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Environmental Approach in Modelling of Urban Growth: Tehran City, Iran

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Abstract: The rapid growth of urbanization has put heavy pressure on the land and its surrounding resources, reduction of vegetation cover, open spaces and serious social and environmental problems. Therefore, a basic step for managing and planning urban growth, as well as evaluating its cumulative effects, is to study and simulate the physical growth of the city. The purpose of this study is to understand the factors that influence the physical growth in Tehran on the basis of sustainable urban development in terms of environmental dimension and the preservation of environmental conditions in the next two decades. For this, using Landsat multi-temporal satellite imagery and object-based classification, land-use was assessed during the period from 1990 to 2015. In the next step, using the multi-criteria analysis model and the environment-based growth model, the impact of independent variables on urban growth, including 18 variables, was calculated from 1990 to 2015 and the map of urbanization potential was produced. Then the area of change for the expected year was predicted quantitatively using the Markov chain analysis. Finally, using Cellular Automata model, urban growth simulation for 2015 was performed with relative accuracy of 0.91 and Kappa coefficient of 0.87, and this model was used to estimate urban growth in 2025. The results show that urban growth will accelerate in 2025, as in the period 2003-2015, and often in the western and northeastern parts of the city, if the nature and extent of the impact of factors affecting urban growth will remain constant.

Key words: Urban growth modelling, cellular automata, object-based classification, Tehran.

Introduction

Urban growth, which is associated with industrialization, economic development and population growth, is an inevitable process throughout the world (Walker, 2001). Urban sprawl is the external, unequal and unplanned growth of urban areas and, which results in inefficient use of resources, especially land (Sudhira and Ramachandri, 2007). Urban sprawl occurs when the rate of non-agricultural or non-natural land use exceeds the rate of population growth (Batta, 2010).

The tendency to reduce urban density is a sign of urban sprawl (Borget, 2009). Among the effects of physical growth, is sprawl of the city's outskirts or rural-urban areas of the city and beyond the administrative boundaries of cities. This urban growth has pushed towards external areas, and caused changes in land-use. The larger the city, the more land it needs, thereby increasing the risk of environmental degradation (Bahreini, 1989). One of the most important issues of the 21st century is about the sustainability of the city and how the city grows and spreads in space. The shape of the city is defined as the pattern of spatial development of human activity in a given period of time (Anderson et al., 1996) which is divided into two main patterns: urban expansion and urban density. Since urban sprawl

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or horizontal expansion of new constructions around the city have caused socioeconomic damage and environmental degradation in and around cities, with the sprawl of the city, many arable land of neighbouring cities may be used for building.

Urban growth as a spatial and demographic process has two opposing faces: on the one hand, large cities act as engines of economic and social growth, and on the other hand, most of these cities suffer from social, economic and environmental problems such as poverty, creeping towards land of agricultural value, increased use of private cars and fuel consumption, the collapse of central urban areas, and low use of existing built-up areas. Urban growth, especially in its unfavourable form of urban sprawl, is blamed for its negative effects on the environment, human health and social and economic issues. The amount of agricultural land, forests and outdoor pastures has declined sharply, and the ecosystem and animal habitat have become seriously vulnerable to destruction, as well as air and water quality, followed by human health and quality of life.

As urbanization, with its rapid growth, will become a major environmental change in the near future, knowing and understanding the changing patterns of urban growth is essential. However, the patterns of urban growth and the socio-economic process in them, which cause the formation of certain spatial patterns, are the subject of study significantly (Seto and Fragkias, 2005). The effects of land use/land cover change are generally divided into two categories: environmental and socio-economic, and environmental impacts have attracted greater attention (Briassoulis, 2000). Cicero (1989) identified five types of ecological studies in urban environments:

1. Comparison of different types of land use in urban areas (these studies confirm that the city is a heterogeneous environment in space, which means that the urban environment is a mixture of areas with different physical characteristics)
2. Comparison of an urban area with an adjacent natural area (these studies compare urban areas with non-developed areas outside the city)
3. Gradient analysis, the ecological effects of urbanization are examined along a slope (usually the distance from the city's geographical centre is considered in these studies, not a slight slope of variables such as housing density, air quality, etc.)
4. Dynamic urban growth studies by monitoring a distinct area over time (a number of studies address changes in ecological patterns and processes over time and measure the extent of changes in natural and semi-natural ecosystems)
5. Ecological footprint study (ecological economic analysis to see the effects of the city's social and economic system as part of the ecosystem, with emphasis on transport capacity and scale related to human population growth and its activities) (Nancy et al. 2000).

