# A SPATIO-TEMPORAL URBAN EXPANSION MODELING A CASE STUDY TEHRAN METROPOLIS, IRAN

**SASSAN MOHAMMADY**

University of Tehran, College of Engineering, Department of Geomatic and Surveying Engineering,
Iran, P.O. Box: 11365-4563
E-mail: sassanmohammady@yahoo.com

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**Abstract**
During the past decades, urban growth has been accelerating with the massive immigration of population to cities. Urban population in the world was estimated as 2.9 billion in 2000 and predicted to reach 5.0 billion in 2030. Rapid urbanization and population growth have been a common phenomenon, especially in the developing countries such as Iran. Rapid population growth, environmental changes and improper land use planning practices in the past decades have resulted in environmental deterioration, haphazard landscape development and stress on the ecosystem structure, housing shortages, insufficient infrastructure, and increasing urban climatological and ecological problems. In this study, urban sprawl assessment was implemented using Shannon entropy and then, Artificial Neural Network (ANN) has been adopted for modeling urban growth. Our case study is Tehran Metropolis, capital of Iran. Landsat imageries acquired in 1988, 1999 and 2010 are used. According to the results of sprawl assessment for this city, this city has experienced sprawl between 1988 to 2010. Dataset include distance to roads, distance to green spaces, distance to developed area, slope, number of urban cells in a 3 by 3 neighborhood, distance to fault and elevation. Relative operating characteristic (ROC) method have been used to evaluate the accuracy and performance of the model. The obtained ROC equal to 0.8366.

*Keywords:* ANN, Urban Expansion Modeling, Shannon Entropy, ROC, Tehran

## 1. Introduction

Half of the world population lives in urban areas in 2008. Moreover, most of the urban population growth has been occurred in the developing countries (UN, 2009). In some cases, the space taken up by urban areas is increasing faster than the urban population itself (Pijanowski et al, 2010). Socioeconomic processes such as urban sprawl, migration from rural area to urban areas, agriculture, and forest patterns often contribute to the urbanization (Portnov et al., 2007; Thapa – Murayama, 2009).

Since the Industrial Revolution, cities have developed rapidly expanding worldwide in conjunction with socioeconomic development. This rapid growth of urban areas has caused complex problems such as environmental pollutions, endanger natural resources, reduced open spaces, unsatisfied infrastructures and unplanned or poorly planned land development (Parka et al., 2011). It also has caused an unprecedented urban environmental degradation and shortage of adequate urban infrastructure needed to support the population. Urban growth is defined as modification of environment or the replacement of natural or agricultural land cover with urban land use (e.g., buildings, transportation, parking lots) (Slemp et al., 2012).

Urban growth is an irreversible phenomenon involving the spatio-temporal changes of all physical and socioeconomic components at different scales. City planners, urban managers and resource managers therefore need advanced approaches and a comprehensive knowledge of the cities under their jurisdiction to make the informed decisions necessary to guide sustainable development in rapidly changing urban environments (Pham et al., 2011). Needless to say, providing trunk urban infrastructure in built-up areas is more expensive and especially in informal developed areas (Angel et al., 2005).

A great number of approaches have been applied for modeling urban patterns and predict the future of cities. Urban growth models as important tools have been used to measure land-use change in peri-urban and rural regions (Clarke and Gaydos, 1998; Herold et al., 2003; Mundia – Murayama, 2010; Tobler, 1970; White et al., 1997) which have had a strong connection with decision support systems. Integration of urban growth models, Geospatial Information Systems (GIS) tools and remote sensing data have prepared a practical and non-expansive way for monitoring, analyzing and modeling changes in land use and boundaries of the cities.

