

## URBAN GROWTH MODELLING WITH ARTIFICIAL NEURAL NETWORK AND LOGISTIC REGRESSION. CASE STUDY: SANANDAJ CITY, IRAN

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**ABSTRACT** – Cities have shown remarkable growth due to attraction, economic, social and facilities centralization in the past few decades. Population and urban expansion especially in developing countries, led to lack of resources, land use change from appropriate agricultural land to urban land use and marginalization. Under these circumstances, land use activity is a major issue and challenge for town and country planners. Different approaches have been attempted in urban expansion modelling. Artificial Neural network (ANN) models are among knowledge-based models which have been used for urban growth modelling. ANNs are powerful tools that use a machine learning approach to quantify and model complex behaviour and patterns. In this research, ANN and logistic regression have been employed for interpreting urban growth modelling. Our case study is Sanandaj city and we used Landsat TM and ETM<sup>+</sup> imageries acquired at 2000 and 2006. The dataset used includes distance to main roads, distance to the residence region, elevation, slope, and distance to green space. Percent Area Match (PAM) obtained from modelling of these changes with ANN is equal to 90.47% and the accuracy achieved for urban growth modelling with Logistic Regression (LR) is equal to 88.91%. Percent Correct Match (PCM) and Figure of Merit for ANN method were 91.33% and 59.07% and then for LR were 90.84% and 57.07%, respectively.

**Keywords:** urban growth modelling, ANN, logistic regression, GIS

### INTRODUCTION

Urbanization is a worldwide phenomenon that has increased significantly in the last century (Aguilera *et al.*, 2011). During the past decades, urban growth has been accelerating with the massive immigration of population to cities. Urban population in the world is estimated at 2.9 billion in 2000 and predicted to reach 5.0 billion in 2030 (United Nations, 2007, Han *et al.*, 2009). Rapid urbanization and population growth have been a common phenomenon, especially in the developing countries with an increasing desire for prosperity which has imposed significant pressure on environmental and natural resources. This urban demographic shift has been accompanied with large-scale urban land expansion and the resultant loss of agricultural land throughout the country (Seto *et al.*, 2000; Tan *et al.*, 2005).

Urbanization can be defined as the changes that occur in the territorial and socio-economic progress of an area including the general transformation of land cover/use categories from being non-developed to developed (Weber, 2001, Pham *et al.*, 2011). Urban growth is recognized as physical and functional changes due to the transition of rural landscape to urban forms. It occurs when the

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population distribution changes from being village to town and city (Bhatta *et al.*, 2009). Many regions of the developing countries are experiencing rapid urban growth (Dewan and Yamaguchi, 2009). Socio-economic processes such as migration, urban sprawl, agriculture, and forest patterns often contribute to the urban growth (Antrop, 2005; Thapa and Murayama, 2009; Weng, 2007).

A vital component of the research on land use/cover change is the analysis of rates and patterns of land use change (GLP, 2005; Lambin and Geist, 2006; Rindfuss *et al.*, 2004; Turner *et al.*, 2007; Pijanowski and Robinson, 2011). Urban growth models have proved to be important tools to measure land-use change in peri-urban and rural regions (Clarke and Gaydos, 1998; Herold *et al.*, 2003; Mundia and Murayama, 2010; Tobler, 1970; White *et al.*, 1997). Geospatial information systems (GIS) have widely contributed to the advancement of studies that evaluate the evolution of the ecological and the social fabric of landscapes. However, there is an increasing interest in the use of spatial data and GIS in assessing visual attributes of the landscape (Ayad, 2005). This application of spatial models to achieve a balance between the environment and the management of scarce resources supports the adequate decision-making strategies. One of the key elements within the context of socio-economic land-use change is that within the inherent complexity of environmental change, man-induced change is fundamentally self-organized (Moussaïd *et al.*, 2009).

