nucleus of the present-day Bojnord town on a flat and flat land flowing from the northwest to the plains and from the south to the plains was not a major natural disruption to the city's physical development. Due to the economic and social changes of the recent century, the population growth of the city, the relatively centralized fabric of the city began to expand in almost all directions, and the interconnected tissue of the urban area of Bojnord has had considerable physical development in the last two decades.
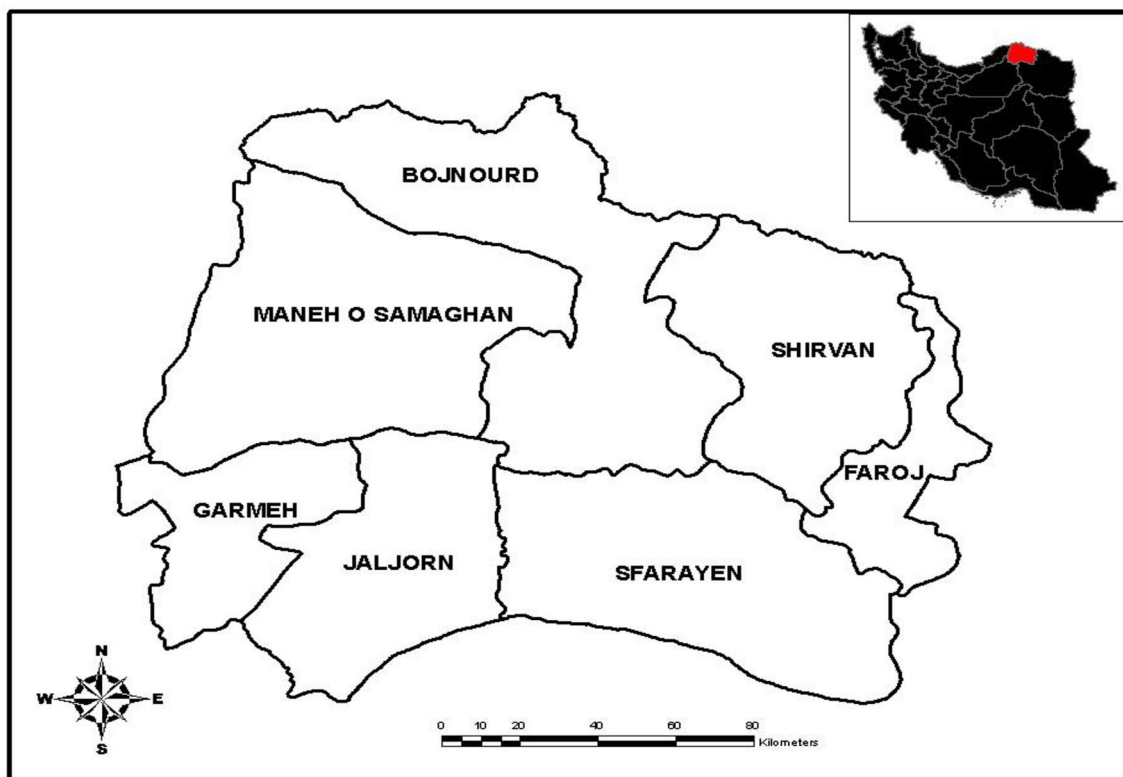

Fig. 1 Location of Bojnord city in Northern Khorasan

Methodology

CA–Markov model have been had three steps: (1) creating transition matrix using Markov change. (2) Creating suitability maps using Multicriteria evaluation method. (3) Cellular automata algorithm with the number of iterations and a 5×5 contiguity filter (Fig. 2).

Markov chain

Markov chain is a probabilistic chain that was calculated probability of change one state to another one. In other words, the probability of a change from a state in T time depends on the state of the past $(T - 1)$. Theoretically, a certain portion of land use may be converted to any other group at any time from a land use group. Markov's analysis uses matrices that represent all the land-use variations among all the individual groups of land use.

Multicriteria evaluation

A method for generating suitability maps with respect to the parameters affecting the suitability of pixels. The multi-criteria evaluation analysis has three main methods for producing such maps, which include: Boolean subscription, weight line composition, and weighted sorted average. In this paper, weighted linear combination (WLC) was selected for creating suitability maps. Here is a brief explanation of the use of the linear weight composition method in this paper, weighted linear combination (WLC) was selected for creating suitability maps.

Fig. 2 A flow-chart of the modeling process (Mitsova 2011)

Weighted linear combination (WLC)

They are based on the concept of a weighted average. The decision maker directly assigns weights of "relative importance" to each. A total score is then obtained for each alternative by multiplying the importance weight assigned for each attribute by the scaled value given to the alternative on that attribute and summing the products over all attributes. When the overall scores are calculated for all the alternatives, the alternative with the highest overall score is chosen. Formally, the decision rule evaluates each alternative, A by the following formula:

$$S = \sum w_i x_i,$$

where X_{ij} is the score of the ith alternative with respect to the jth attribute, and the weight W_i is a normalized weight, so that $\sum W_i = 1$. The weights represent the relative importance of the attributes (Malczewski 1998).