GIS are widely used to represent, analyze, and display various spatial data such as topographic maps, satellite imageries and Digital Elevation Model (DEM). Many researchers use GIS as a reliable science and technology to find the spatio-temporal characteristics of landscape (Xi and Cho, 2007; Peccol et al., 1996; Jat et al., 2008). Using remote sensing data with GIS techniques provides a powerful tool to analyze, model and project environmental change. Therefore, integration of remote sensing and GIS have been recognized as powerful and effective methods in monitoring environmental change, especially in detecting the land use/ land cover change (LUCC) (Weng, 2002; Güler et al., 2007; Gao et al., 2006).

In this study, firstly, we measured urban sprawl in Tehran Metropolis using Shannon Entropy. Then, an ANN structure has been implemented for modeling urban growth in Tehran Metropolis during 1988 to 2010.

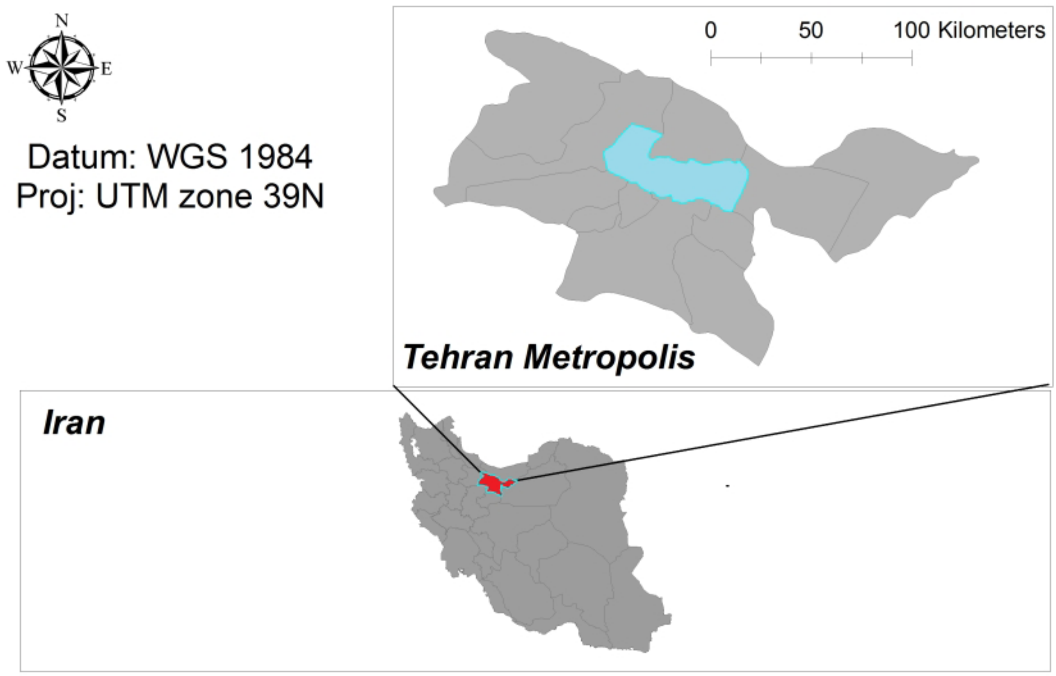


Fig. 1. Study Area

## 2. Materials and Methods

### 2.1. Case study

The case study in this research is Tehran Metropolis, capital of Iran which covers around 429 ($km^2$) in 2010. Fig. 1. shows the position of this city in Iran. The population of this city in 1976 was about 4530233 and reached 7711230 in 2006 (Statistical Centre of Iran) (Fig. 2.). The attraction of this city as the capital of Iran and socio-economic potential of the city and population growth were the most important reason to this rapid population growth in the few last decades in Tehran Metropolis.