The technological development of remote sensing imagery with higher accuracy has led to the creation of high-resolution spatial imagery which makes it possible to extract more accurate topological and geo-morphological characteristics (Picón-Feliciano *et al.*, 2009; Sawaya *et al.*, 2003; White *et al.*, 2000), which are fundamental for spatial modelling experiments. The factors involved are of multiple dimensions including physical, environmental, social, economic, and political dimensions (Ding *et al.*, 2007, Qi Zheng *et al.*, 2012). Satellite data enable periodically repeated analysis and identification of the urban changes in the city and catchment areas and sea (water) pollution more accurately and rapidly (Coskun *et al.*, 2006; Fan *et al.*, 2007). To a great extent, acquiring accurate and timely information on the past history, present status, and trends of human-dominated ecosystem has attracted researchers and policy decision makers (Ozcan *et al.*, 2003; Zhang and Seto, 2011).

In this research we want to obtain an urban growth model using ANN and LR. Applications of LR for modelling urban growth are found in Cheng and Masser, 2003; Fang *et al.*, 2005; Hu and Lo, 2007; Huang *et al.*, 2009, 2010; Tayyebi *et al.*, 2010; Overmars *et al.*, 2003; Theobald and Hobbs, 1998. Artificial neural networks in land use change modelling have been used by Li and Yeh (2001), Weng (2002), Pijanowski *et al.* (2002) and Tayyebi *et al.* (2011).

## METHODOLOGY

### Logistic regression

Empirical estimation models use statistical techniques to model the relationships between land use changes and the drivers based on historic data. Statistical methods can easily recognize the effects of the independent variables and provide the reliability regarding their contribution. In many cases, empirical estimation models provide a good fit spatial processes and land use change outcome reasonably well (Irwin and Geoghegan, 2001). Urban growth modelling aims to understand the dynamic processes and, therefore, interpretability of models is becoming crucial. Logistic regression as a statistical technique is more general case of linear regression. Our aim is modelling the dynamics of the urban growth process and, on the other hand, the ability to interpret the models is very important. Due to the discrete nature of the land use change, a common method to approximate the logistic regression is to develop a function through which the development probability for each pixel is determined which of the observations are pixels. Binary dependent variables represent urban or non-urban status of the pixels in the corresponding period of the model output. This function is a monotone curvature and the output function is between zero and one. Equation 1 represents the regression function (Cheng and Masser, 2003).

URBAN GROWTH MODELLING WITH ARTIFICIAL NEURAL NETWORK AND LOGISTIC REGRESSION. CASE STUDY: SANANDAJ CITY, IRAN

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

where,

$P$  : Probability of land use change for each cell

$X_i$  : Effective parameters in urban growth

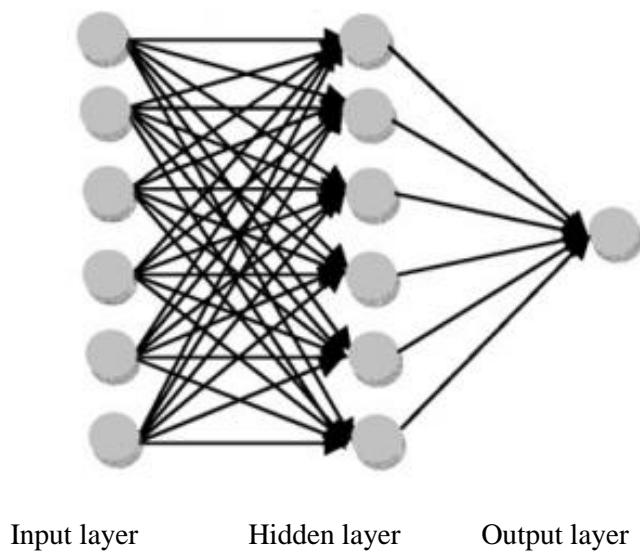
$B_0$  : Constant parameter

$B_i$  : Coefficients of each of the independent parameters that must be calculated

The output of the logistic regression is the probability of urban expansion by using variables that are exponential functions of their elements. Various coefficients are determined using the method of the least squares (Mohammady, 2013).