If Boolean constraint is used, calculated suitability is multiplied in constraint:

$$S = \sum W_i X_{i*} \Pi C_j.$$

Weighting criteria

Several weighting methods are available to determine the weight of the criteria used to produce competency maps, including rating, grading, and comparisons of pairs (AHP) methods used in this study because of the use of the pair comparison (AHP) method.

Analytic hierarchy process

In this method, the matrix is compared to the pair comparisons. Pair comparisons are considered as inputs and relative weights are produced as outputs. AHP is involved these steps:

1. Development of the pairwise comparison matrix: the method employs an underlying scale with values from 1 to 9 to rate the relative preferences for two criteria (Malczewski 1998).
2. Computation of the criterion weights: computation of weights for each criterion was run that values are between 0 and 1 (0 is the lowest value and 1 is highest value).
3. Estimation of the consistency ratio: in this step we determine if our comparisons are consistent. The consistency ratio (CR) is designed in such a way that if CR < 0.10, the ratio indicates a reasonable level of consistency in the pairwise comparisons; if, however, CR ≥ 0.10, the values of the ratio are indicative of inconsistent judgments (Malczewski 1998).
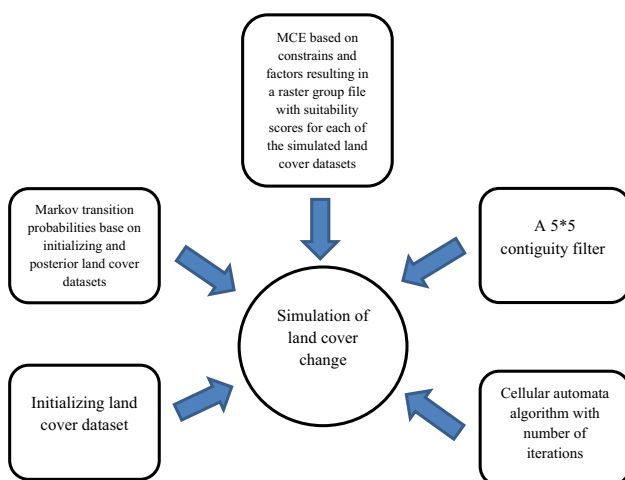
Cellular automata

One of the basic spatial elements that underlies the dynamics of many change events is proximity: areas will have a higher tendency to change to a class when they are near existing areas of the same class (i.e., an expansion

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

Fig. 3 5×5 contiguity CA filter

phenomenon). These can be very effectively modeled using cellular automata. A cellular automaton is a cellular entity that independently varies its state based on its previous state and that of its immediate neighbors according to a specific rule (Clark Labs 2006). CA has been had several elements: latter, cell state, neighborhood, time and transition roles that is important section of model. In CA–Markov model, transition matrix has been played as transition role. Cellular automaton is one of the urban planning support systems.

CA–Markov

Both Cellular automata and Markov chain are discrete in time and location. Markov chain has not been generated