Looking at this classification, it is clear that this paper falls into the fourth category in the classification of ecological studies. In recent years, satellite imagery has been used extensively in the study of urban sprawl and the prediction of its pattern of growth. SLEUTH (Silva and Clarke, 2002; Oguz et al., 2007) and CA (Feng et al., 2011; Rabbani et al., 2012) models are among the most popular models used in urban growth modelling.

Zain et al. (2005) in a study entitled "Assessment of Urban Growth in the Tampa Bay Basin", using remote sensing data, with reference to natural landscape conversion to urban landscape as a result of population growth, prepared land-use change maps using Landsat satellite imagery, and they estimated urban land growth three times during the study period and predicted urban growth by 2025 using the SLEUTH model (Jian et al., 2009). Baroda et al. (2003) in a study entitled "Urban Sustainability in Metropolitan of Developing Countries" modelled and forecasted the future of urban growth in Lagos, and with reference to rapid population growth and urban accumulation of 27 million in the next 20 years and the need for urban land with an area of approximately 969 square kilometres, they simulate physical growth in the Lagos and using the Cellular Automata Model and focusing on environmental aspects, the physical growth process was predicted by 2020 (Barredo and Demicheli, 2003).

Gong et al. (2009) in a study entitled "Assessment and prediction of Urban Environmental Security based on Cellular Automata Model: A Case Study of Guangzhou, China", predict urban environmental security changes; they used the cellular model of urban environmental assessment in Guangzhou during the period 1990-2005. By modifying the proposed model to conform to changing planning rules for years (2010-2020), they achieved 72.09% simulation accuracy, and using a one-bit assessment network for 2005, simulated the environmental security model for the year 2020, and given the current environmental security, the overall decline in environmental security has been recognized over the next 15 years, despite the implementation of urban plans (Yu, 2002). Wenting Zhang et al. (2014) in the article titled "Modeling urban growth by the use of a multiobjective optimization approach: Environmental and economic issues for the Yangtze watershed, China" by comparing the results of the MOP and CA model, they have concluded that the MPO approach is more suitable for modelling the urban growth pattern in the Yangtze basin than the CA model, because the CA model only considers the historical growth model as the basis for the future growth pattern; in addition, according to the spatial clustering index, the predicted urban growth pattern in the MPO model is more logical (Walker, 2000).

According to studies, most researchers have used the cellular automata model with a combination of other models to simulate urban dynamics. The distinguishing feature of this paper is the use of an ecological-based growth model that attempts to use environmental, economic and social parameters that affect urban dynamics. The second dimension of innovation in this paper is the use of multi-criteria analysis system to adapt the results of urban dynamics compared to the ecological growth model. There are many views regarding sustainable urban development, its principles, its objectives and its various dimensions. With the importance of different dimensions of sustainable urban development (social, economic and ecological), there is great interest to its environmental dimension.

The Study Area

The study area is the metropolis of Tehran. The city is the capital of Iran, with an area of 730 km^2 between 35 degrees 34 minutes to 35 degrees 59 minutes north latitude and 51 degrees 5 minutes to 51 degrees and 53 minutes east longitude. The city is bordered to the north by the Alborz mountain chain, from the east to Lavasanat, from the west by Karaj, and from the south by Varamin. Tehran is divided into 22 districts and 119 zone and 362 neighbourhoods in terms of administrative divisions. Figure 1 indicates the position of the study area. The heights of Tehran are composed of three mountainous, foothill and plain areas. Mountainous areas cover altitudes above 1800 metres. In Tehran, land rises from the south to the north, in the lowlands reaching an altitude of about 900 metres and at heights up to 1800 metres.