**Artificial neural network**

Artificial neural network (ANN) with learning ability can identify complex behaviours and patterns (Fisher *et al.*, 2000). Artificial neural networks with capacity of nonlinear, parallel and highly complex processing have been employed in many fields (Fisher *et al.*, 2000), climate forecasting (Panagoulia, 2006), agricultural land suitability assessment (Wang, 1994), remote sensing (Morris *et al.*, 2005), and land use (Zhang and Zhen, 2006; Pijanowski *et al.*, 2002; Tayyebi *et al.*, 2011). One type of urban growth model, the Land Transformation Model (LTM), offers methods for assessing these needs for further analysis with a flexible parameterization process using GIS technologies and machine learning, specifically artificial neural network (ANN) algorithms (Pijanowski *et al.*, 2002). Li and Yeh (2001) combined neural networks and cellular automata to simulate potential urban development patterns. Fischer and Sun (2001) developed a multi-layer, multi-units back-propagation neural net. The net contains a multiple unit input layer, a hidden layer with multiple units, and an output layer with only one unit. Figure 1 shows a typical feed-forward back-propagation neural network.

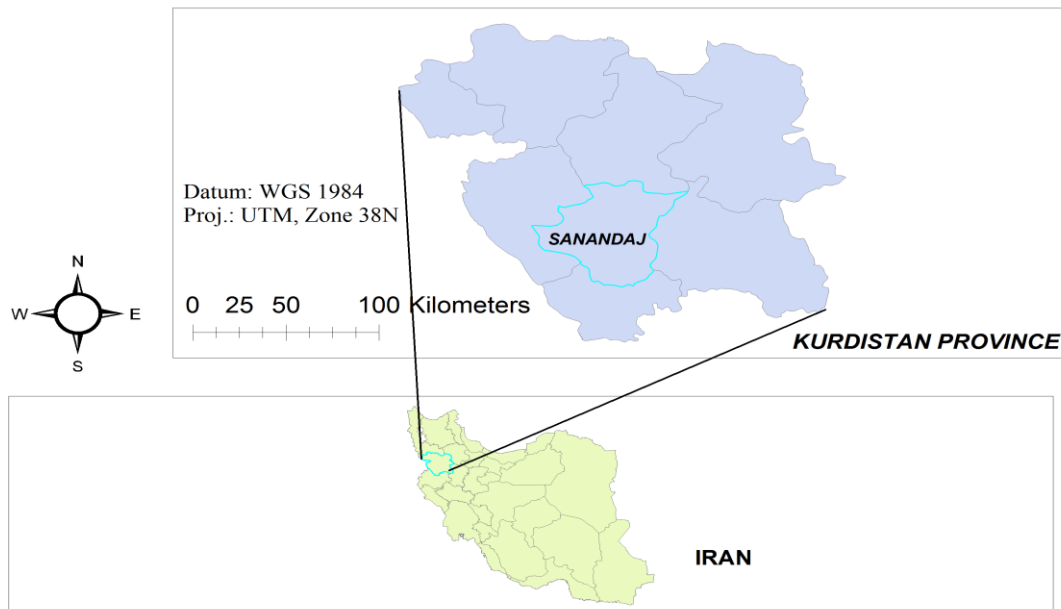


**Figure 1.** A typical feed-forward back-propagation neural network

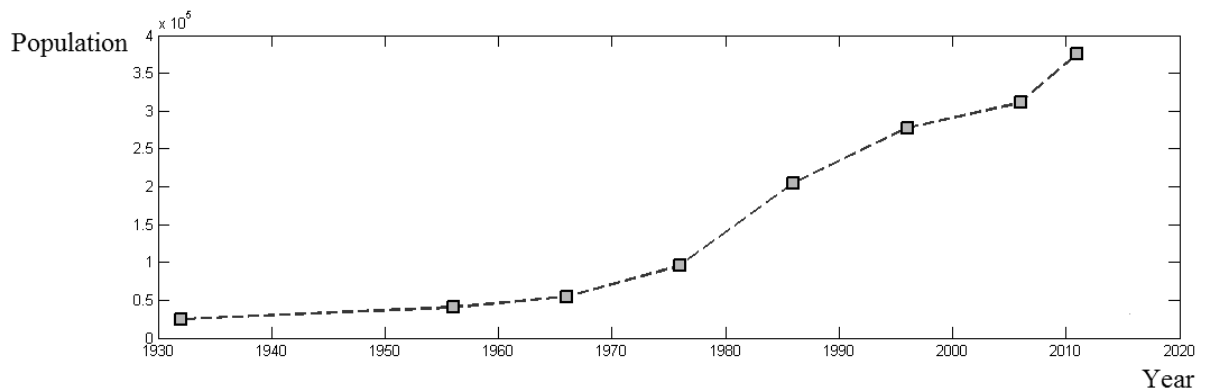
According to Kolmogorov’s theorem (Kolmogorov, 1957), if  $n$  is the number of neurons in the input layer,  $2n + 1$  hidden neurons can guarantee the perfect fit of any continuous functions and reduction of the neurons may lead to lesser accuracy. Neural network used in the model has 5 input nodes, 11 nodes in the hidden layer and 1 node for output layer. We use 10% of the data for training the net and 90% for checking the net. Net used delta method for adjusting error between nodes. We obtained 0.0316 for MSE in 500 cycles.