Landuse map 1994

Landuse map 2004

Landuse map 2009

■ Out of study area
■ Bare land
■ Agriculture
■ Built_up areas

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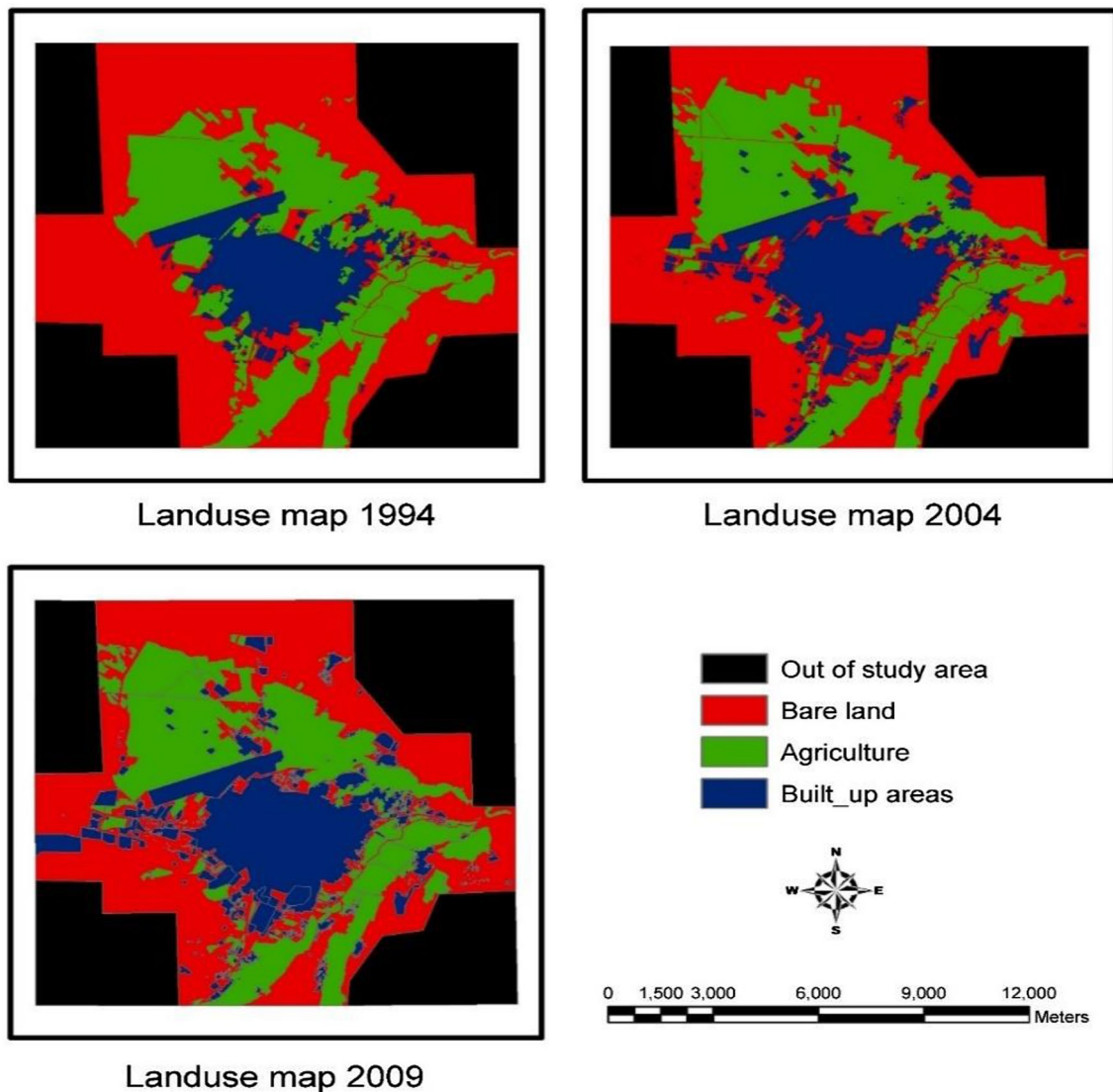0 1,500 3,000   6,000   9,000   12,000
Meters

Fig. 4 Land use maps of Bojnord

spatial understanding. Transition probability might in each land use consists of accurate and precision but have not been had knowledge and awareness from random spatial contribution in each land use. Cellular automata have been added to model for spatial understanding. As a CA–Markov model is set in motion, a 5×5 contiguity CA filter (Fig. 3) re-weights the suitability maps during each iteration increasing the suitability of pixels in close proximity to contiguous areas of the same category. The reweighted maps undergo a multi-objective land allocation process that resolves land allocation conflicts using the highest suitability score (Eastman et al. 1998). During each iteration, pixels with the highest transition probability and highest suitability score for a particular class transition to a new class while pixels with lower probabilities and lower suitability scores remain unchanged (Eastman 2006).

Data preparation

Land use maps

In this research, land use maps and several criteria maps were extracted from aerial photograph in 1994. The mosaics of several aerial photographs were used to cover the entire study area. Satellite images used are images with high resolution spatial resolution of the QuickBird satellite for the years 2004 and 2009. The spatial resolution of multispectral images was increased by image fusion method to 60 cm. All aerial photograph and Satellite images were georeferenced using 37 GCP that were picked up by GPS. RMS error the polynomial function of grade 2 is estimated to be less than one pixel. For re-sampling, the nearest neighbor method was used. All aerial photographs are fixed to satellite imagery. Land use maps were extracted by vectorizing on aerial photo and satellite images (Fig. 4). According to the characteristics of the region, three main land use maps were extracted. Bare lands which does not have any use, agricultural lands including farmland, gardens, trees and built areas including residential areas, industrial centers, military centers, commercial centers and airports. Each land use map was reviewed several times for three periods of study to ensure their accuracy.

Calculating Markov transition matrix

Markov transition matrix was calculated with two land use map. Tables 1, 2, 3, 4 and 5 were shown values.