Due to costly construction and legal constraints, physical development in this area is very limited. Therefore, the growth of Tehran has occurred mainly in the foothill and the plain on the southern slopes of Alborz. The southern parts of the city have grown in a vast, flat plain. The northern and eastern highlands have limited the growth of the city on this side, and the special desert geographical conditions in the south and high groundwater levels have also limited growth in this area. The metropolis of Tehran, due to the concentration of industries and services, and consequently population growth and political centrality, suffers from sharp physical growth compared to other cities in Iran.

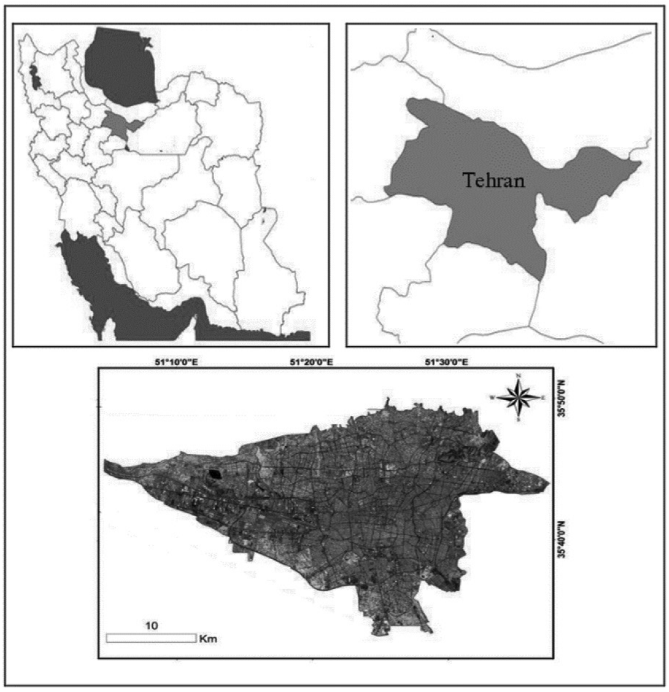

Figure 1: The study area.

Materials and Methods

The data used in this study are generally divided into two main categories: data used to extract land use in the study area, including satellite imagery, and data used to describe urban sprawl and land-use change. These data are cited as driving forces for changes. Details of the data used in this article are shown in Table 1.

In general, the methods used in this research are divided into three general categories that are: (1) the methods used to classify satellite images which the object-based classification has been used for this purpose; (2) the methods used to identify the appropriate lands to urban development with an environmental approach, as well as a map of the probability of urban sprawl for future periods. In this section, the fuzzy weighted linear combination (WLC) method is used; and (3) the methods used to estimate the changes

Table 1: The data used

The data used	*Time of data acquisition*	*Properties*
Landsat Satellite Images	1990, 2003 and 2015	Resolution 30 m.
Digital Elevation Model	-	Resolution 30 m.
Land use	211	Vector
Demographic density by urban block	2011	Vector
Main rivers	-	Vector
Roads network	2006	Vector
Iran faults	2006	Vector
Isorain lines	2006	Vector
Commercial areas, industrial complexes, military areas	2011	Vector
Power transmission lines	2011	Vector

and their spatial distribution which for this purpose, Markov chain and Cellular Automata analysis methods have been used. Object-based classification means a set of adjacent pixels within an area where the similarity (such as digital number and texture) is the most common criterion among them.

In the classification and processing of the image, the object-based approach refers to image processing in the object space rather than pixel space, where the object is a basic component of the object-based image processing. In this type of classification, the segment is a technique that converts the image into objects. In general, object-based classification is a three-step process, in which the image is initially segmented with the desired scale factor; in the second step, the training areas are selected from the results of the previous step for the required classes, and finally, the final classification is done based on the selected training areas.

Segmentation technique in this study is a multi-segmentation. This type of segmentation is based on the methods of combining areas according to the homogeneity criterion. This algorithm is the best procedure, since the scale factor (the high values of the scale factor causes the creation of large objects, the smaller values makes smaller objects) reduces the average of heterogeneity and thus increases homogeneity. The process of segmentation begins with an object of the image which is initially a single pixel and then is expanded continuously in several loops by combining the adjacent pixels until they reach homogeneity threshold. This homogeneity criterion can be defined on the basis of a combination of spectral and spatial homogeneity.

