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A Spatio-Temporal Urban Growth Modelling. Case Study: Tehran Metropolis

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A B S T R A C T

Different models have been attempted for modelling urban expansion. Models are tools for detecting changes and considering the relationship between land use and land use change factors. In this research we used the Logistic Regression method for modelling the urban expansion pattern in Tehran Metropolis during 1988-2010, employing landsat imageries acquired in 1988, 1999 and 2010. The effective parameters employed in this study include distance to principle roads, distance to developed region, distance to faults, distance to green space, elevation, slope and the number of urban pixels in a 3 by 3 neighbourhood. Percent Correct Match, Kappa statistics and Figure of Merit have been used for evaluating the accuracy of the model. We concluded that the distance to the residential area influences the urban development of Tehran greatly as compared to other factors. On the other hand, the number of urban pixels in a 3*3 neighbourhood had the lowest impact on urban development for this megacity in this period of time.

1. INTRODUCTION

The urban population in the world increased from 22.9% in 1985 to 47% in 2010. Tendency to urbanization and rapid population growth resulted in 2% of Earth's land surface covered by urban areas [1]. One of the results of this urban population growth is large-scale urban expansion [2], [3]. The rapid growth of urban areas has led to complex problems including reduced open space, traffic problems, environmental pollution, and the deterioration of old and unplanned or poorly planned land development [4]. One of the major problems in the intelligent management of cities is the lack of proper and scientific development and as a result destruction of agricultural land, urban development in high slopes and elevations, environmental deterioration and natural hazards, increased infrastructure and utility costs and the lack of optimum use of land have been encountered. Thus, monitoring land use changes is needed to understand and predict the dynamic process of land use patterns at different moments. A vital component of the research on land use/cover change is the analysis of rates and patterns of land use change which is a powerful tool for urban planners, city and resource managers [5], [6], [7], [8]. Land use change models as a tool are used to show where, when and how land use changes could arise in the future, in order to adapt current land management public policy [9], [10]. In the past decades, different models have been developed to exhibit and quantify land use changes [11], [12], [13], [14], mainly in land-use change (LUC) models. In recent decades, remote sensing data and geospatial information systems (GIS) have been widely applied for identification and analyses of land use change in the metropolitan area [15], [16], [17], [18], [19], [20], [21]. GIS are widely used to represent, analyze, and display various spatial data such as remote sensing, topography, soil type, rainfall and vegetation [29]. Remote sensing data have been used in urban growth modelling, in urban morphology and land use [22], [23], [24], in quantifying land use dynamics and urban growth [25], [26], [27], [28]. In this paper, we implemented the Logistic Regression (LR) algorithm for modelling urban growth in Tehran Metropolis. We used three Landsat imageries acquired in 1988, 1999 and 2010 for monitoring and modelling urban growth in Tehran Metropolis. We also used PCM, Kappa statistics and Figure of Merit (FoM) for goodness of fit assessment.

2. THEORY AND METHODOLOGY

Three Landsat TM and ETM+ images with 28.5 m and 30 m spatial resolution, acquired in 1988, 1999 and 2010 were used (Table 1). These imageries were obtained from the United States Geological Survey (USGS) portal. Data was projected to a World Geodetic System (WGS) 1984, Universal Transverse Mercator (UTM) Zone 39N coordinate system. The 1988 and 1999 and 2010 Landsat imageries were classified with ENVI 4.7 according to Anderson et al (1976) level 1 classification scheme using the Maximum Likelihood classification (MLC) method which is one of the supervised classification methods [29]. The overall classification accuracy and the kappa coefficient of these classified imageries were 89.43% and 82.22% in 1988, 87.12% and 72.73% in 1999 and 91.33% and 88.67% for 2010, respectively.

According to Anderson et al (1976), all of the obtained overall accuracies were acceptable [29] and according to Pijanowski et al (2005) the obtained kappa statistics for 1988 and 2010 classified imageries were excellent and for 1999 was very good [30]. Figure 1 shows the classified imageries.

Table 1. The images employed.