Table 1 Markov transition matrix for 1994–2004 years

2004	Bare lands	Agricultural lands	Built-up areas
1994			
Bare lands	0.89	0.063	0.047
Agricultural lands	0.0672	0.9046	0.0264
Built-up areas	0.0127	0.0004	0.9869

Table 2 Markov transition matrix for 2004–2009 years for predicting 2020 year

2009	Bare lands	Agricultural lands	Built-up areas
2004			
Bare lands	0.8538	0.0288	0.1174
Agricultural lands	0.1739	0.8121	0.0141
Built-up areas	0.038	0.0074	0.9547

Table 3 Markov transition matrix for 2004–2009 years for predicting 2030 year

2009	Bare lands	Agricultural lands	Built-up areas
2004			
Bare lands	0.7560	0.0459	0.1981
Agricultural lands	0.2737	0.6870	0.0393
Built-up areas	0.0649	0.013	0.9220

Table 4 Markov transition matrix for 2004–2009 years for predicting 2040 year

2009	Bare lands	Agricultural lands	Built-up areas
2004			
Bare lands	0.6754	0.0584	0.2662
Agricultural lands	0.3434	0.5844	0.0722
Built-up areas	0.0884	0.0183	0.8933

Table 5 Markov transition matrix for 2004–2009 years for predicting 2050 year

2009	Bare lands	Agricultural lands	Built-up areas
2004			
Bare lands	0.6089	0.0674	0.3238
Agricultural lands	0.3902	0.5001	0.1097
Built-up areas	0.1088	0.0231	0.8682

Criteria maps

To produce suitability maps for the built-up areas, six criteria maps and one restriction map were used (Fig. 5). Bare lands and agricultural lands map was developed to minimize
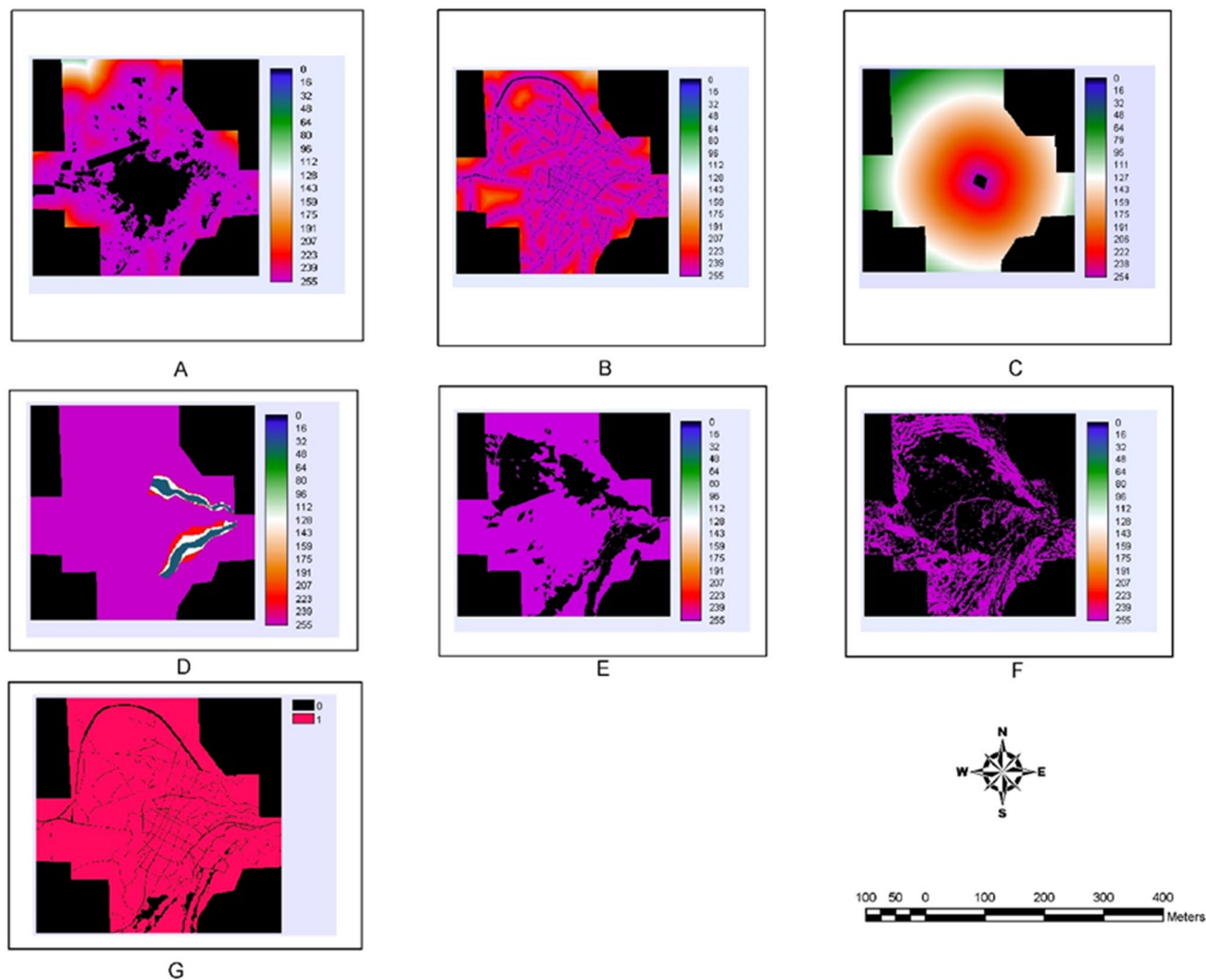
Fig. 5 Criteria maps for creating suitability maps for built-up areas: **a** distance map from downtown. **b** Map of the bare lands and agricultural lands. **c** Slope map. **d** Watercourse zoning map. **e** Distance map from the built-up areas. **f** Distance map from the connective routes. **g** Restrictions map