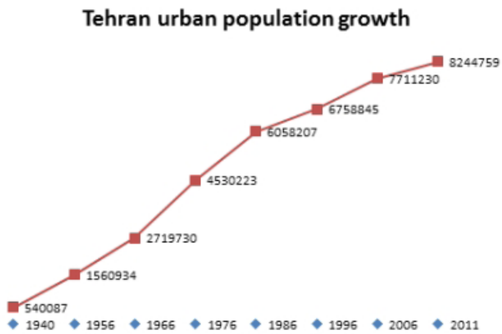


Fig. 2. Tehran population growth between 1940 to 2011

### 2.2 Data preparation

Landsat imageries acquired in 1988, 1999 and 2010 with ground pixel size 28.5 m and 30 m have been used for modeling urban growth in Tehran Metropolis. The related images are classified based on Anderson Level 1 (Anderson et al, 1976) with Support Vector Machine (SVM) classification method (Fig. 3). Implementation of SVM gives improved results respect to traditional classifiers like maximum likelihood (Melgani – Bruzzone, 2004; Pal – Mathur, 2005). All of remote sensing processes have done in ENVI 4.7. Satellite imageries data are shown in Table 1. Table 2 shows the classification accuracy. According to Thomlinson et al., 1999, all of overall accuracies are acceptable.

### 2.3 Urban sprawl assessment

The urban areas have been extracted from Landsat imageries and are shown in Fig. 4. Table 3 presents urban and non-urban area in this city for 1988, 1999 and 2010. A single and even policy for the entire city never works with equal degree of effectiveness for all parts of the city (Bhatta, 2009), and study area should divides to smaller region to study the sprawl in them. Thus, we divided the region into 4 regions (Fig. 5.). Table 4 presents urban area in NW, NE, SW and SE directions during 1988 to 2010. Table 5. presents urban expansion in during 1988 to 2010.

#### *2.3.1 Shannon Entropy*

Shannon's entropy is a well-accepted method for determining the sprawled urban pattern (Li – Yeh 2004, Sudhira et al., 2004). 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) indicates that the distribution is much dispersed. The

Table 1. Satellite imageries data

| Projection | Datum | Satellite | Earth pixel size (m) | Sensors | Date |
|---|---|---|---|---|---|
| UTM | WGS-84 | Landsat 5 | 28.5 | TM | 09.08.1988 |
| UTM | WGS-84 | Landsat 7 | 30 | ETM+ | 05.06.1999 |
| UTM | WGS-84 | Landsat 7 | 30 | ETM+ | 06.06.2010 |

Table 2. Classification assessments

| Date | Overall Accuracy (%) | Kappa Statistics (%) |
|---|---|---|
| 1988 | 89.43 | 82.22 |
| 1999 | 87.12 | 72.73 |
| 2010 | 91.33 | 88.67 |

