

Urban sprawl assessment and modeling using landsat images and GIS

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Abstract Nowadays, urban sprawl phenomenon have been seen in many of cities in the developing and developed countries. Urban sprawl is considered as a particular kind of urban growth which comes up with a lot of negative effects. Thus, monitoring, analyzing and modeling of this phenomenon seem to be unavoidable. This paper assess urban sprawl in Tehran Metropolis as the capital of Iran and models urban sprawl in this mega city utilizing artificial neural networks and adaptive neuro-based fuzzy inference system methods with remote sensing data and geospatial information systems spatial analyses and modeling capabilities to simulate Tehran urban growth. The results confirm that this city has experienced sprawl and sprawl has an increasing rate. Three Landsat imageries from TM and ETM+ sensors taken in 1988, 1999 and 2010 and seven predictor variables include distance to road, distance to green space, slope, elevation, distance to fault, distance to developed area and number of urban cells in 3 by 3 neighborhoods have been used for urban sprawl assessment and modeling. Relative operating characteristics (ROC) and sensitivity analyses have been used to evaluate simulation results. In this research, two evaluation steps have been implemented using ROC and on the both of them, ANFIS presented the best performance vs two different proposed ANN structures.

Keywords Urban sprawl · Modeling · Tehran Metropolis

Introduction

In the last century urbanization has increased significantly as a worldwide phenomenon. Urban growth has been accelerating in the past few decades with the massive immigration of population to cities. In 2005, over 50 % of global human population lived in the cities (UNEP 2005). Based on current growth rate, it is estimated that over 60 % of global population will be found in urban areas by 2030 (Moeller and Blaschke 2006; Odindi and Mhangara 2012). Urban area is increasing faster than the urban population itself (Tewolde and Cabral 2011). With this rapid growth, cities exert a heavy pressure on lands and resources available (Leao et al. 2004; Rafiee et al. 2009). Urbanization is the most dramatic form of irreversible land transformation of agricultural and prolific lands to urban areas (Luck and Wu 2002), affecting landscapes and people who live in and around cities. Basically, the transformation of the rural areas to cities and towns can be considered as urban growth, but this urbanization comes up with some costs. Degradation of the environment, above all in the loss of farmlands and forest are some of environmental cost of this phenomenon (Deep and Saklani 2014). Ecosystem structure, function, and dynamics have experienced various impacts in transformation of rural landscapes to urban landscapes (Mesev 2003; Weng 2007). Urban expansion has direct negative effect consists in a physical loss of agricultural land as well as of natural or cultural landscapes, while it has indirect effects, too. Landscape fragmentation, surface sealing, increased run-off, soil erosion as well as biodiversity decline are some of the indirect results of urban growth (Ceccarelli et al. 2014). Also, urban

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growth has caused the deterioration of urban environment, including increased air and water pollution, reduction of vegetation cover and rising level of diseases (Hana et al. 2009). If this unavoidable phenomenon is left unchecked, then it causes unplanned urbanization. In fact, unplanned urbanization always creates problems like pollution, traffic, deforestation, and congestion of places (Deep and Saklani 2014). Due to crowding, housing shortages, insufficient infrastructure, and increasing urban climatological and ecological problems in urban areas, consistent monitoring of urban regions is unavoidable (Miller and Small 2003). Thus, city managers and resource managers need advanced and reliable methods and a comprehensive knowledge of cities to make the informed decisions necessary to guide sustainable development in rapidly changing urban environments (Pham et al. 2011).

Nowadays, urban systems are regarded as complex, self-organizing and non-linear systems, where the dynamic transitions from one form of land use to another occur over a period of time (Sathish Kumar et al. 2013). Spatial models are developed to achieve a balance between the environment and the management of scarce resources (Goudie 2006) which supports the adequate decision-making strategies. Using these models, policy makers and urban managers can analyze different scenarios of land cover and land use change and also, evaluate their effects. Thus, such models can be useful and unavoidable in land use policy and planning (Rafiee et al. 2009; Veldkamp and Lambin 2001). In fact, urban expansion modeling is an interdisciplinary field as it involves numerous scientific areas, such as GIS, complexity theory, urban geography and remote sensing (Cheng 2003; Rui 2013). In this situation, GIS and remote sensing are proven as very powerful science and technology for managing and analyzing spatial information and extracting valuable information concerning urbanization and its dynamics (Hasse 2007; Kumar et al. 2008; Masser 2001). In the recent past decade, there has been increasing research attention on the use of remote sensing, GIS and photogrammetric data in the simulation modeling of urban growth (Dadras et al. 2015). Urban expansion models attempt to recognize land transformer factor, their importance and project future changes in urban areas based on historical trends (Pijanowski et al. 2009) and also, to project spatial changes in land use based on scenarios of changes in its drivers (Meiyappan et al. 2014).

During last decades, artificial intelligence (AI) and computational based algorithms have been used in so many researches including engineering and non-engineering area due to their abilities. Artificial neural networks is one of the most popular AI methods which have been used widely in so many topics. Ability of dealing with large volume of data, fast processing, pattern cognition and learning ability, parallel processing and the ability of dealing with noised

data, made this algorithm so popular. ANNs have been used in land use change modeling and urban growth modeling by (Pijanowski et al. 2009, 2002, 2014; Tayyebi et al. 2011; Li and Yeh 2001; Almeida et al. 2008). However, this method has some disabilities, too. One of the most important disadvantages is that it is unable to deal with uncertainty. Uncertainty is an unavoidable part of spatial phenomena (Al-Kheder et al. 2008) and needless to say its importance in so many concepts of this science like neighborhood, topology (relations between objects), buffer and other topics which clearly, 0 or 1 does not clarify and present them properly. In this condition, fuzzy logic has the ability to work with uncertainty. Thus, combination of these methods can discard many of their disabilities individually. By integrating artificial neural networks and fuzzy inference systems, the capabilities of ANNs self-learning with the linguistic expression function of fuzzy inference can be fused (Pahlavani and Delavar 2014) and also, overcome many of their shortages. In this research, we propose an ANFIS structure for urban land use change modeling and compare the results of the proposed model with predefined ANNs ones.

Materials and methods

In this study, Tehran urban sprawl assessed and modeled for 1988, 1999 and 2010. Figure 1 presents the research flowchart. At first, data preprocessing have been done. After classification, urban sprawl assessment has been analyzed using Shannon's Entropy. Then, urban growth modeling using proposed ANFIS structure have been done and then, modeling have been done using ANN structure for comparing with ANFIS result ones for 1999 and 2010. Relative operating characteristics (ROC) has been used for evaluating goodness of fit of these models. Finally, sensitivity analysis has been used for clarification of each factor effect in Tehran urban growth during 1988–2010.