The size of the segments is determined by the scale parameter, so that the higher values of this parameter make larger objects and the smaller values make smaller objects. The homogeneity criteria in this segmentation are divided into two types, colour homogeneity and spatial homogeneity. Colour homogeneity is based on the standard deviation of spectral colours and spatial homogeneity on shape and compression parameters. The shape parameter determines the degree of effect of the shape compared to the colour, and similarly the compression parameter is relative weight versus the smoothness of the segmentation.

In this study, the nearest neighbour method with a fuzzy approach was used to classify objects created by multi-resolution segmentation. The nearest neighbour classifier puts the value of the membership function between zero and one based on the distance from the nearest neighbour in the Feature Space Objects of the image. Objects with different degrees of membership are initially classed into more than one class, and then according to the membership degree relative to each class, classification is performed based on the nearest neighbour's algorithm.

Weighted Linear Combination (WLC) Method for Data Fuzzification

To identify the appropriate areas for development in Tehran through an environmental approach, based on previous studies, variables were used including height, distance from faults, slope percent, temperature, rainfall, distance from the river, land use, distance from the city centre, distance from commercial centres, Distance from industrial areas, distance from military areas, distance from barren lands, distance from built-up lands, distance from urban services centres, distance from main roads, distance from power lines and the number of urban cells in 3×3 window.

To prepare the database of the layers listed, ArcGIS10 software and fuzzy WLC model in the Idrisi software environment have been used and then the dependent variable of urban change between 1990 and 2015 along with the independent variables were prepared for modelling by the year 2038 in the form of automated Markov chain cells. Multi-criteria analysis model is designed to examine the defined objective or objectives on the basis of several criteria. The composition of the layers in these models is different (And, Or, WLC, ...). In the present study, the Fuzzy WLC Weighted Linear

Combination method is used due to its more flexibility than other methods. Standardization of layers is an important part of this model. In addition, the weight of each of the factors is also very sensitive and the overall weight of the factors in this method is 1. To achieve this, weights were obtained using the AHP method.

The Weighted Linear Combination method is the most commonly used technique in the multi-criteria analysis. This technique is also called the scoring method. This method is based on the concept of weighted average. An analyst or decision maker directly assigns weights to the criteria on the basis of the relative importance of each criterion, then, by multiplying the relative weight in the value of that feature, a final value is obtained for each option, for example (the element of the image in the spatial analysis). Once the final value of each option is specified, the option with the highest value will be the most appropriate option for the desired goal. The desired goal can be to determine the land suitability for a particular application or to assess the potential of a particular occurrence. In this decision rule method, the value of each option A_i is calculated by the equation (Jokar, 2012):

$$A_i = \sum_{i=1}^{n} w_j \cdot x_{ij} \tag{1}$$

where w_j is the weight of j index, x_{ij} is the value that place i accepted for himself in relation to the j index. In other words, this value can indicate the degree of the suitability of i in relation to the j index. N is the total number of indices, and A_i is the value that eventually belongs to place i. As mentioned earlier, in this method the total weights should be equal to 1, in the event that such a situation does not occur, A_i should be divided in the last step on sum of total weights.

In this case, the output of A_i will be a number between 0 and 1. Of course, since the greater or lesser the amount of output can be the reason for the more appropriate or inappropriate option, we can ignore the normalization of weights. Of course, since the greater or lesser the amount of output can be the reason for the more suitable or not suitable of an option, we can ignore the normalization of weights. Finally, the ideal option will be the option with the highest A_i (Hwang, 2004). The Weighted Linear Combination method can be implemented using the GIS and overlapping capabilities of this system. The overlapping techniques in the GIS allow hybrid maps to combine to produce a layer (Dongjie et al., 2011).

In order to perform fuzzy integration operations and extrapolation of the suitability maps for urban development using the WLC method, due to the extensive capabilities of Idrisi software in the multi-criteria decision analysis issues, this software was used and constraint and criteria maps were combined with the application of the corresponding weights as standard weights. After extraction of maps, and applying correlation coefficient between the layers, the layers with a correlation coefficient higher than 0.8 were excluded from the analysis process and in the Export Choice software, the preference for the remaining layers was determined for each other and the final weights of each layer were obtained with a coefficient of instability of 0.4 which, given its value less than 0.1, the final model was implemented by Weighted Linear Combination method.