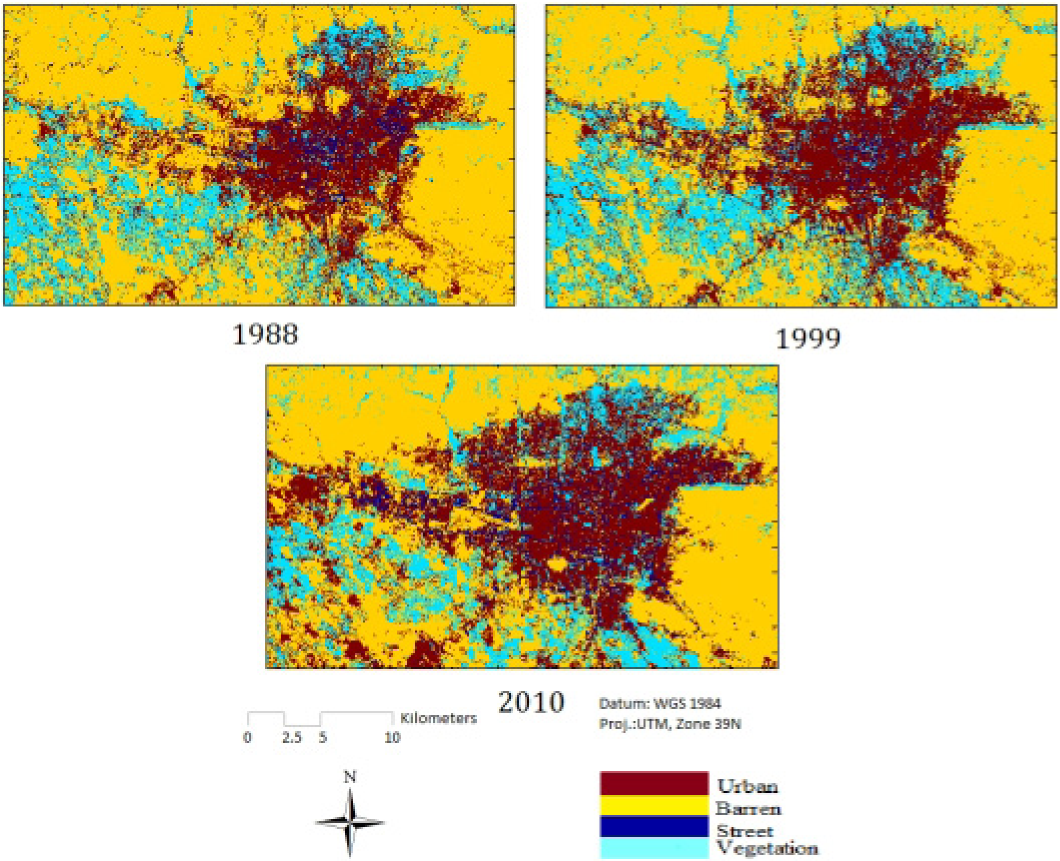


Fig. 3. Classified imageries

Shannon's entropy is considered,

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

$i$=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.

### 2.4 Proposed methodology

This study has considered a number of influencing factors to predict potential urban growth modeling. The dataset include distance to roads, distance to green spaces, distance to developed area, slope, number of urban cells in a 3 by 3 neighborhood, distance to fault and elevation. All of the required maps such as land use and transportation are also formatted in Shape file using ArcGIS 9.3. All of the input maps are normalized using Eq. 2. Fig. 6 shows the normalized maps.

$$x_{norm} = \frac{x_{real} - x_{\min}}{x_{\max} - x_{\min}} \qquad (2)$$

According to recent works on ANN, this nets trend to overfitting or underfitting errors (Almeida et al., 2008). Thus, finding the training and checking data must be done carefully. The training data (5% data) and checking data (10% data) are selected randomly from 1988 to 1999 data. In this study, the ANN calibration procedure is done using 1988 to 1999 data. Then, the 2010 map is simulated using trained ANN.