Study area

Iran as a developing country in Asia, is witnessing continual large-scale urbanization (Rafiee et al. 2009; Hosseinali et al. 2013). Urban population in Iran has increased from 47 % in 1976 to 61 % in 1996 (Rafiee et al. 2009; Fanni 2006) and number of towns and cities in Iran has also increased significantly, from 199 towns in 1956 to 1200 in 2012 (Statistical Center of Iran). The case study in this research is Tehran Metropolis. Tehran's residential population, nearly doubled from 1975 to 2010 and this fast population growth made the city the world's 17th-largest and one of the cities with the largest annual growth in Asia (Jokar Arsanjani et al. 2013; World Gazetteer 2012).

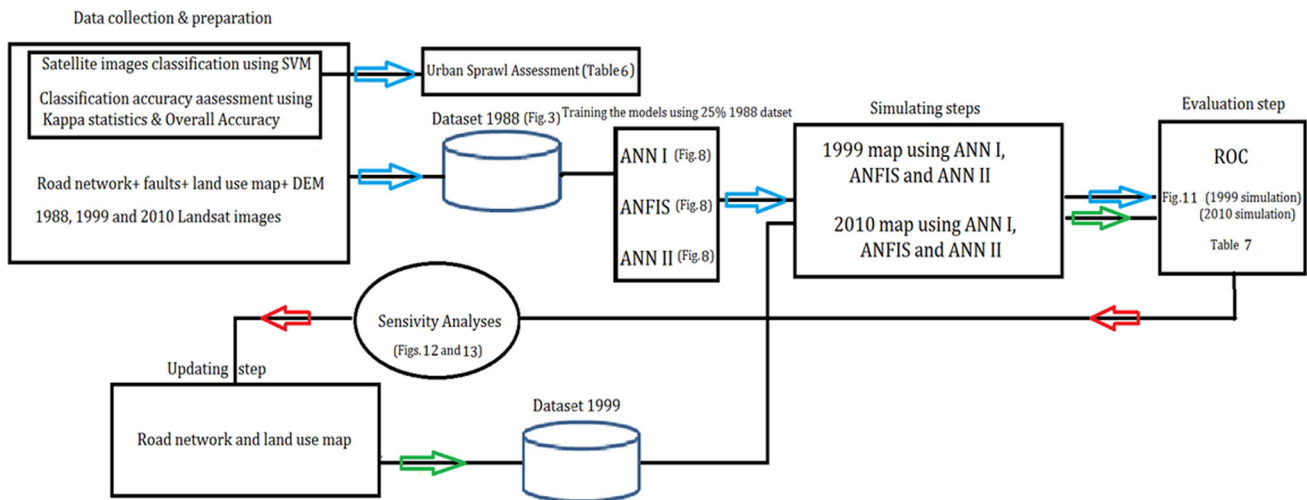


Fig. 1 Research flowchart

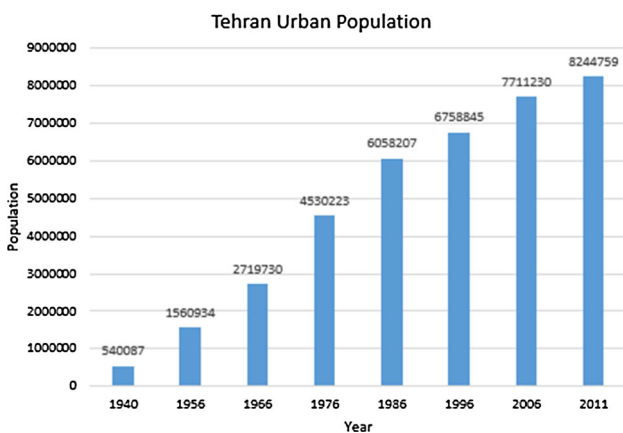


Fig. 2 Tehran remarkable growth in the past few decades

Tehran has shown remarkable growth in the past few decades (Fig. 2). Migration from nearby cities and even provinces to the city because of its economic and social attractiveness are the most important reasons for the rapid population growth.

Data preparation

Satellite imageries has played an important role in the assessment of urbanization by measuring land use and land cover change for cities and their surroundings (Alberti et al. 2002; Jürgens 2003). Remote sensing as a reliable source of data, provides spatially consistent coverage of large areas with temporal frequency and high spatial detail, which are useful for analyzing time dependent phenomenon such as urban expansion (Jensen and Cowen 1999). As a result, remote sensing is an effective and accurate source of data for monitoring urban expansion,

especially where information on land use management is inconsistent and insufficient. In this study, three Landsat imageries from TM and ETM⁺ sensors which came from 164 and 35 for row and column, respectively, acquired in 1988, 1999 and 2010 were rectified and registered to Universal Transverse Mercator (UTM) WGS 1984 zone 39N. Support vector machine (SVM) classification was used to classify the imageries to different land-use categories according to Anderson level 1 (Anderson et al. 1976) using ENVI 4.8. SVM gives better results than the traditional classifiers like maximum likelihood (Melgani and Bruzzone 2004; Huang et al. 2002; Pal and Mathur 2005). Support vector machines (SVMs) are superior image classification techniques in airborne and satellite imagery, applying a set of machine learning algorithms and having their roots in statistical learning theory (Erfanifard et al. 2014). Due to its ability to handle the nonlinear classifier problem, SVM is able to go beyond the limitations of linear learning machines by implementation of the kernel function, which paves the way to find a nonlinear decision function (Aghababae et al. 2013). User accuracies and producer accuracies of all of classifications are presented in Tables 1, 2 and 3. Overall accuracy and Kappa of classification assessment of these imageries are presented in Table 4. According to (Pijanowski et al. 2005), Kappa obtained from all of the three imageries, classified as excellent and according to (Thomlinson et al. 1999; Anderson et al. 1976), all of the obtained overall accuracies are acceptable. The database developed for this study includes distance to road, distance to developed area, distance to green space, and elevation, slope, number of urban cell in a 3*3 neighborhood and distance to fault (Fig. 3). The elevation data came from AsterDEM 1996. Also, slope data obtained directly from the AsterDEM 1996 using ENVI 4.8. The layers of roads, developed areas, green

Table 1 User and producer accuracy (1988)

CLASS	User accuracy (%)	Producer accuracy (%)	User accuracy (Pixel)	Producer accuracy (Pixel)
Building	87	93.8	3058/3515	3058/3260
Road	69.03	39.61	263/381	263/664
Vegetation	98.83	99.8	1014/1026	1014/1016
Bare ground	96.34	96.64	5587/5799	5587/5781

Table 2 User and producer accuracy (1999)

CLASS	User accuracy (%)	Producer accuracy (%)	User accuracy (Pixel)	Producer accuracy (Pixel)
Building	93.78	96.6	3149/3358	3149/3260
Road	83.53	65.53	289/346	289/441
Vegetation	98.13	98.01	787/802	787/803
Bare ground	98.07	98.04	5190/5292	5190/5294

Table 3 User and producer accuracy (2010)

CLASS	User accuracy (%)	Producer accuracy (%)	User accuracy (Pixel)	Producer accuracy (Pixel)
Building	95.53	97.73	3186/3335	3186/3260
Road	90.8	82.77	/365/402	365/441
Vegetation	99.04	99.13	1139/1150	1139/1149
Bare ground	97.97	97.19	4526/4620	4526/4657

Table 4 Classification accuracy assessment

Image	Overall accuracy (%)	Kappa statistics
1988	92.55	0.875
1999	96.09	0.933
2010	96.94	0.951

spaces and the number of urban in a 3*3 neighborhoods obtained from classified imageries data. The layer of fault, has been used in ArcGIS 9.3. All of the input data normalized between 0 and 1. Normalization of the input data to a uniform range before applying them, prevent larger numbers from prevailing smaller ones and also, to scale data in the same range of values for each input feature in order to minimize bias within the dataset for one feature to another (Wu et al. 2005).