**STUDY AREA**

Our case study is the city of Sanandaj in Iran that covers around 3,688.6 (ha) with the geographical coordinates of 35° 18’ 40’’N and 46° 59’ 40’’E. Figure 2 shows the position of this city in Iran. This city has had a large urban population growth in the last decades. The most important reason of this growth is migration from its neighbourhood cities and provinces to this city. Figure 3 shows urban population growth in this city since 1930.



**Figure 2.** Study Area



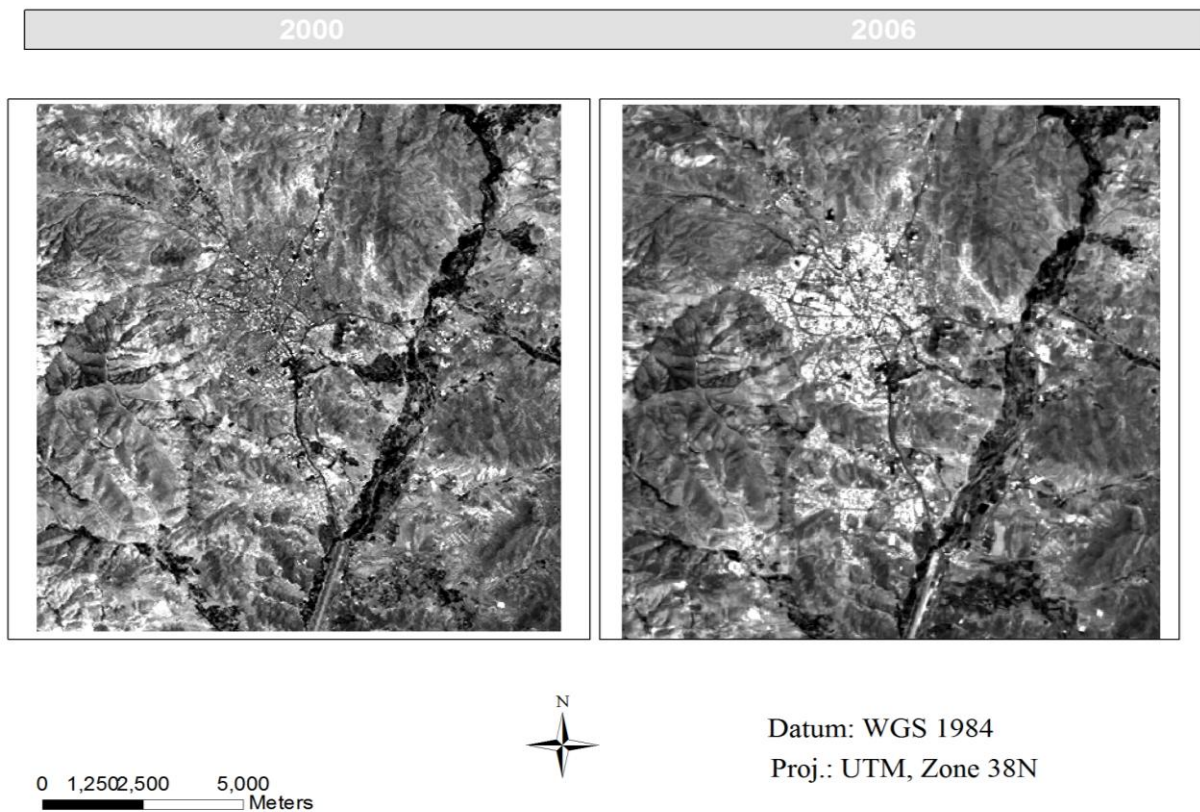
**Figure 3.** Sanandaj’s urban population growth