ANNs are powerful tools that use a machine learning approach to quantify and

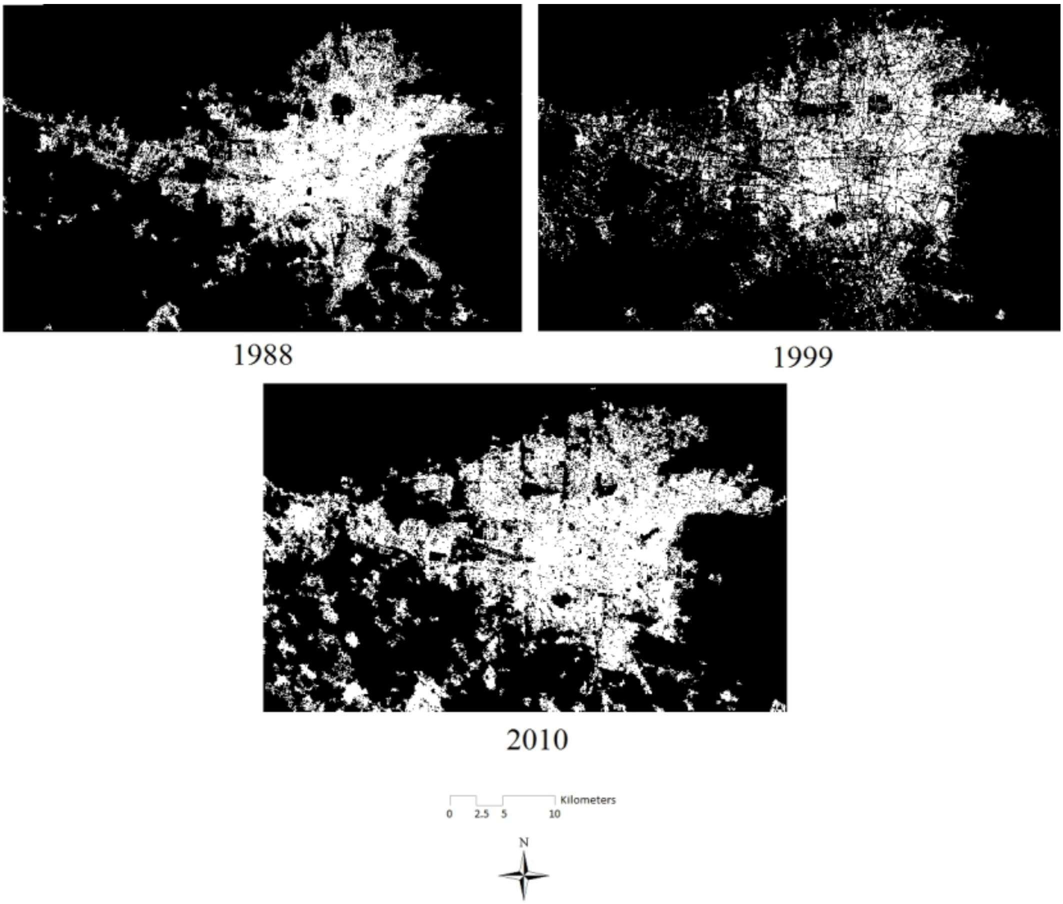


Fig. 4 Urban expansion during 1988 to 2010

model complex relationships between input and output vectors which are very difficult to embody in conventional algorithmic methods. This task is carried out by a process of learning from samples presented to the ANN. Artificial Neural network due to the possibility of learning is an appropriate tool for land use change modeling (Li – Yeh, 2001; Pijanowski et al., 2002; Almeida et al, 2008; Tayyebi et al., 2011). During learning, known input-output pairs called the training set, are applied to the ANN. The ANN learns by adjusting or adapting the strengths of the connections between processing units, by comparing the output of the ANN to the expected output (Padmanaban, 2012; Zhang et al., 1998). These networks are composed of three layers including input, intermediate and output. This type of networks is used to identify non-linear relationships as more practical issues faced by non-linear phenomena; this type of network is very useful. Fig. 7. shows the training error for ANN model. The ANN structure with Tang Sigmoid function as the transfer function trained in 500 cycles. The Mean Square Error (MSE) curves for training and checking data started around more than 1 and 0.5 and reached below 0.15 in 500 cycles.

## 2.5 Accuracy assessment

**ROC**

Relative operating characteristic (ROC) method in land use/cover change modeling have been used by Pontius and Schneider, 2001 to measure the relationship between simulated change and real change (Pontius – Schneider, 2001). ROC is a parameter which is used to validate the suitability map of the urban growth (Foroutan – Delavar,