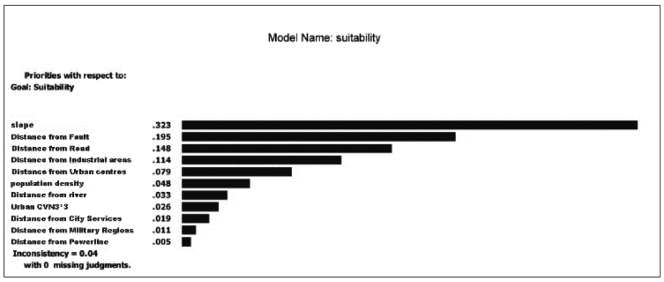

Figure 2: Final weights and coefficient of instability in the Expert Choice software environment.

Cellular Automata and Markov Chain

Cellular Automata are models in which adjacent and continuous cells, such as cells that may include a quadrilateral network, change their state or attributes through repeating the application of simple rules. CA models can be based on cells that are defined in several dimensions. Rules of changing the cell from one state to another can be a combination of growth or decrease, such as a change to a developed cell or without development. This change is a function and source of change that occurs in the adjacent cell. Neighbourhood is usually defined as adjacent cells or cells that are close together (Liu, 2009).

Markov chain analysis is a useful tool for modelling land cover changes, especially when describing changes in the landscape is difficult (Zhang et al., 2010). Theoretically, a kind of cover or land use can be changed at any time to any kind of land use or land cover. Markov chain analysis uses matrices that represent all the multi-directional changes of the land use or land cover between all of the land cover classes. This process can be described as a set of states $S = \{S_0, S_1, S_2, ..., S_k\}$, which, in creating states, indicates the types of cover classes. Each process starts from one of

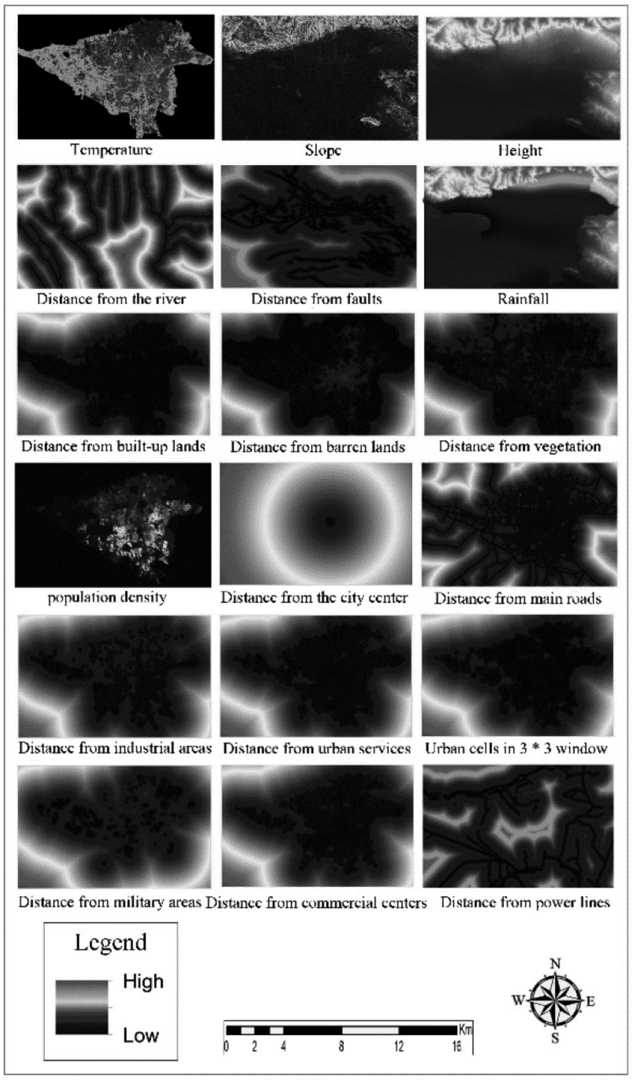

Figure 3: A set of standardized information layers.

these states and then moves to the next state here each move is called a step. If the desired chain is now in the S_i state, then in the next step, with P_{ij} probability, moves to the S_j state. Here, the P_{ij} probability is called transition probability.