Date	Sensors	Pixel size (m)	Satellite	Datum	Projection System
09.05.1988	TM	28.5	Landsat 5	WGS-84	UTM
05.06.1999	ETM+	30	Landsat 7	WGS-84	UTM
06.06.2010	ETM+	30	Landsat 7	WGS-84	UTM

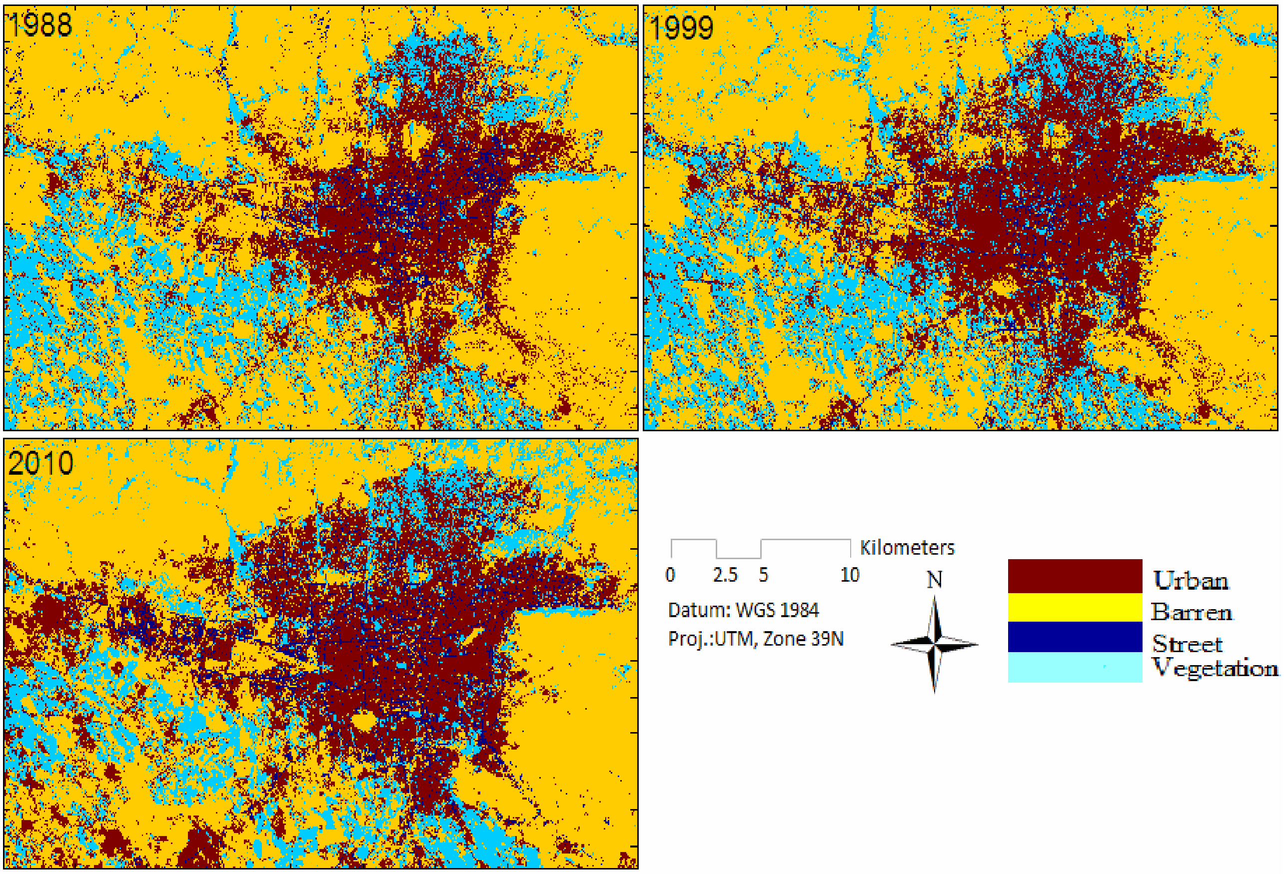

Fig. 1. The classified 1988, 1999 and 2010 Landsat imageries.

We used 1988 and 1999 imageries for calibrating the LR model and then simulated the urban pattern for 2010. The implemented datasets included seven parameters such as distance to roads, distance to green spaces, distance to developed areas, and distance to faults, slope, elevation and number of urban pixels in a 3*3 neighbourhood.