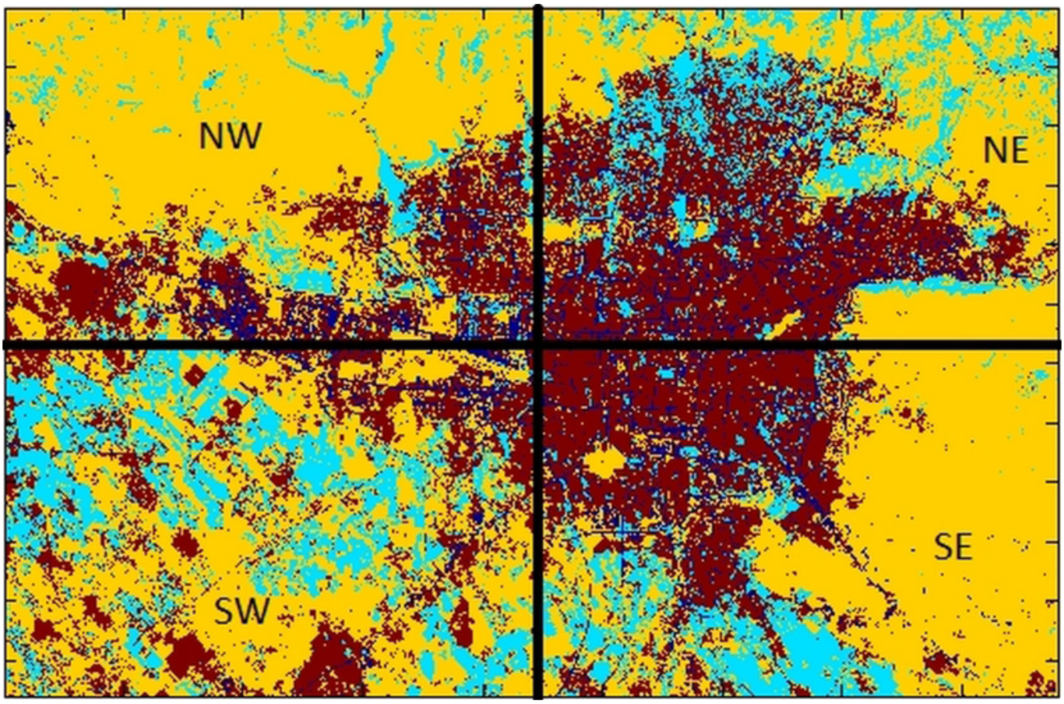


Fig. 5. The 4 regions of Tehran

Table 3. Urban and Non-urban areas in 1988, 1999 and 2010

| Date | Urban Area (Km2) | Urban Area (%) | Non-Urban Area (Km2) | Non-Urban Area (%) |
|---|---|---|---|---|
| 1988 | 298.813 | 18.02 | 1359.477 | 81.98 |
| 1999 | 345.9779 | 20.86 | 1312.312 | 79.14 |
| 2010 | 428.0549 | 25.81 | 1230.235 | 74.19 |

Table 4. Urban areas in NW, NE, SW and SE direction (in Km$^2$)

| | Direction | | | | |
|---|---|---|---|---|---|
| Year | NW | NE | SW | SE | Total |
| 1988 | 91.4927 | 88.0227 | 41.8211 | 77.4765 | 298.813 |
| 1999 | 122.744 | 91.1011 | 45.4291 | 86.7036 | 345.9779 |
| 2010 | 164.9948 | 119.296 | 55.4751 | 88.2891 | 428.0549 |

Table 5. Urban expansions during 1988 to 2010 (in Km$^2$)

| | Direction | | | | |
|---|---|---|---|---|---|
| Temporal Span | NW | NE | SW | SE | Total |
| 1988-1999 | 31.2513 | 3.0784 | 3.608 | 9.2272 | 47.1649 |
| 1999-2010 | 42.2508 | 28.1948 | 10.0459 | 1.5855 | 82.077 |

2012). This method is known as threshold-independent method because there is no need to define threshold value for generating simulated land use map (Beguería, 2006). The ROC values range from 0 to 1. Values closer to 1 indicates the better agreement between simulated and real map while the values closer to 0 indicates disagreement between simulated and real map. ROC is a curve which plot True positive (Eq. 3.)