Urban sprawl assessment

After land use classification, the urban areas have been extracted from Landsat imageries and are shown in Fig. 4. The urban and non-urban area in this city for 1988, 1999 and 2010 are presented in Fig. 5. According to Bhatta (2009), an even policy for the entire city (all parts) never works with equal degree of effectiveness for all parts of the

city and study area should divides to smaller region to study the sprawl in them. Thus, the map is divided into 4 regions (SW, SE, NW and NE regions). Figure 6 presents urban area in NW, NE, SW and SE directions during 1988–2010.

Shannon's entropy

In this study, Shannon entropy has been implemented for analyzing urban sprawl during 1988–2010 in Tehran Metropolis. Shannon's entropy as a well-accepted manner in assessment of urban sprawl has been used in a variety of researches like (Sudhira et al. 2004; Bhatta 2009; Li and Yeh 2004). In fact, Shannon entropy, as a scientific method determine the city is sprawled or not. The Shannon's entropy is considered a follows:

$$H_i = - \sum_{j=1}^m p_j \log_e(p_j) \quad (1)$$

i = temporal span j = target zone p_j = proportion of the variable in the j-th target by: built-up growth in j-th zone/sum of built-up growth rates for all zones and m = number of zones.

The Shannon entropy values ranges from 0 to $\log_e(n)$, values closer to 0 (smaller values) indicates very compact distribution and the value closer to $\log_e(n)$ (larger values)

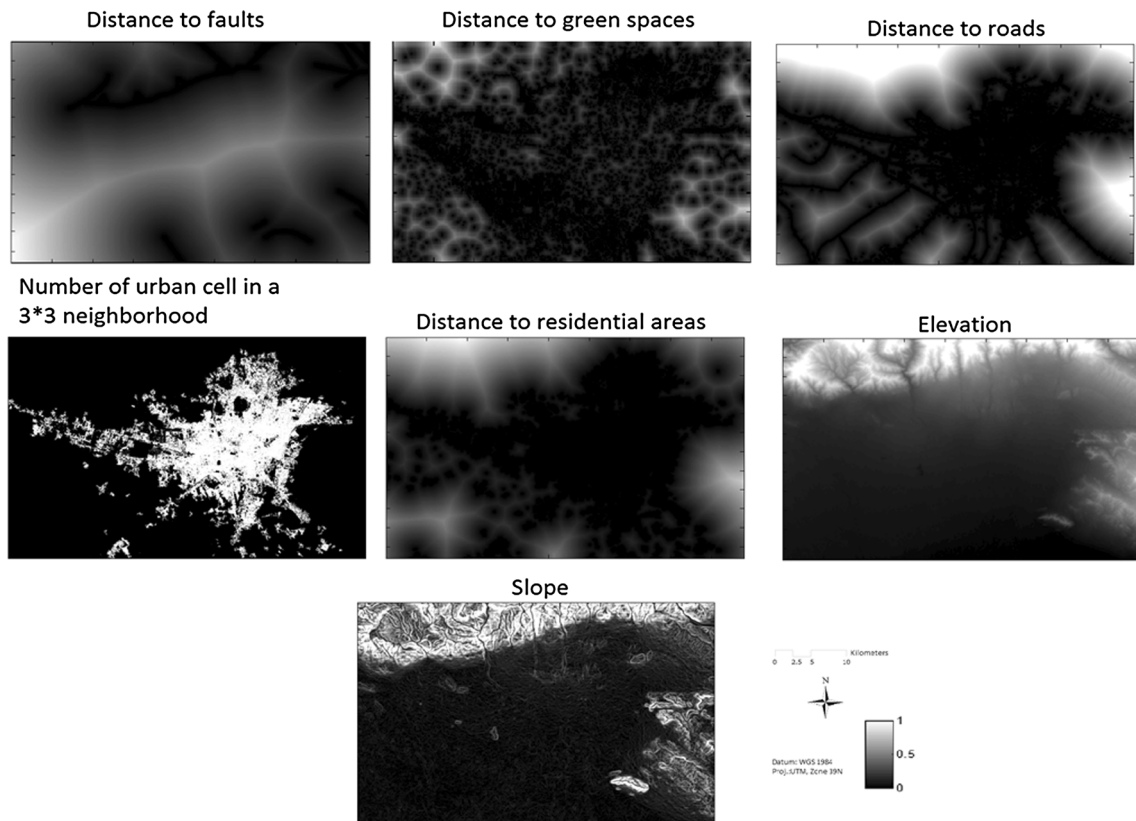


Fig. 3 Implemented input data

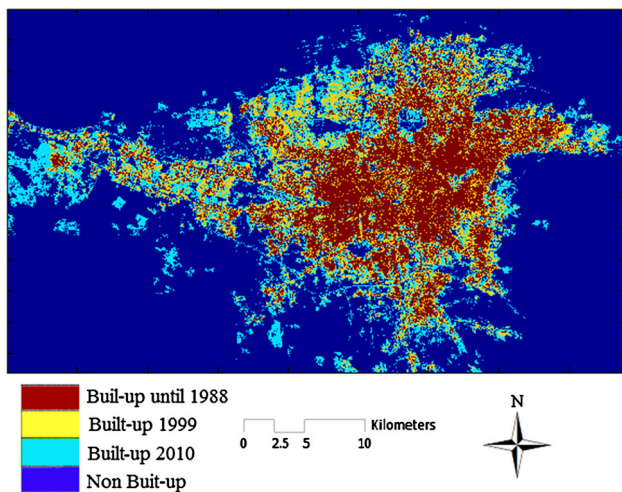


Fig. 4 Urban areas have been extracted from Landsat imagery

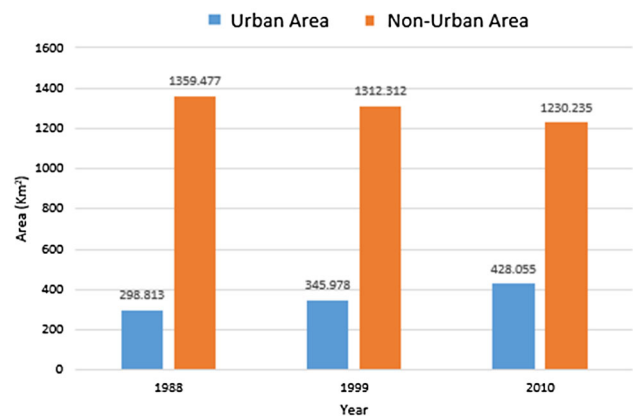


Fig. 5 The urban and non-urban area for 1988, 1999 and 2010

indicates that the distribution is much dispersed (Bhatta 2009).