Following the model of Pijanowski et al (2005), all of the input parameters were normalized (fig. 2).

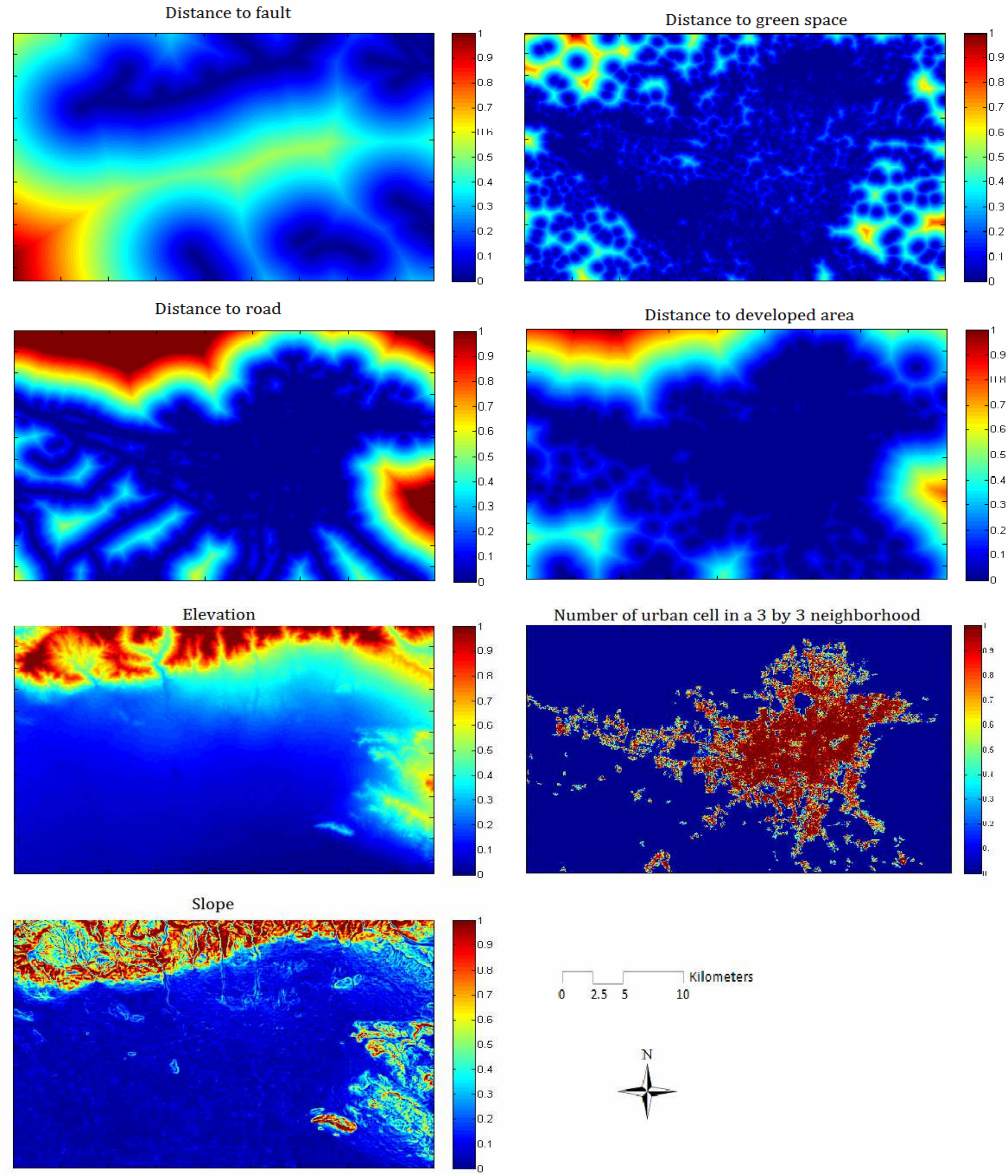

Fig. 2. The normalized input parameters.

2.1. Logistic regression

Logistic regression is one of the most popular models in environmental modelling such as the urban expansion pattern [31].