Table 6 Slopes classification for creating suitability map of the built-up areas

Slopes classification (percentage)	Importance rate
0–3 and slopes higher than 15	Minimum
3–15	Maximum

Table 7 Weights of criteria with AHP method for creating built-up areas suitability maps

Criteria maps	Weight
Map of the bare lands and agricultural lands	0.0694
Distance map from downtown	0.1627
Distance map from the built-up areas	0.3743
Distance map from the connective routes	0.2561
Slope map	0.379
Watercourse zoning map	0.0997
Consistency ratio	0.02

the value of agricultural lands and maximize the value of bare lands in modeling. The watercourse zoning map was generated using the DEM 1:2000 area. All road maps were extracted from aerial photos and satellite imagery. For each connective route from the central line of the road, a 10-m buffer is drawn from each side to exclude paths from development. Selection of buffer size based on field visits and surveys on satellite imagery, with emphasis on ways that crossed agricultural lands.

To create a slope map, DEM 1:2000 and 1:25,000 were combined. DEM 1:2000 covers only the metropolitan area and is used to cover the entire 1:25,000 DEM area. The slope map is re-categorized based on the slope of the region in
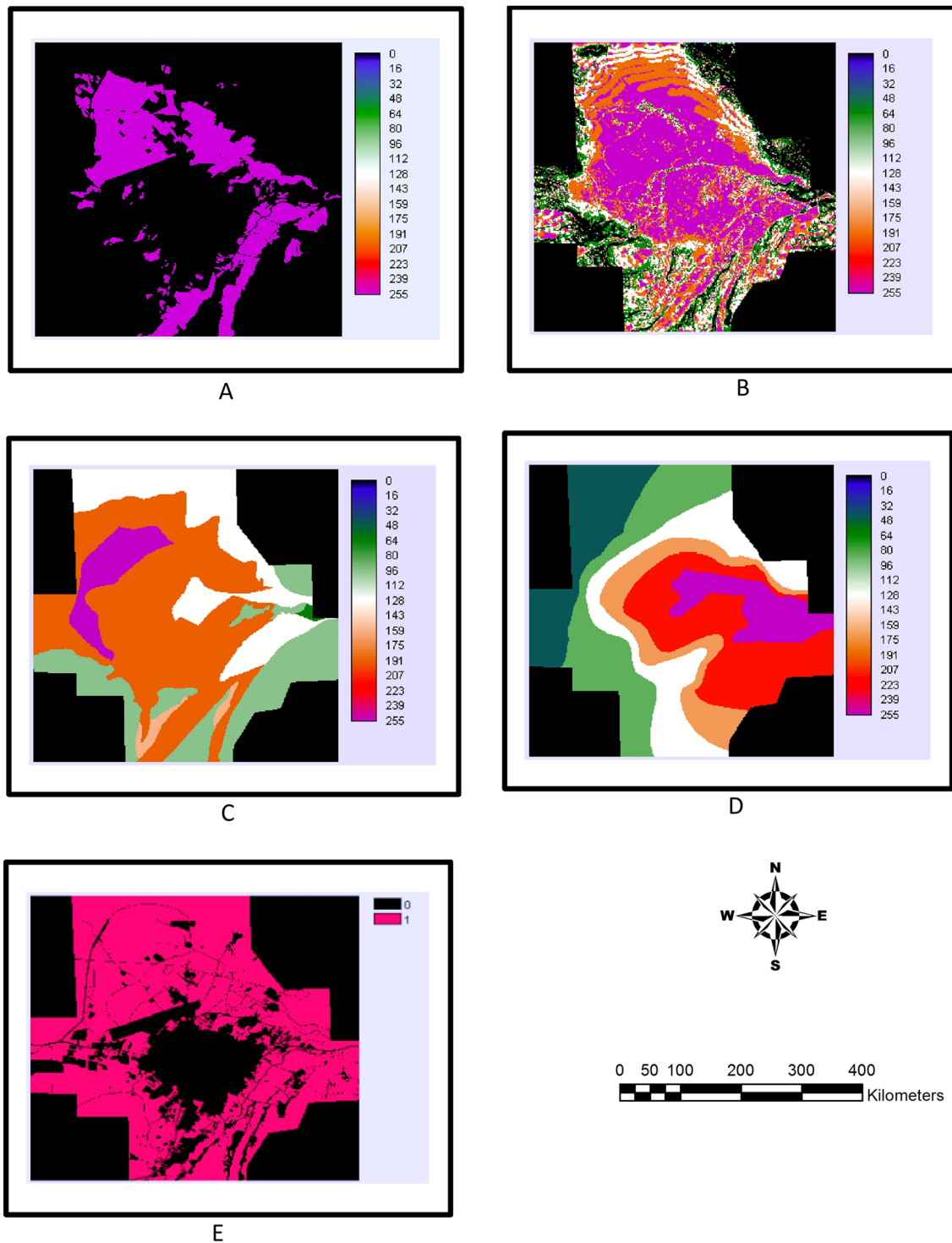
Fig. 6 Criteria maps for creating suitability maps for agricultural lands and bare lands: **a** map of the bare lands and agricultural lands. **b** Slope map. **c** Soil classification map. **d** Depth of groundwater map. **f** Restrictions map