In this research, i = temporal span (here is 1988–1999 and 1999–2010. i.e. 1, 2), j = target zone (SW, SE, NW and NE), p_j = proportion of the variable in the j -th target (calculated (Table 5) by: built-up growth in j -th zone/sum

of built-up growth rates for all zones and m = number of zones = 4. The urban sprawl assessment is presented in Table 5.

The results of urban sprawl assessment confirm that this city has experienced sprawl. The results show that Tehran is becoming more sprawled. In fact, the Shannon’s entropy values is becoming bigger during two period (1988–1999 and 1999–2010). This Megacity due to population growth, attraction of the city as the capital of Iran and social,

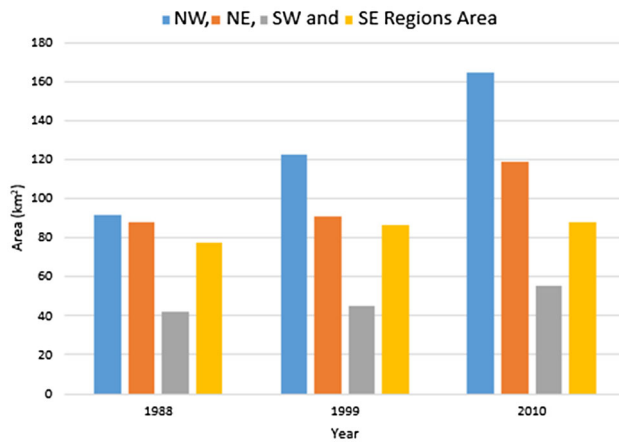


Fig. 6 Urban area in NW, NE, SW and SE directions during 1988–2010

Table 5 Sprawl assessment

Temporal span	Shannon entropy
1988–1999	0.9667
1999–2010	1.0422

economic potential of the city have increased very fast. These factors have resulted urban land and urban population growth very fast in this city (Mohammady and Delavar 2015).

Urban sprawl modeling

In the last two decades, due to accessibility to free to less expensive remote sensing data, GIS tools and using spatial analyzing tools and high computing capability computers, modeling of urban growth has significantly accelerated. These models usually classify to raster based and vector based method (Hu and Lo 2007). Raster based method are so popular due to simplicity of the definition of their environment. ANN is one of the most common raster based methods in urban growth modeling (Triantakostas and Mountrakis 2012) due to parallel processing and pattern recognition ability which has been used by (Pijanowski et al. 2002; Li and Yeh 2001; Almeida et al. 2008; Tayyebi et al. 2011). This method has some disadvantages such as lack of flexibility. It is also, unable to deal with qualitative uncertainty. Another popular raster based method is Logistic Regression (Triantakostas and Mountrakis 2012) due to simple structure which has been used in urban growth modeling by (Hu and Lo 2007; Tayyebi et al. 2010; Xie et al. 2009; Huang et al. 2009; Dubovyk et al. 2011). This method is also, unable to recognize non-linear

relations. And finally, cellular automata is the most popular method in urban growth modeling (Triantakostas and Mountrakis 2012) which has been used by (Batty et al. 1999; Liu 2009; Maithani 2010; Foroutan and Delavar 2012). Finding the proper transferring rule is the most important disadvantage of cellular automata method. As mentioned, there are some disadvantages in these models. Thus, implementation a structure which modify all or part of the mentioned disadvantages help the pattern and relation between effective factors recognized better and consequently the training procedure and modeling process done completely. In this study, we proposed an ANFIS structure for modeling urban growth and compare the ANFIS results with ANN result which is one of the most common methods in urban growth modeling.

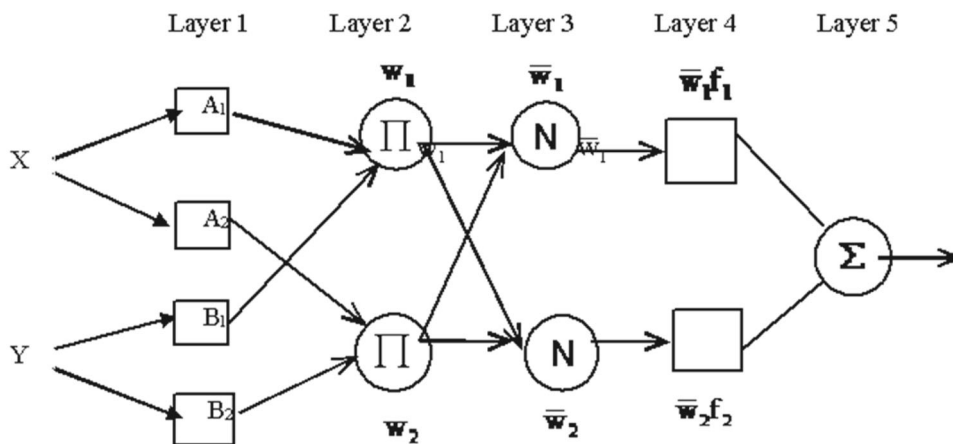
ANFIS

Fuzzy inference system ability to apply human knowledge and expertise which makes it very close to human perception is one of the most important features of it. Also, it is considered as a powerful tool for modeling uncertainties associated with human cognition, thinking and perception (Gupta and Rao 1994). Fuzzy inference allows us to linguistically describe the concepts related to urban growth (Al-Kheder et al. 2008) which flexibility is one of its advantages. The most important problem in fuzzy inference systems is finding proper membership function for each fuzzy variable which can be solved by training only. ANN as the one of the most common methods in urban growth modeling has the ability to learn pattern and relationship between data from training data. By combining ANN and fuzzy inference systems, learning and human knowledge can be integrated together and at the same time, it covers many of their shortcomings (Pahlavani and Delavar 2014), such as the problem of finding the correct position and shapes for membership functions in fuzzy inference system and lack of flexibility in neural network. In other words, ANFIS take advantage of learning, use of human knowledge and flexibility which makes it very suitable to solve some of the problems. In this algorithm, during the training process, membership functions change (in figures and location) toward their optimal values. ANFIS was first proposed by Jang (1993) based on the Takagi–Sugeno model based fuzzy inference systems and neural network structures (Jang 1993). ANFIS is a multi-layer adaptive network-based fuzzy inference system which has been widely employed in many fields. A typical two input ANFIS architecture is shown below (Fig. 7).