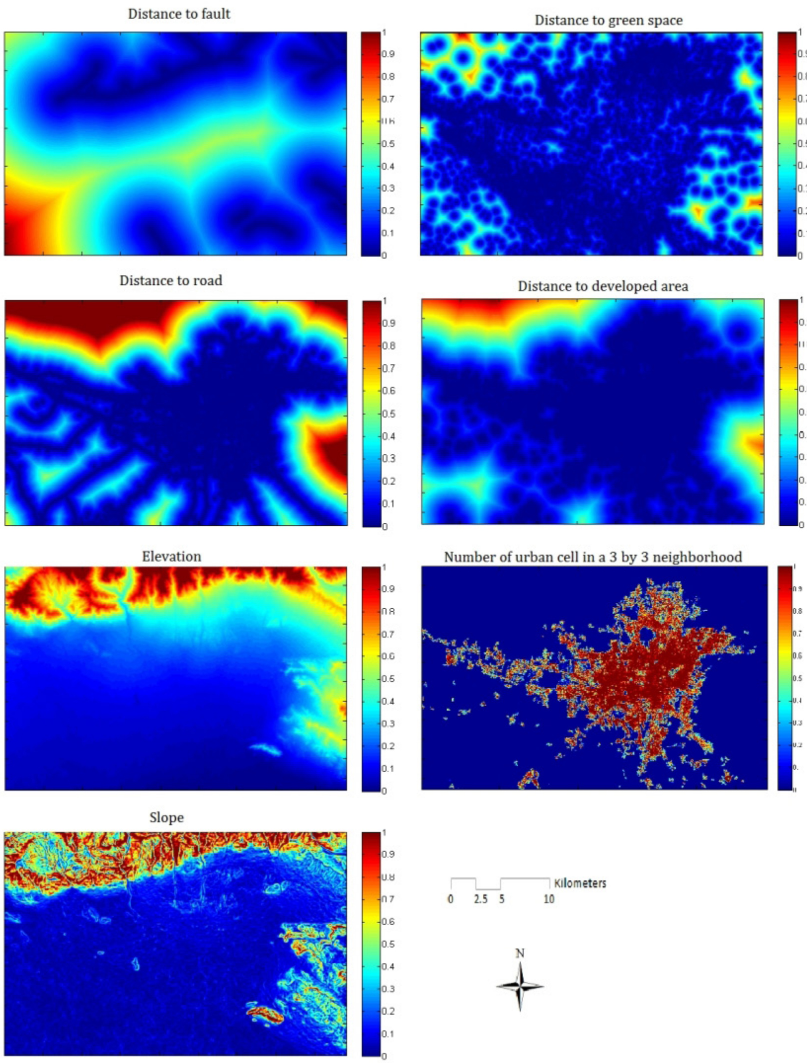


Fig. 6. Normalized dataset parameters

versus False positive (Eq. 4.). ROC statistic is the area under the curve that connects the plotted points and can be calculated from trapezoidal rule (Eq. 5.) (Pontius – Schneider, 2001). Table 6 shows the Confusion matrix.

$$True\ Positive\% = \frac{A}{A+C} \qquad (3)$$

$$False\ Positive\% = \frac{B}{B+D} \qquad (4)$$

$$AUC = \sum_{i=1}^{n}[FP_{i+1} \quad FP_i][TP_i + TP_{i+1} \quad TP_i / 2] \qquad (5)$$

## 3. Results

If the entropy value goes below the half-way mark of   then only it can be said that the city is non-sprawling (Bhatta et al., 2010, 2009). Table 7. shows Shannon's Entropy Analysis. The obtained entropy values are much higher than the half-way mark of i.e. 0.6931. Therefore it can safely be said that the city is sprawled and the sprawling tendency is increasing. In other words, Tehran Metropolis area is becoming more sprawled with the change of time and shows a tendency of increasing sprawl.

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 |

Using more satellite imageries increase the number of urban sprawl assessment steps using Shannon Entropy and provide continues monitoring of the study area. Also, satellite imageries with better earth pixel size enable us to reach better precision on ground scales. Thus, using IKONOS, Quick bird imageries may change the obtained accuracies and cause less error.