URBAN GROWTH MODELLING WITH ARTIFICIAL NEURAL NETWORK AND LOGISTIC REGRESSION. CASE STUDY: SANANDAJ CITY, IRAN

**DATA**

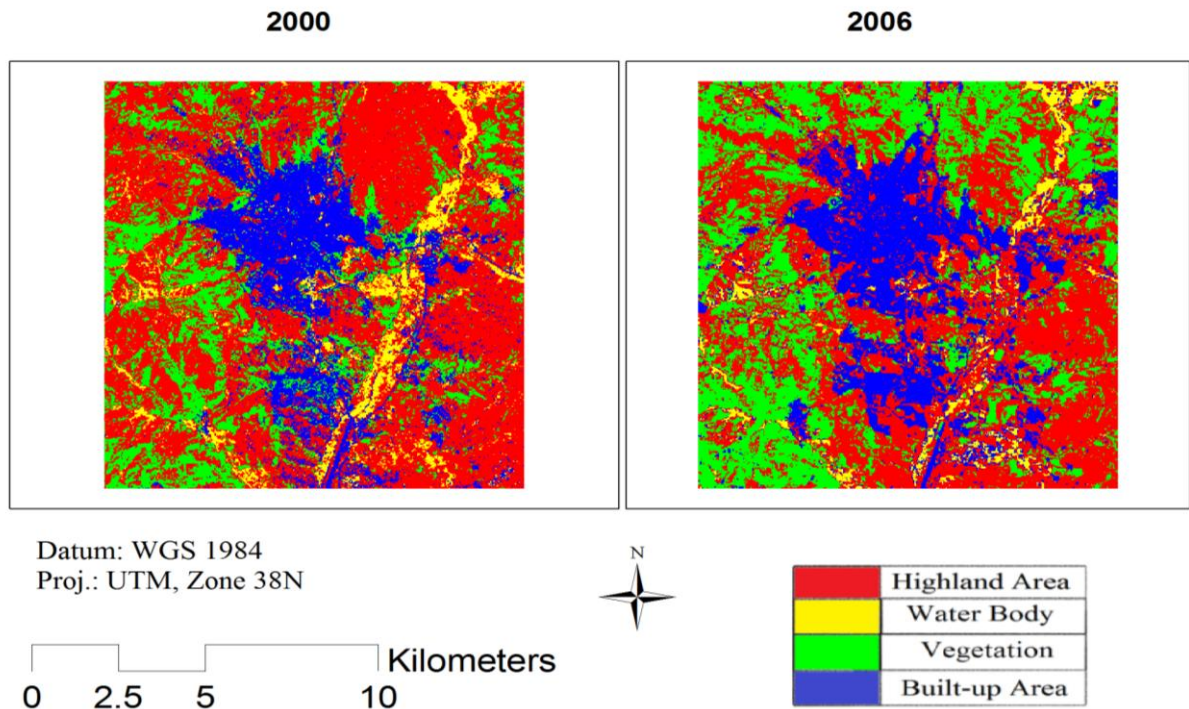
Remote Sensing and GIS have been recognized as powerful and effective science and technologies in monitoring environmental change at broad scales, especially in detecting the land use/land cover change (LUCC). Satellite imageries with temporal frequency as a reliable and accurate data sources are valuable data for analysing, monitoring and mapping urban growth and monitoring urban land use change (Im *et al.*, 2008; Goodchild, 2000), urban land use dynamics (Herold, 2003) and urbanization (Weng, 2007).

Data used in our research are Landsat TM and ETM<sup>+</sup> imageries related to years 2000 and 2006 (Figure 4) with pixel sizes of 28.5 and 30 meters, respectively. The main road map, attractive areas (such as parks), faults, slope, elevation, land use maps and others are also formatted in shapefile (.shp), using software ArcGIS 9.3 ESRI. All processes on satellite images are done using ENVI 4.7. Tables 1 and 2 express some statistics of Landsat satellite imageries classification evaluation.



**Figure 4.** *Sanandaj satellite imageries*

The related images are classified based on Anderson Level 1 with Maximum Likelihood classification. The results of the classification and accuracy of classification have been showed in Figure 5 and in Tables 1 and 2.