The implementation of this method can also be found in Tayyebi et al (2010), Dubovyk et al (2011), Xie et al (2009). Simple structure, ease of use and fast computation are the most important features of this method. According to Eq. 1, logistic regression calculates the probability of urban development for each cell [35].

The input for the function P can be any value, while the output is always a value between 0 and 1 [36].

$$P=\frac{\exp(B_0+\sum_{i=1}^{n}B_iX_i)}{1+\exp(B_0+\sum_{i=1}^{n}B_iX_i)} \quad (1)$$

where:

P - probability of land use change for each cell;

B_i - model parameters to be estimated;

B_0 - an intercept of the model;

X_i - independent parameters.

2.2. Accuracy assessment

2.2.1. Percent Correct Match (PCM)

Percent Correct Match (PCM) is a way to evaluate models of urban development. This method compares only the parameters of the original diameter of the A and D in the Confusion matrix using Eq.2 (Table 2) [33]. PCM values range from 0 to 1. Zero value indicates there is a complete disagreement between reality and the simulated map, 1 indicates a perfect agreement between the two maps and 0.5 indicates the randomly distribution of land use classes in the map [32].

$$PCM=\frac{A+D}{A+B+C+D} \quad (2)$$

Table 2. Confusion matrix.

Model	Reality		
	Change	Non Change	Total
Change	A (TP)	B (FP)	A+B
Non Change	C (FN)	D (TN)	C+D
Total	A+C	B+D	A+B+C+D

2.2.2. Figure of merit

Figure of Merit (Eq. 3) is a method to evaluate resemblance between the actual and simulated map suggested first time by Pontius et al (2008). If a simulated map has a high goodness of fit to its actual map, Figure of Merit will be high and vice versa [38].

$$Figure\ of\ Merit=\frac{b}{a+b+c+d} \quad (3)$$

where:

a - error due to observed change predicted as persistence;

b - correct due to observed change predicted as change;

c - error due to observed change predicted as wrong gaining category;

d - error due to observed persistence predicted as change.

2.2.3. Kappa statistics

Kappa coefficient as a statistical method has been used for comparing two maps. In fact this factor is significantly used to show the rate of compatibility between the reality map and the simulated map.

In other words, this factor can be used to measure the spatial distribution of the amount of similarities between the two maps. According to Pijanowski et al (2005), Kappa values for map agreement are: >0.8 is excellent; 0.6-0.8 is very good; 0.4-0.6 is good; 0.2-0.4 is poor, and <0.2 very poor [30].

The calculation of Kappa is based on the contingency matrix [39] (Table 3).

$$P(A)=\sum_{i=1}^{C}P_{ii}$$

$$P(E)=\sum_{i=1}^{C}P_{iT}.P_{Ti}$$

$$KS=\frac{P(A)-P(E)}{1-P(E)}$$

Table 3. The contingency matrix.

	Model					Total
Reality	Class	1	2	…	C	
	1	P_{11}	P_{12}	…	P_{1C}	P_{1T}
	2	P_{21}	P_{22}	…	P_{2C}	P_{2T}
	…	…	…	…	…	…
	C	P_{C1}	P_{C2}	…	P_{CC}	P_{CT}
Total		P_{T1}	P_{T2}	…	P_{TC}	1

3. RESULTS AND DISCUSSIONS

3.1. Case study

The study area in this research is Tehran Metropolis, capital of Iran. In the past few decades, Tehran has shown remarkable urban growth.

One of the reasons for the rapid population growth in this megacity is migration from neighbouring cities and even from neighbouring provinces to the city because of the economic and social potential of this megacity.

Figure 3 shows the urban population growth of the megacity in recent years.

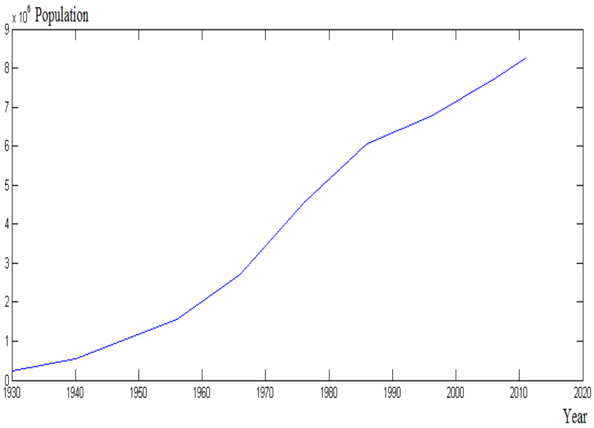

Fig. 3. Urban population growth in Tehran.