Table 7. Shannon's Entropy

| Temporal Span | Shannon Entropy |
|---|---|
| 1988-1999 | 09667 |
| 1999-2010 | 1.0422 |

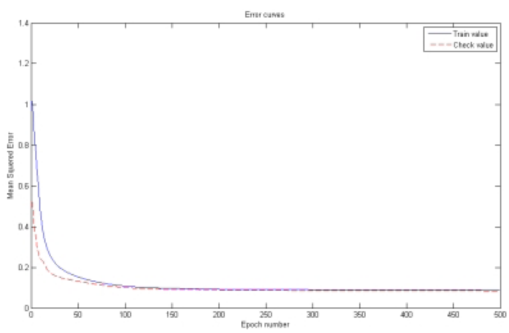


Fig. 7. Training and checking error for ANN

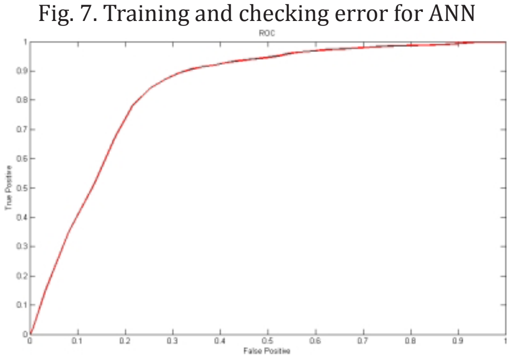


Fig. 8. ROC

City planners, economists and resource managers need advanced methods and a comprehensive knowledge of the cities to make the informed decisions necessary to guide sustainable development in rapidly changing urban environments. Remote sensing provides spatially consistent coverage of large areas with both high spatial detail and temporal frequency, which are useful for examining historical time series (Jensen – Cowen, 1999.). Moreover, remote sensing data is effective to monitor the land use change in areas, especially where information on land use management is inconsistent and insufficient.

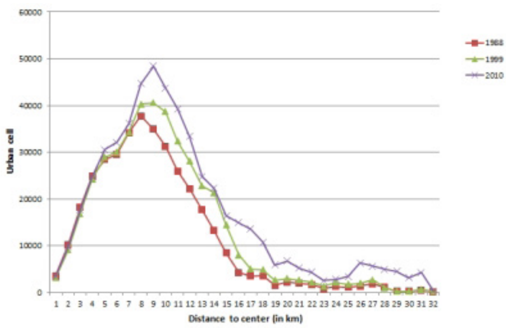


Fig. 9. Dispersion of urban cells around the city center during 1988 to 2010

## 4. Discussion

GIS and remote sensing are capable of providing necessary information for planning proposals and can be assumed as a powerful and useful monitoring science and technology during the implementation of plans. Integration of remote sensing data, GIS spatial analyzing and modeling and mathematical methods such as artificial neural networks algorithm can be used for analyzing and modeling environmental phenomena such as urban expansion which has the potential to support such models for urban planning. The integrated model contributes to urban growth assessment and the demand for urban planning decision-support tools.

Many of conventional methods for modeling urban growth such as SLEUTH, CLUE-S lame to project social parameters such as population density in modeling processes. ANN has the ability to project social parameters, too. ANN due to parallel processing, learning ability and fast computation has been used significantly in environmental modeling. The purpose of using urban growth models for the given period of time is to know and regulate the location and intensity of land development.

This paper has measured sprawl in Tehran Metropolis during 1988, 1999 and 2010 Landsat imageries data. According to the obtained results from sprawl analyses, Tehran has experienced sprawl during 1988 to 2010 and this dispersion is becoming bigger during time. Next, an ANN structure has been used for modeling urban growth in Tehran Metropolis during 1988 to 2010. The input parameters in this study for training the ANN structure included distance to roads, distance to green spaces, distance to developed area, slope, number of urban cells in a 3 by 3 neighborhood, distance to fault and elevation. At final, Relative operating characteristic (ROC) method has been used for accuracy assessment of simulated map. The ROC value was 0.8366.

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