three classes, and the values are considered to minimize and maximize (Table 6) distance from the city center and distance from the built-up areas were generated by distance function. Fuzzy membership function was used to standardize all the maps between 0 and 255 values. Watercourse, connective routes and areas with high level of altitude changes were configured as limitation map. Weights

Table 8 Classification of soil maps

Constraints	Class	Category
No constraint for cropping	1	1
Topography, high moisture, mixture of sub-classification	2	2
Topography, mixture of sub-classification	3+2	3
Topography, high moisture, mixture of sub-classification	3	4
Topography, mixture of sub-classification	4+3	5
Bedrock	4	6

Table 9 Slopes classification for creating suitability maps of agricultural lands and bare lands

Slopes classification (percentage)	Importance rate
0–2	6
2–4	5
4–8	4
8–16	3
16–32	2
More than 32	1

Table 10 Weights of criteria with AHP method for creating agricultural lands and bare lands

Criteria map	Weight
Map of the bare lands and Agricultural lands	0.2839
Soil classification map	0.5183
Depth of groundwater map	0.0989
Slope map	0.989
Consistency ratio	0.00

of criteria maps were calculated AHP method for built-up areas (Table 7).

For creating suitability maps of agricultural lands are used four criteria maps and one restrictions map (Fig. 6). Bare lands and agricultural lands map to maximize the value of agricultural lands and to minimize the value of bare lands in preparation to produce suitability maps. The classification map of soils of the region according to the classification of soils according to topography, moisture, gradient, and soil type based on the CLI system (Canadian Soil Information Service 2013) were classified into six classes, the highest value for the first-grade soils (Table 8). The depth of groundwater in the studied area is measured at depths of 5–30 m in 5 m intervals, and the map is based on this in six classes, where groundwater with low depth is the highest value. The DEM maps of 1:2000 and 1:25,000 was used to produce the slope map. Which were graded in five classes based on the slope of agricultural lands in the region, based on percentage (Table 9). Weights of criteria maps were calculated AHP

method (Table 10). In addition, the map of restrictions includes built-up areas, connective routes, and watercourse of the region.

Bare lands Suitability map was created with criteria maps of agricultural lands with reversed values that mean pixels are had the highest value is gone the lowest.

Creating suitability maps

Suitability maps was created by method. Fig 7. Was illustrated the suitability maps produced for 2009, which are the basis for modeling land use changes.

Implementation of the model

First, for the calibration of the model maps of 2004 and 2009, the CA–Markov model was developed. All the criteria maps of three land uses for model calibration were prepared and all maps were weighted. Then simulated maps with land use maps were compared using the Validate method, a statistical method for validating the data. The Kappa coefficient calculated for the compliance rate of the simulated land use map in 2004 was 0.8483 and also for 2009 was 0.8812 which reflects the matching of simulated maps with reality. Then, until 1430, changes in land uses were simulated (Fig. 8).