Layer 1 For any node, the output is:

$$O_{1,i} = \mu_{A_i}(x) \quad \text{for } i = 1, 2, \quad (2)$$

Fig. 7 A typical two input ANFIS architecture



$$O_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i = 3, 4, \tag{3}$$

Every node in this layer is an adaptive node. There is no limitation about the membership functions but in this study we have used Gaussian membership function as follows:

$$\mu_{A_i}(x; \sigma_i, c_i) = \exp(-(x - c_i)^2 / 2\sigma_i^2), \tag{4}$$

where σ_i and c_i are parameters to be learnt.

Layer 2 Every node in this layer is a fixed node. This is where the t-norm is used to ‘AND’ the membership grades—for example the product:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2. \tag{5}$$

Layer 3 This layer, contains nodes which calculates the ratio of the firing strengths of the rules:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \tag{6}$$

Every node in this layer is a fixed node. The i th node of this layer normalizes the firing strength of the previous node with respect to firing strengths of others.

Layer 4 The layer 4’s nodes are adaptive and perform the consequent of the rules. The output of this node is given by:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \tag{7}$$

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5 There is a single node here (a fixed node) that computes the overall output and acts as an accumulator and it adds up all the outputs coming from the previous layer to give the final classifier function as,

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \tag{8}$$

ANN

The time–space relationship as an unavoidable parts of urban dynamic process, plays an important role in understanding the dynamic urban growth process. This process consists of a nonlinear and complex interaction between several components. Such nonlinear relationships between land use change and its driving factors can be addressed smoothly by artificial neural network (ANN) modeling framework as evidenced by Yeh and Li (2003), Almeida et al. (2008). Artificial neural network due to the possibility of learning is an appropriate tool for environmental modeling. One of the key issues in this research was the design of the neural networks architecture. A number of mathematical formulations have proposed to determine hidden neurons by different researchers, but until now they have not yet come to an agreement on a certain method to determine the optimal number of the hidden layers and the ideal number of neurons in the hidden layer (Almeida et al. 2008). According to Kavzoglu and Mather (1999), Paola and Schowengerdt (1997), nets with more neurons being less influenced by the initial random weights and capable to learn more complex patterns. Also, according to (Haykin 1999), nets with more neurons demand more time for training and do not generalize well with unknown data. However, there is a general consensus among researchers in the field of urban modeling that empiricism is a reasonable way to determine the most optimum and the best structure in neural net for a specific problem (Yeh and Li 2003; Li and Yeh 2001; Guan and Wang 2005; Almeida et al. 2008). In this study, we implemented ANN algorithm in two different structures. For the first one, according to (Pijanowski et al. 2002), the input data has been normalized between 0 and 1. Sigmoid function has been used in the hidden layer and output layer as the transfer function

(Pijanowski et al. 2009; Tsoukalas and Uhrig 1997). A structure including seven input neurons, 15 neurons for hidden layer and one neuron for output layer have been used. For the second one, the input data has been normalized between -1 and 1 . This kind of normalization helps our data to have negative values, too. This enables negative values to play their role in calculations, equations and nets weights values. The second proposed structure including seven nodes in input layer, 15 nodes in the hidden layer and 2 nodes (urban and non-urban) in the output layer. Tang-sigmoid in the hidden layer and linear function in the output layer as the transfer function are used. Tang-sigmoid has been used to model the non-linear space and linear function has been used to model the linear spaces of the structure.

Selection of training data and calibration

The overall number of cells in this study come from a satellite image with 1760 cells by 1160 cells dimension (2,041,600 cells). The training points (training data) in this study area included 10 % of all the cells (in fact 200,000 cells). 25 % of the training cells (50,000 cells) are entered the models (ANFIS and ANNs) to train them and estimate the bias and parameters and 75 % of training data (rest of training data equal to 150,000 cells) are used as the data check. The training data have been chosen randomly in an unbiased manner in a way that are chosen from all the image space. These 200,000 cells were approximately 10 % of the 1988 image data which have been used for calibrating the models which means training and checking for ANN and ANFIS models. The rest of data 1988 data (90 % of all) were used for first step goodness of fit assessment [comparing simulated data (1999 map) with real one] using ROC. In the second accuracy assessment step, the 2010 map simulated using the three models and compared with real 2010 map (Ground truth) and ROC has been used for evaluating goodness of fit of these simulated maps with reals ones.

Accuracy assessment factor

In this research, relative operating characteristics (ROC) proposed by (Pontius and Schneider 2001), as an excellent method to evaluate the goodness of fit between the simulated and real maps (Hu and Lo 2007), has been used to evaluate the goodness of fit. ROC is a threshold independent method (Beguería 2006) which ranges between 0 and 1. A ROC value 1 means there is complete agreement between simulated and real maps while 0.5 means random distribution of land uses. ROC curve plots the rate of true positive (Eq. 9) to positive classifications against the rate of false positive (Eq. 10) to negative classifications as

Table 6 Confusion matrix

Model	Reality		
	Change	Non-change	Total
Change	A	B	$A + B$
Non-change	C	D	$C + D$
Total	$A + C$	$B + D$	$A + B + C + D$

threshold value change from 0 to 1 (Foroutan and Delavar 2012). The true positive and false negative obtain from confusion matrix (Table 6) (Hu and Lo 2007). A set of true positive and false positive can be calculated with applying each threshold value between 0 and 1.

$$\text{True Positive \%} = \frac{A}{A + C}, \quad (9)$$

$$\text{False Positive \%} = \frac{B}{B + D}, \quad (10)$$

Results

The training procedure of models are continued until the threshold value is achieved. Number of the epochs or predefined root mean squared error (RMSE) value can be considered as the threshold value. In this research, the number of epochs has been chosen as the threshold value. ANN (I) error curves are shown in Fig. 8. The ANN (I) error curve (RMSE) for training and checking data starts around 0.65 and reached under 0.3 after 500 epochs for both of them. The ANN (II) error curve for training and checking data (Fig. 8) starts around 1.1 and after 1000 epochs reached around 0.8 for the checking data and under 0.6 for the training data. The ANFIS error curves for the training and checking data (Fig. 8) starts around 0.291 and after 500 epochs reached under 0.284. Using the ANFIS model described about, we have used Gaussian membership function with 0.1 as the initial step size. The step size decreasing rate and step size increasing rate were selected equal to 0.9 and 1.1, respectively. In this study, due to large volume of the training data (large dimension), the sub clustering method implemented for generating FIS structure. Sub clustering method is a well-known method in generating FIS structure for the big size data. Sub clustering method selects the number of membership function from the input data. The input membership functions and final membership functions are showed in Fig. 9. ANFIS method had the least RMSE value according to Fig. 8. On the other hand, ANN (II) had the highest RMSE (Fig. 8).