In the Markov chain, a prime distribution probability is defined as S (0), and this distribution probability determines the starting state (Cabral et al., 2009). This idea easily moves to the region which is divided into a number of cells and each cell can be occupied by a particular type of land use at a given time. The probability of transmission is then calculated based on observable data over time; in this way a cell of a particular type of land use is slowly transitioning to another type of land use. This probability is related only to the current state of the cell, i.e., the current state of the land-use and does not depend on the types of land use that have been occupied in the past. Clearly, justification and appropriateness depend on the time interval under study.

Assuming the *p*-transition matrix, its application in predicting land-use change in the future is as follows. It is necessary to have a vector *lt* that can represent the distribution of different land-use types at the beginning of the period. The vector *lt* shows the distribution of land uses at the end of the prediction period as determined by the following equation (White and Engelen, 1997):

$$L_t = l \times P \tag{2}$$

The distribution of land uses types after the *k* period (from a certain time) is obtained by exponentiation of matrix *p*.

$$L_k = l \times P^k \tag{3}$$

Considering the time period in this study, using the Markov chain model for the next 23 years, the matrix of area and probability was calculated using classified images of 1990 and 2015. Given the time period considered for this study, using the Markov chain model the area and probability matrices were calculated for the next 23 years, using classified images of 1990 and 2015. They were performed as input in the Cellular Automata of Markov chain model along with the independent variable of urban changes resulting from the subtraction of the class of built-up lands in 1990-2015 and the six classes of suitability of uses while preserving the ecological conditions approach to growth modelling in Tehran.

Results

Extracting Land-use Map

At this step, after radiometric and atmospheric corrections, the segmentation of images was done based on object-based classification and multi-resolution segmentation methods with equal weights for all the bands and parameters. After creating the objects with the appropriate scale factor, in the next step, the training areas were selected from objects created in five user classes: built-up lands, pathways, vegetation, water zones and barren areas. Then, by nearest neighbour classifying with fuzzy approach, land-use maps were extracted for the years 1990, 2003, and 2015. The overall accuracy of the object-based classification is in the range of 88 to 92 percent, and the kappa coefficient is in the range of 0.84 to 0.87, where the highest accuracy is obtained for the image of 2015, and the 1990 classification received the lowest accuracy.

Table 2: Segmentation parameters of used images

Segmentation parameters	*Image 1990*	*Image 2003*	*Image 2015*
Scale parameter	16	18	45
Shape parameter	0.23	0.23	0.5
Compression parameter	0.3	0.15	0.55

Analysis of Changes

In this step, changes in land use in the periods 1990-2003 and 2003-2015 were analyzed. The results show that in both periods, urban use has the most area changes compared to other uses, so that the area of this class from 35.64% of the total area of the study area in the 1990s reached to 52.58% and increased by 6.42% in the next period. That is, it has experienced an overall increase of about 22,000 hectares during these two periods. The spatial distribution of urban growth in the first period is such that the highest urban growth occurred in the northwest, west and northeast regions, and in the second period, this growth occurred in the west and northeastern regions of the study area, respectively. Also, in terms of urban growth rate, the first period has more acceleration while in the second period, this acceleration has decreased by about three times.

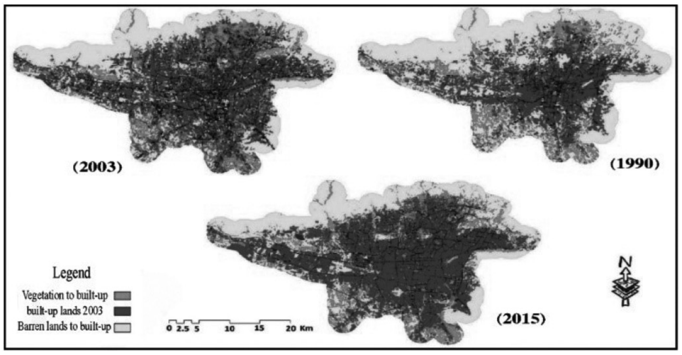

Figure 4: Land use maps extracted from the Landsat image 1990-2003-2015.