The output of the logistic regression is providing urban expansion by using variables that are exponential functions of their elements. Various coefficients are determined using the method of least squares.

Table 4 shows the coefficients of the logistic regression.

Table 5 represents the correlation between the input parameters.

For evaluating the performance of the model, the study area is divided into four regions. Different development strategies, different slope and elevation in this area, and non-uniform distribution of facilities are the most important reasons for this division.

Table 4. The coefficients of the logistic regression model.

Variable	Coefficient	Standard error	Exp.(Coefficient)
(1) Distance to green spaces	-1.775	.138	.169
(2) Distance to roads	-2.203	.148	.110
(3) Distance to residential areas	-27.612	.511	.000
(4) Elevation	-.226	.207	.798
(5) Slope	-3.016	.172	.049
(6) Distance to faults	-2.255	.123	.105
(7) Number of urban pixels in 3*3 neighbourhood	-.028	.321	.972
Constant	1.270	.333	3.560

Table 5. The correlation between the input parameters.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	1	-0.113	-0.184	-0.226	0.126	-0.461	0.029
(2)		1	-0.384	-0.194	-0.074	-0.107	0.059
(3)			1	-0.006	-0.062	0.003	-0.019
(4)				1	-0.481	0.759	0.011
(5)					1	-0.260	0.021
(6)						1	0.001
(7)							1

The domains are measured in accordance with the north of the map (Table 6).

Table 6. The measured domains in accordance with the north of the map.

Domain (^{o})	District ID
360 (0)-90	2
90-180	4
180-270	3
270-360	1

Figure 4 shows the obtained Figure of Merit (FoM), Percent Correct Match (PCM) and Kappa statistics versus the threshold value. After the model calibration using historical observed data of the years 1988 and 1999, the model predicted the future urban growth (year 2010) based on the current urban growth trends. Based on the results of the urban growth modelling for Tehran Metropolis using LR, distance from developed areas had the biggest coefficient. Thus, this factor is the most important one in the development of the megacity.

The number of urban pixels in the 3*3 neighbourhoods had the smallest coefficient and thus it had the smallest impact in the development of Tehran.

4. CONCLUSION

Monitoring urban growth requires detailed and accurate datasets and appropriate methods for their analysis, modelling, and interpretation. Nowadays, one of the most common questions in urban planning is related to the acceptable amount of urban development (location and dimension). According to Table 5, there is no significant correlation between the input parameters. This means that these parameters are independent. According to Figure 4, the FoM and Kappa statistics values for region 2 and 4 were greater than the obtained values for regions 1 and 3.

It seems that the implemented LR model has had a better goodness of fit in modelling urban growth in the eastern part of the megacity.