After the models calibrated using historical data 1988 (10 % of all), the models simulated the 1999 map and then, future (year 2010) urban expansion based on urban

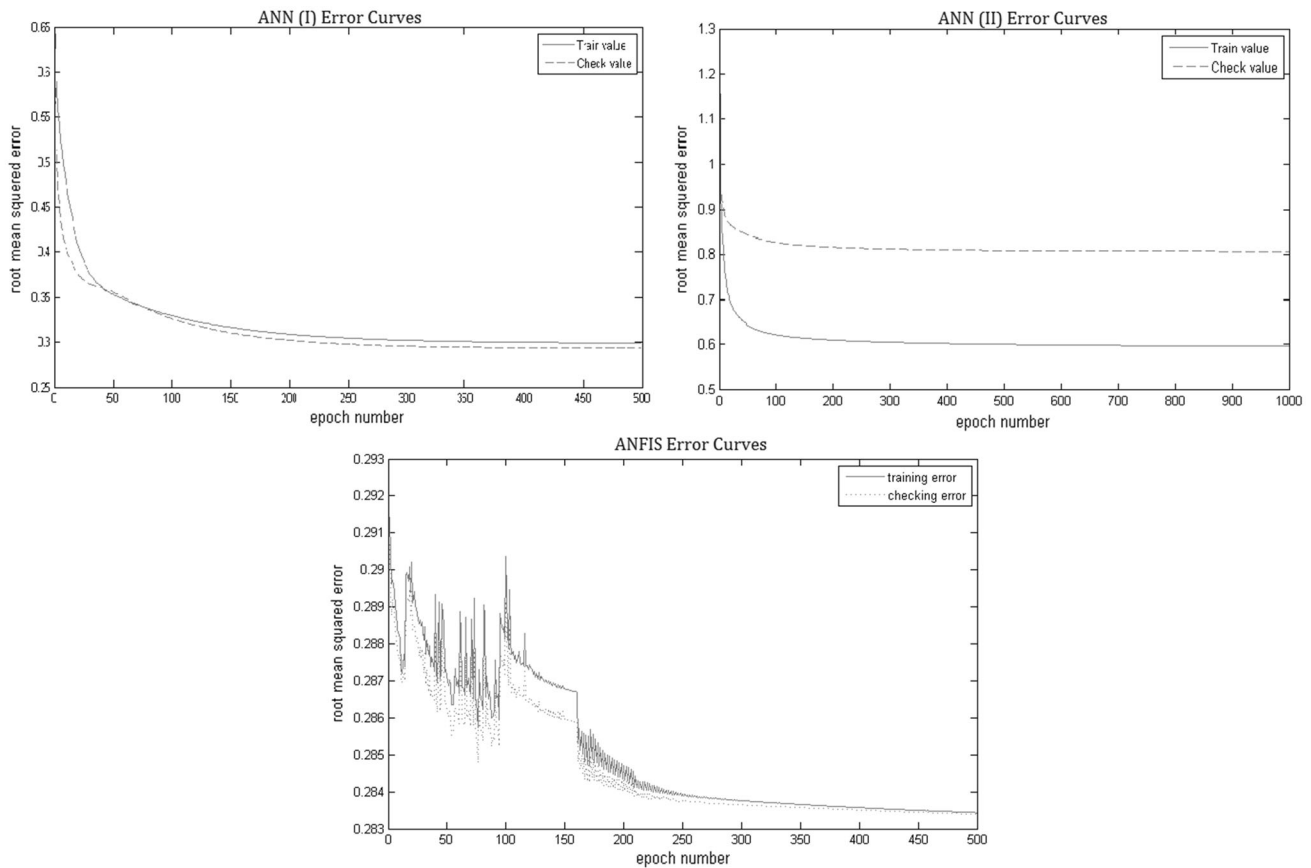


Fig. 8 The models error curve

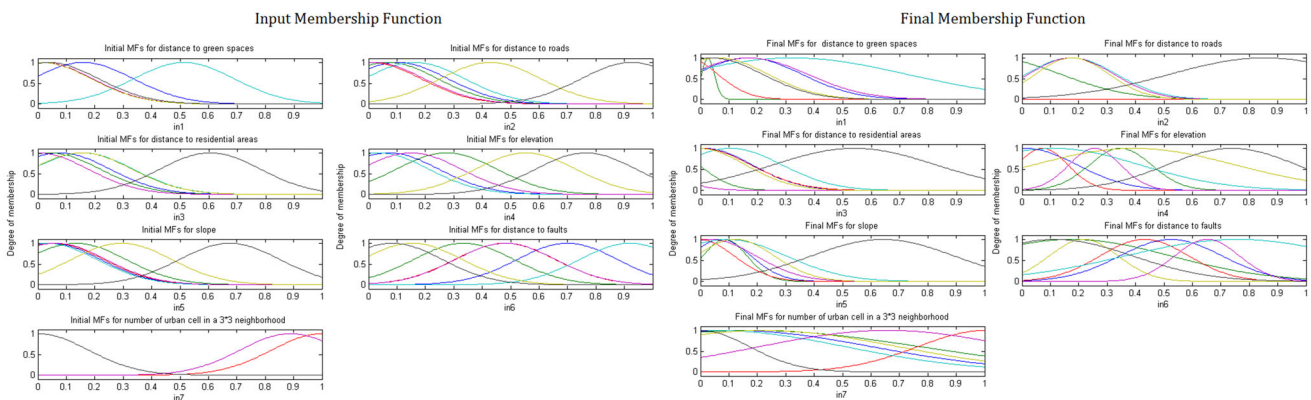


Fig. 9 Input membership functions and final membership functions

expansion trends (1988–1999). The accuracy obtained from the modeling using the three models are shown in Table 7 and Fig. 10. According to the results shown in Table 7 and Fig. 10, ANFIS approach had the best ROC value and goodness of fit among the three models (ANFIS, ANN (I) and ANN (II)) in modeling urban expansion for Tehran Metropolis in 1988–1999 and 1999–2010, too.

As it mentioned in the Table 7, the proposed ANFIS structure had the best goodness of fit in two accuracy assessment steps (1988–1999 and 1999–2010). Thus, this method is chosen as the modeler of Tehran urban growth and consequently, the 1999 and 2010 Tehran’s map simulated by ANFIS model. Figure 11 present the simulated 1999 and 2010 map.