Modelling Urban Growth

In order to make better modelling, it can be assumed that water bodies do not grow automatically and by certain standards and if they changed, this change is due to human manipulation and lacks a process that can be modelled. For example, Chitgar artificial lake can be named. Other changes in Tehran's water bodies, either as seasonal changes are negligible or unpredictable. Because of these issues, this class was merged with the barren class prior to the start of the modelling phase. Thus, each of the images classified in the previous steps after their integration into three classes of urban areas, barren areas and vegetation areas were prepared in a separate layer to modelling in the Idrissi software. In this section, in order to evaluate the optimality and validation of the proposed model, using probability growth map inputs for 2015 created by WLC and also, calculating the transition matrix by Markov chain analysis using cellular automata, urban growth is predicted for 2025. The detailed description of this process is as follows.

Calculate Transition Matrix Using Markov Chain Analysis

The Markov process predicts the amount of land use change and urban development in the future by the quantity of changes made in the past, by calculating the transition probability matrix of land use to each other. In fact, the transition probability matrix expresses the probability that each pixel in its class can be converted to other classes over a given time period. Thus, by having the quantity of land cover changes in each period, the probability matrix and the area transition matrix were calculated (Tables 4 and 5). The numbers in the main diameter of the transition probability matrix represent the probability of not changing user classes and other numbers expressing the probability of transition of other classes to each other.

Probability Map of Urban Sprawl

Figure 5 illustrates probability lands for future sprawl of urban land-use using a multi-criteria analysis system

Table 3: The amount of land cover changes between 1990 and 2015

	1990		*2003*		*2015*	
	Area (ha)	*Percent*	*Area (ha)*	*Percent*	*Area (ha)*	*Percent*
Urban areas	34200	35.6	50464	82.68	56633	59
Vegetation	17256	18.0	12116	12.63	9456	9.14
Water zones	34	0.03	31	0.03	158	0.16
Barren areas	4447	46.4	333545	34.76	29718	31

Table 4: The transition probability matrix calculated for 2015

	Vegetation	*Urban areas*	*Barren areas*
Vegetation	5229.81	2352.69	2103.39
Urban areas	0	50464.44	0
Barren areas	1571.4	7449.48	24364.89

Table 5: The area transition matrix calculated for 2015

	Vegetation	*Urban areas*	*Barren areas*
Vegetation	0.6322	0.1943	0.1736
Urban areas	0	10000	0
Barren areas	0.471	0.231	0.7298

with an ecological growth pattern related to urban growth in the period 1990-2003 and 2003-2015. The greatest probability of urban growth is in the north and northwest of the study area and the southern margins have less probability for urban growth.

The Prediction of Urban Growth for 2025 Using Cellular Automata

Cellular automata is a competitive land allocation process in which the state of the pixels of land use classes is affected by its former status and the status of its neighbours is based on transition laws and rules defined for urban development. Here the simulation of urban growth in 2015 is based on the 2003 classified image, and to predict growth in 2025, the 2015 classified image was used as input to the model. Transition rules are the probability of urban map for each period created by the WLC model, and its allocation is based on a five-in-five adjacent filter, as well as the amount of area allocated by cellular automata are based on the calculated transition area matrix calculated by

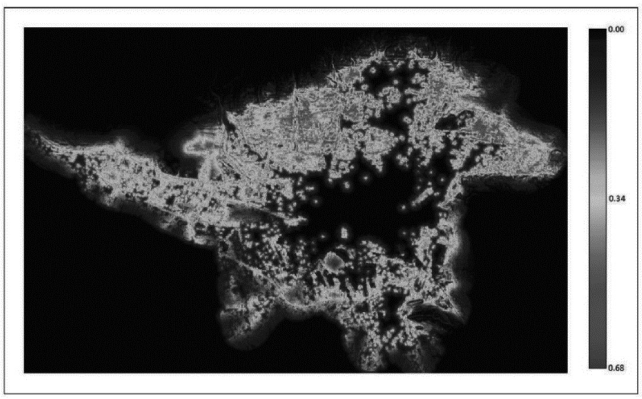

Figure 5: Potential land for development for the simulation of urban growth in 2015.