Conclusion

To calibrate the models, the prediction maps of the land uses were compared to the actual land use maps of the city of Bojnord for the years 2004 and 2009 and the output of the maps was compared using the Validate method. The Kappa coefficient produced by this method shows values higher than 85%, which reflects the correspondence of land use-generated maps with actual land use maps of Bojnord. The value of these coefficients reflects the reliability of user prediction maps produced for Bojnord from 2020 to 2050. Table 11 was shown the percentage of land uses in Bojnord city from 1994 to 2050. In 2004, the percentage of growth in built-up areas was 6.4% higher than in 1994. Of course, it should be noted that this year Bojnord city was selected as the center of the northern Khorasan province, which made it important to grow and Instruments and changes in the
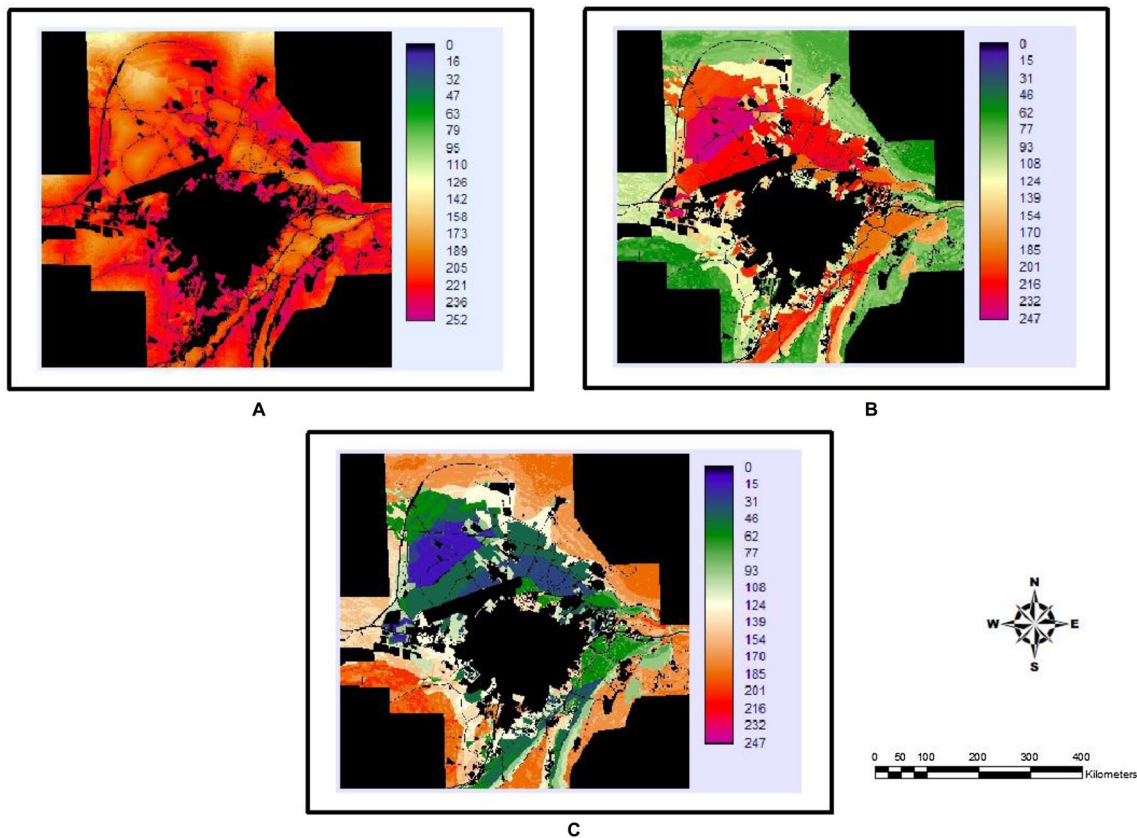
Fig. 7 Suitability maps of 2009 year that are basic suitability maps for land use change prediction using CA–Markov model: **a** built- up areas suitability map. **b** agricultural lands suitability map. **c** Bare lands suitability map

land uses. In 2009, the built-up areas has slightly increased, about 2.3%. In 2004, agricultural lands were 0.13% higher than in 1994. But in 2009, we saw a 1.8% decline in this land use. From 1994 to 2004, the largest change in the land use of bare lands was observed, which in 2009 changed its land use by about 0.5%. In total, from 2004 to 2009, changes in the land uses of the region show a more balanced trend than in previous periods.

From 2020 to 2050, that predicted maps were generated, the output of the model was shown that in 1400, compared to 2009, the built-up areas will grow by about 5.3%, mostly in the marginal areas of the city and in areas with construction and the instruments are scattered. In the following periods, the growth track is an average of 3.5%. In the year 2020, agricultural lands were 3.8% lower than in the same period of 2009. Between 2020 and 2050, in each predicted period, the rate of change and decline in agricultural lands will slow down. Unfortunately, it can easily be understood that the greatest changes in agricultural lands will occur, which may be due to the proximity of the built-up areas.