Table 7 The simulation results

Method	ROC obtained from simulation 1999 map	ROC obtained from simulation 2010 map
ANFIS	0.9205	0.8642
ANN (I)	0.9022	0.6193
ANN (II)	0.9025	0.7148

Sensitivity analyses

For obtaining sensitivity analyses, each of the input data have removed and then, ANFIS, ANN (I) and ANN (II) trained, separately and simulated 1999 maps and calculated ROC. Sensitivity Analyses is used to clarify the importance of each input variable in modeling of Tehran Metropolis expansion. Figure 12 shows the SA results according to the

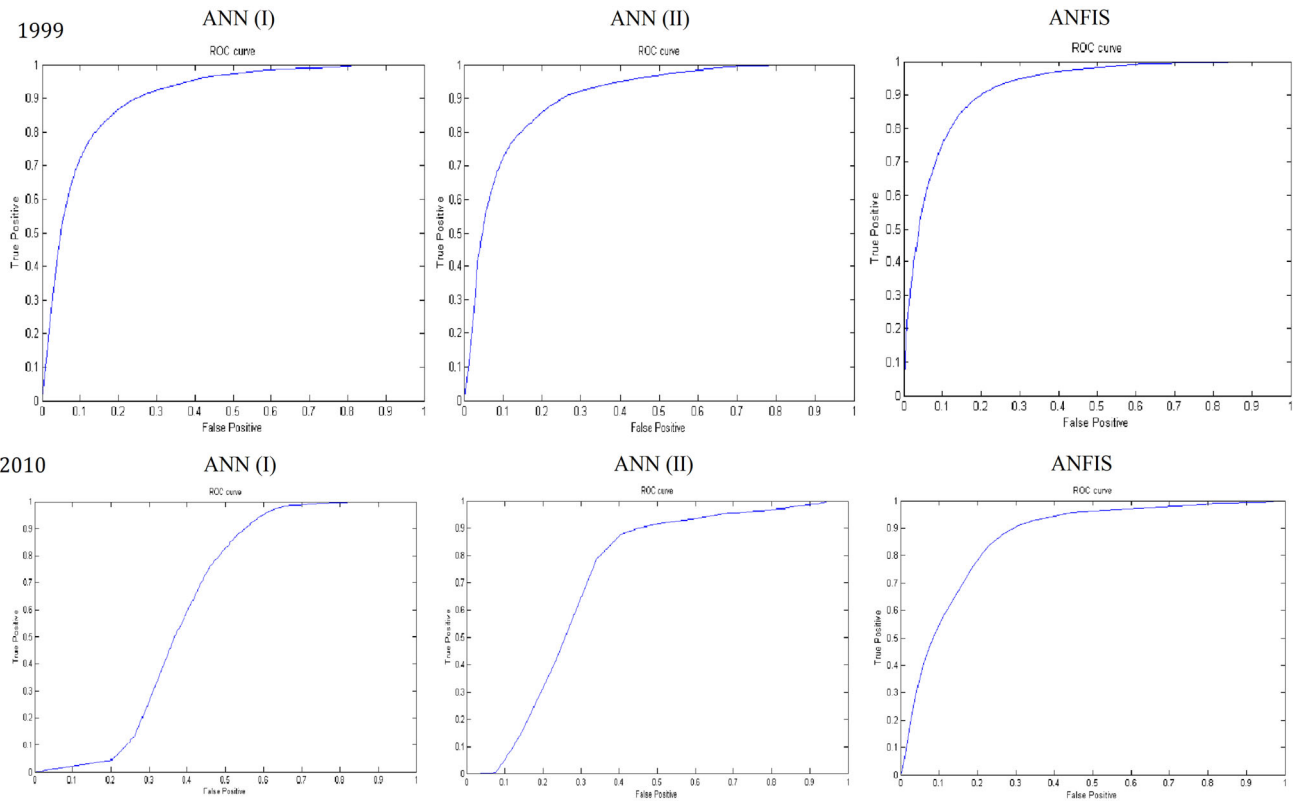


Fig. 10 Accuracy obtained from the modeling using the three models

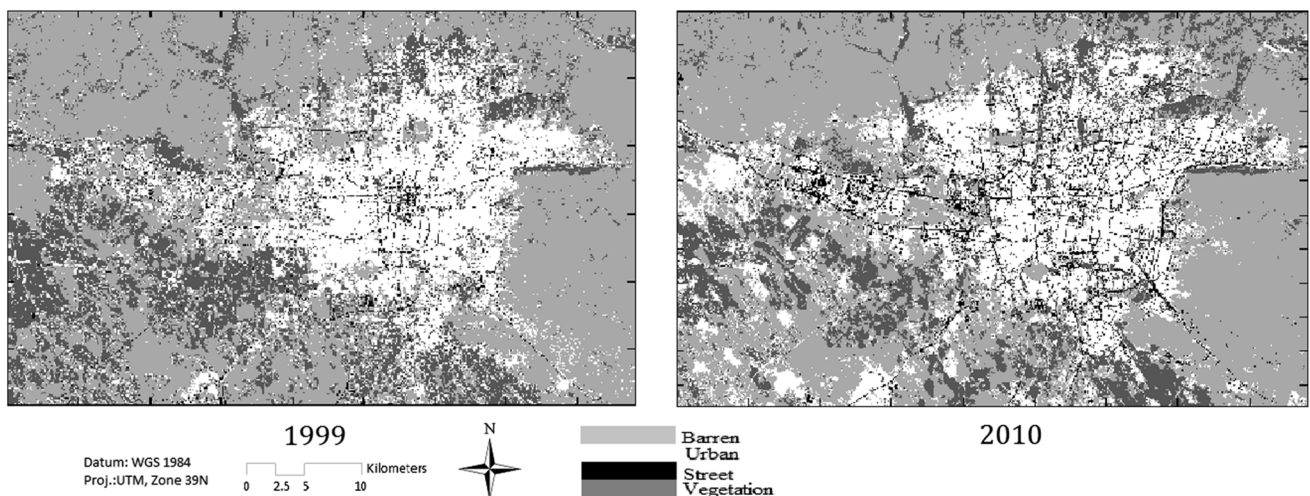


Fig. 11 The simulated 1999 and 2010 map

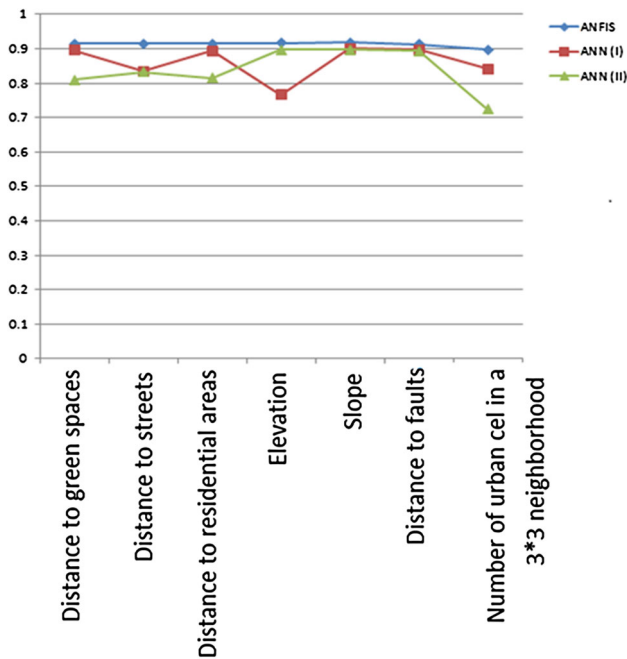


Fig. 12 Sensitivity analyses results

1988–1999 data. Figure 13 shows the ROC obtained from deleting each variable from calculation to determine the importance of the variable.