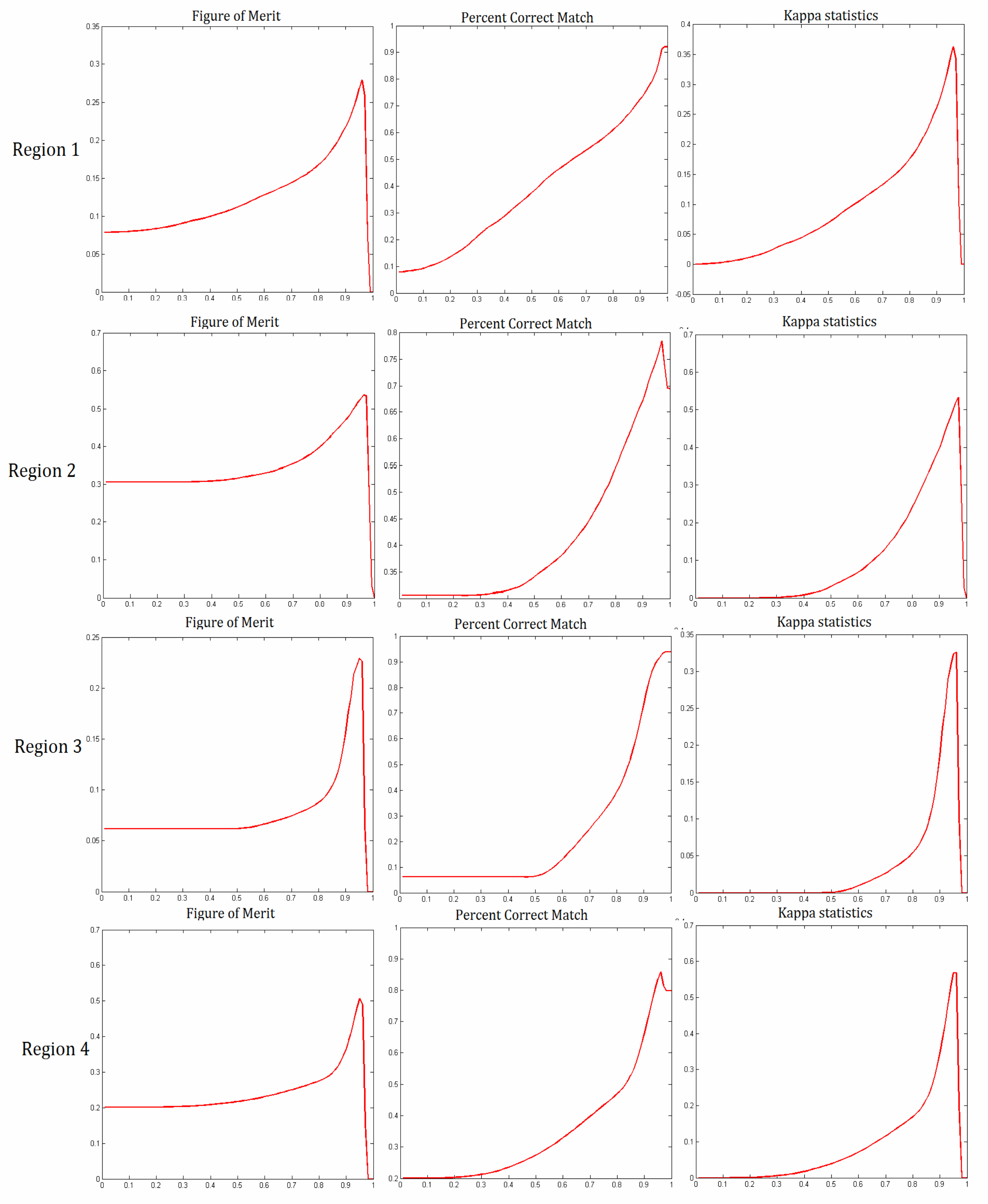

Fig. 4. The accuracy assessment factors versus threshold values.

In fact, there is a huge difference in goodness of fit between the eastern and the western parts of the megacity. It seems that there were no integrated policies in the growth of the megacity in all directions during 1988 to 2010. The simulated 2010 map is obtained using selection of 0.94 as the proposed threshold value. Figure 5 illustrates the comparison between the simulated and the reality maps in 2010. The LR model examines the relationship between the inputs (predictor variable) and the outputs (urban or non-urban) to model urban expansion. This allowed much deeper understanding of the forces driving the growth and the formation of the urban spatial pattern (32).

The LR model, due to its simple structure and fast computation is one of the most popular models in urban growth modelling. In the LR model, the covariance between variables and the importance (weights) of each variable is simply presented, however, in other popular methods like cellular automata and artificial neural network (31), the variable's weight is obtained only by sensitivity analysis which is quite time-consuming. In addition, there is no way to obtain correlations between the variables.

This model can be used with fewer variables and when a quick overview of the situation is required, the models incorporating the main factors can be built to obtain the required information relatively easily (32).