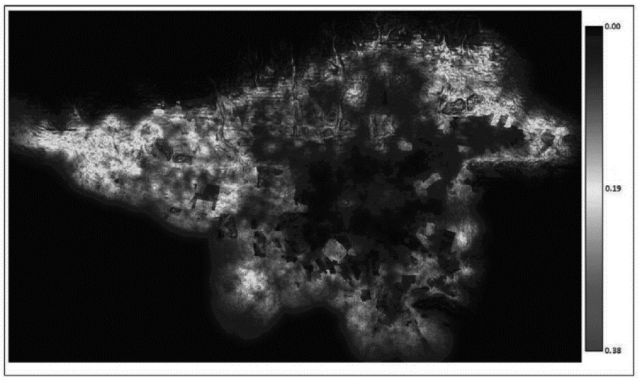

Figure 6: Potential land for development for predicting urban growth in 2025.

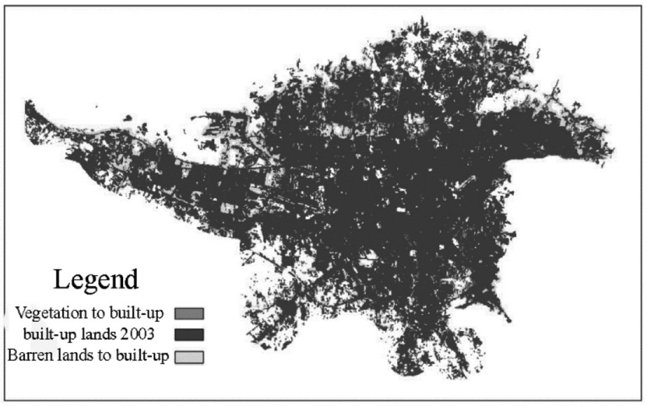

Figure 7: Simulation of urban growth for 2015.

Markov chain analysis. The final result of urban growth simulation for 2015 and urban growth predict in 2025 is shown in Figure 8. Comparing the results of urban growth simulation with the actual growth in 2015 and the Kappa coefficient of 0.87 represent the satisfactory accuracy of the model used.

Conclusion

Land-use changes accrued in the two periods of 1990-2003 and 2003-2015 showed that in both periods, urban use has the highest area change compared to other uses so that, in the first period, these changes occurred mainly in the northwest, west and northeast of the study area, and in the next period, the highest urban growth occurred in the west and northeast regions, respectively. In terms of urban growth rate, the first period has more acceleration while in the second period, this acceleration has decreased by about three times.

The results of studying the effective variables in urban growth and development from environmental and ecological point of view showed that slope, distance from faults, distance from main paths and distance

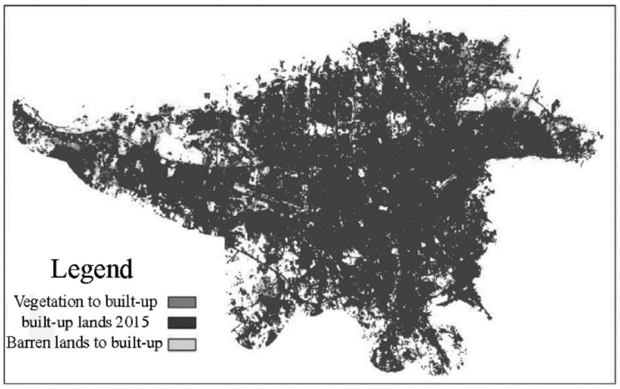

Figure 8: Urban Growth predict for 2025.

from industrial complexes parameters compared to other variables have more effect on modelling and prediction, and distance from power lines had the least impact on modelling. The prediction made for 2025 by the combination of the multi-criteria analysis system, the Markov chain and cellular automata shows that urban growth will accelerate as much as in the period from 2003 to 2015, mostly in the western and northeastern parts of the city, in the absence of a fundamental change in the nature and extent of factors affecting urban growth.

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