Examining the outputs of the model shows that in the 2020 years, the lands located on the edge of the built-up areas was developed and turned into urban areas. This trend was continued for years to come and was shown the marginal areas of development. Of course, we can see the effect of the restriction areas or the low weight of agricultural lands on the output of the models. So, in the northern part of the model, which is close to urban areas, there is less growth than that in areas adjacent to bare lands. It is noteworthy that almost no growth was occurred in the northern part of the airport in Bojnord, and the agricultural lands were not changed to the built-up areas. Of course, some of the agricultural lands were turned into barelans outputs from the model, which is due to the function of the algorithm of the model in converting land uses considering the possibility of converting land uses and the suitability of pixels. In the southern part of the model, which is a settlement in the vicinity of agricultural lands, it is easy to see the impact of the restriction areas by areas with high level of altitude changes. In many areas, the impact of connective routes was boosted growth around built-up areas. According to the results obtained in this research and to achieve sustainable urban development, such issues as: paying more attention to agricultural lands
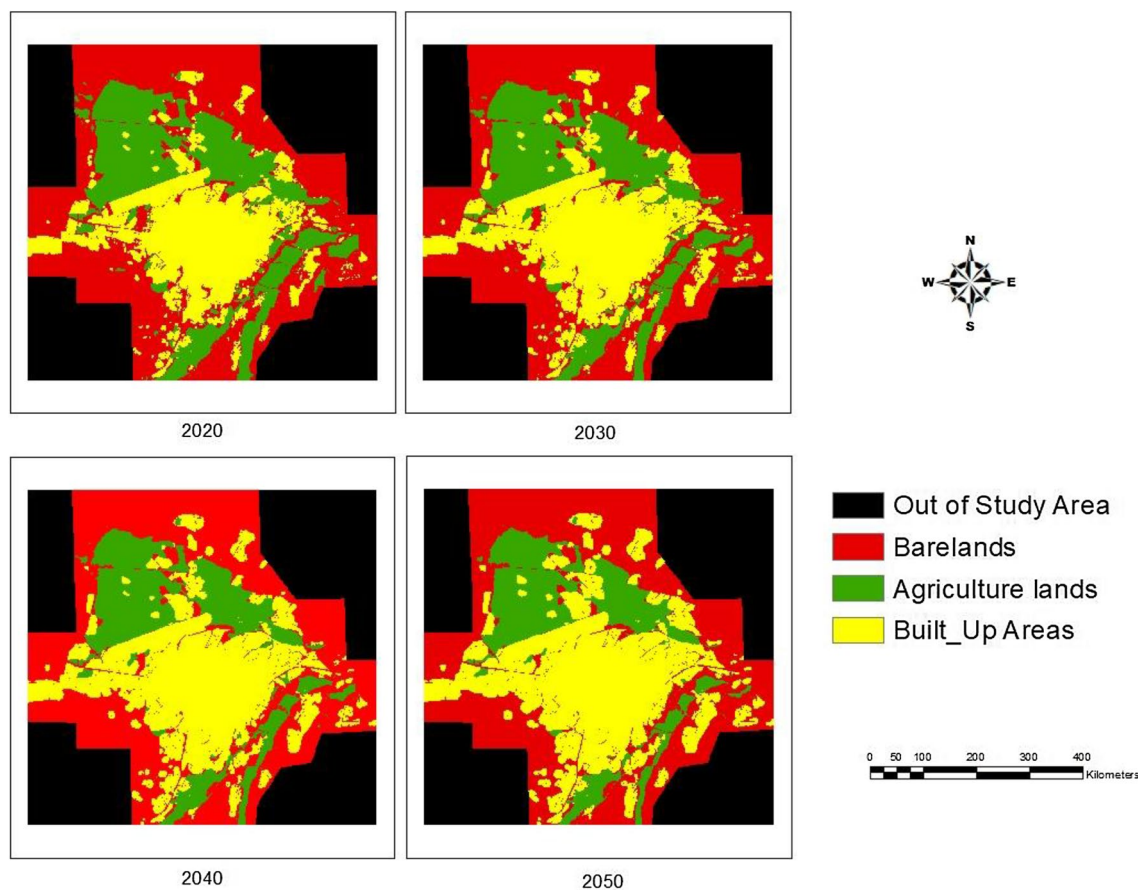
Fig. 8 Predicted land use maps of Boujnord city using CA–Markov model for 2020–2050 years

Table 11 Percentage of land uses of Bojnord city from 1994 to 2050

Land use	Bare lands	Agricultural lands	Built-up areas
Year			
1994	57.2	29.2	13.6
2004	49.7	30.3	20
2009	49.2	28.5	22.3
2020	47.7	24.7	27.6
2030	46.4	22.2	31.4
2040	45	20	35
2050	43.5	18	38.5

to prevent their destruction, preventing scattered construction in the region, paying attention to defined lines for the future development of the city in the Comprehensive Plan and defining different projects and different plans away from agricultural land use and focusing on bare lands, are the issues that need to be respected.

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