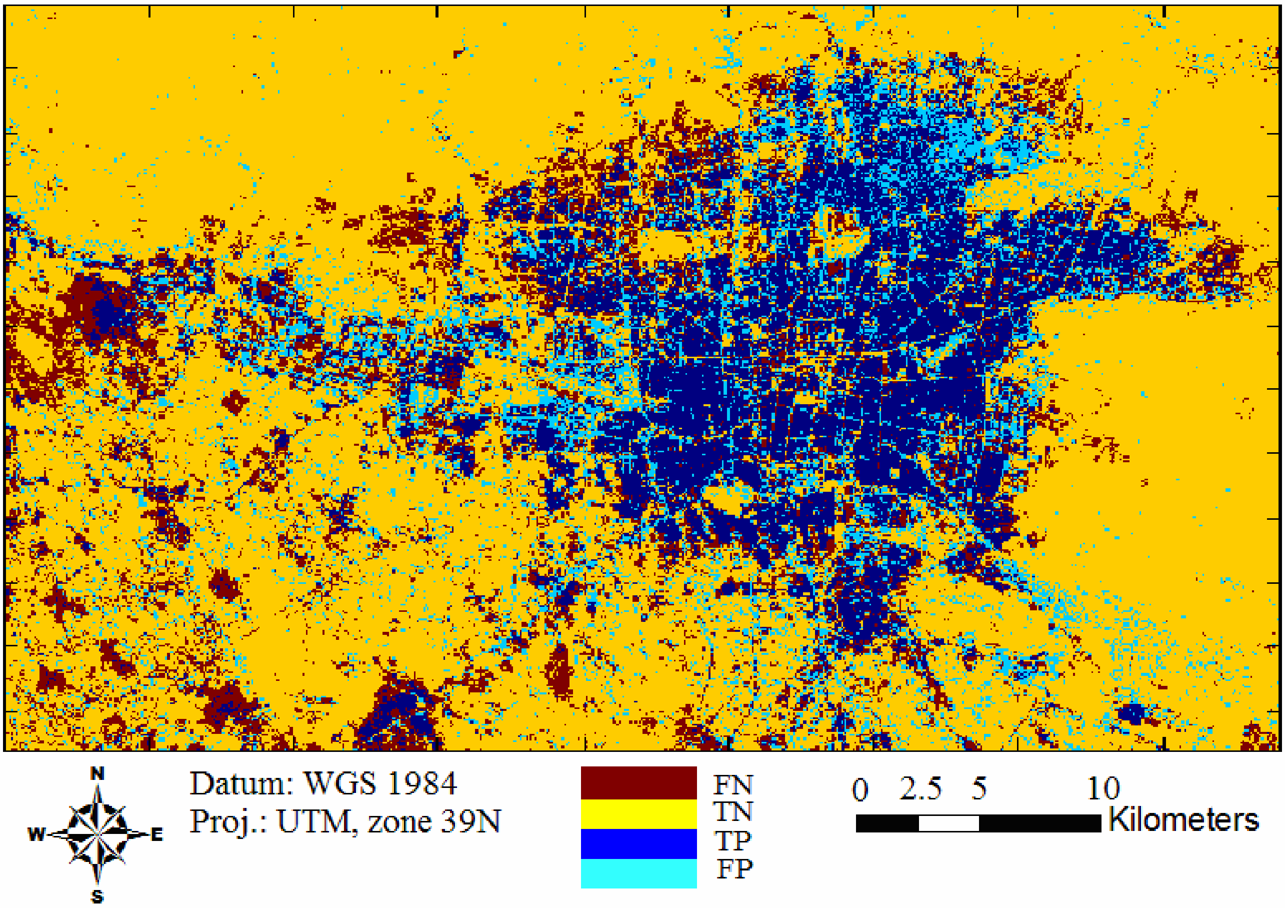

Fig. 5. The comparison between the reality and the simulated maps in 2010.

We concluded that the influence of distance to the residential area in the urban development of Tehran is greater than the influence of other factors. On the other hand, the number of urban pixels in a 3*3 neighbourhood had the lowest impact on urban development for this megacity in this period of time.

The results of this study can be considered as a strategic guide for city planners to help them in optimizing the future land use growth allocation and have a better sense about complex land use system enabling them to balance between urban expansion and ecological environment conservation.

This study modelled the growth of Tehran Metropolis between 1988 and 2010 and also clarified the main factors in developing this area during the respective period.

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