Discussion

In Figs. 12 and 13, it seems that slope due to high value of ROC, in all the three models had the least impact on expansion of the Tehran Metropolis during 1988–2010. Because the ROC resulted by deleting this factor, has had the least difference from modeling using all of the implemented factors. On the other hand, the number of urban cell in a 3*3 neighborhood, had the least ROC values in ANFIS and ANN (II) method and was the third important factor in ANN (I) modeling. It seems that this factor has had a noticeable impact on the expansion of Tehran during 1988–2010. Thus, probably, this factor has had the highest impact on growth of Tehran, and rapid growth of north region of this city is confirmable. During 1988–2010, the areas built up in the north have experienced more and rapid growth than others.

As observed from the existing growth trends until 2010, risk assessments factor such as distance to faults have had a small role in the development of this city. Needless to say that this factor could be a big challenge at high dense and informal urban areas.

ANFIS as a combined method solves many of the weaknesses of ANN and fuzzy inferences systems approaches and uses the advantages of these methods, at

the same time. On the other hand, it has some drawbacks like ANFIS never has been as fast as ANN models. Also, ANFIS run-time correlates with the number of membership function in each input.

According to Table 7 ANN (I) had the lowest ROC result and goodness of fit between these three models and ANFIS had the best goodness of fit among this three models. The influence of number of urban pixels in 3*3 neighborhoods factor in urban development of Tehran Megacity is greater than the influence of other factors and on the other hand, slope had the lowest impact on urban development for this city in this period of time.

Conclusion

The purpose of using urban growth models for a given period of time is to know and regulate the location and intensity of land development. Obviously, it is more expensive to provide trunk urban infrastructure in an informal developed area to provide such services, or at least to protect the right-of-way needed for such services before building takes place. Thus, analyses and control how much a city will expand is seem to be necessary (Shlomo et al. 2005).

Monitoring urban expansion requires accurate and detailed datasets and appropriate methods for their analysis, modeling and interpretation. Nowadays, one of the most common question in the urban planning is how much acceptable degrees of development (location and amount) are reasonable.

Urban sprawl has so many merits and drawbacks. Low rate of crime and being safer urban area zone, clean air and also, low rate of costs are probably the most attracting factors of attracting population to this area. But, this phenomenon means car dependency growth. It has caused increasing daily trips, traffics and pollution, too. It also has increased infrastructure and transport costs.

GIS and remote sensing are capable to provide necessary information for planning proposals and can be assumed as a powerful and useful monitoring tool during the implementation of plans. Combination of remote sensing data, geospatial information systems tools and mathematical methods such as artificial intelligence algorithms as a powerful method can be developed for analyzing and modeling environmental phenomena such as urban expansion and has the potential to support such models by providing data and analytical tools for the study of urban planning.

Results of this study can be considered as a strategic guide for city planner, and help them for optimizing the future expansion allocation and enable them to balance

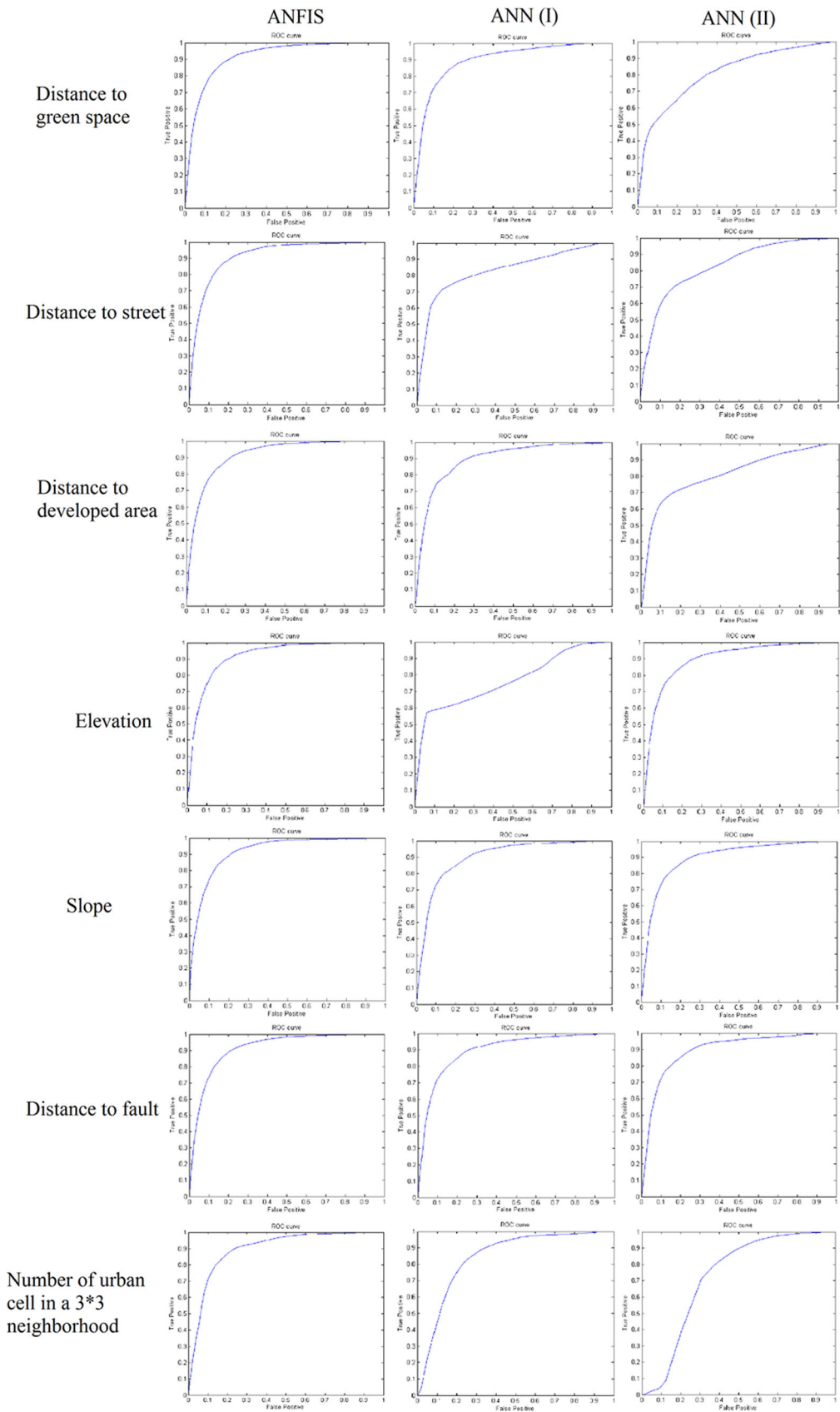


Fig. 13 The ROC obtained from deleting each variable

urban expansion and ecological environment conservation and have a true perception about complex land use system.

Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

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