**Figure 5.** *Classified images*

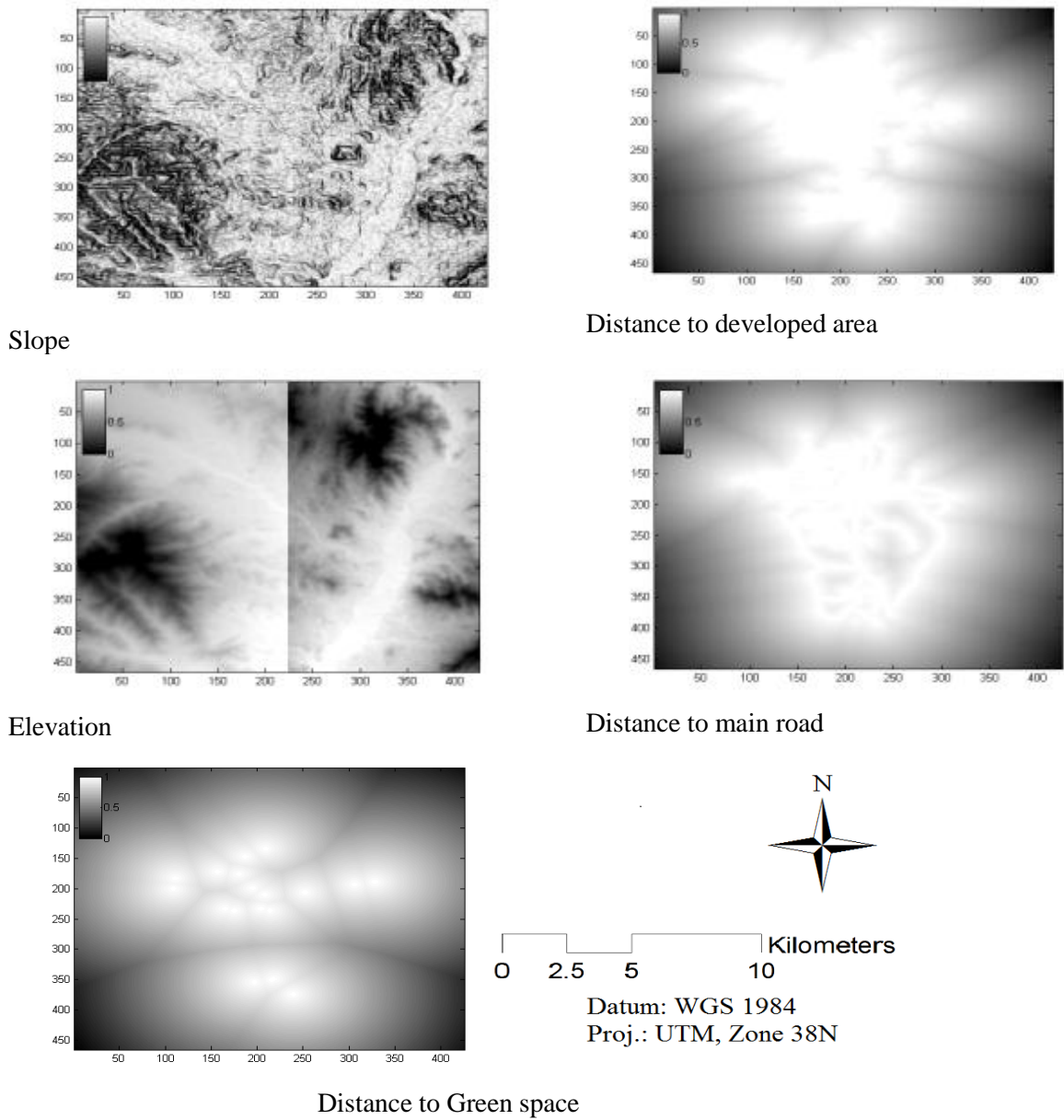
**Table 1.** *Accuracy totals (2000)*

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Water Body	123	120	120	97.56	100
Built-up Area	177	219	173	97.74	79
Highland Area	505	483	455	90.10	94.20
Vegetation	286	269	262	91.61	97.40
Total	1,091	1,091	1,010		

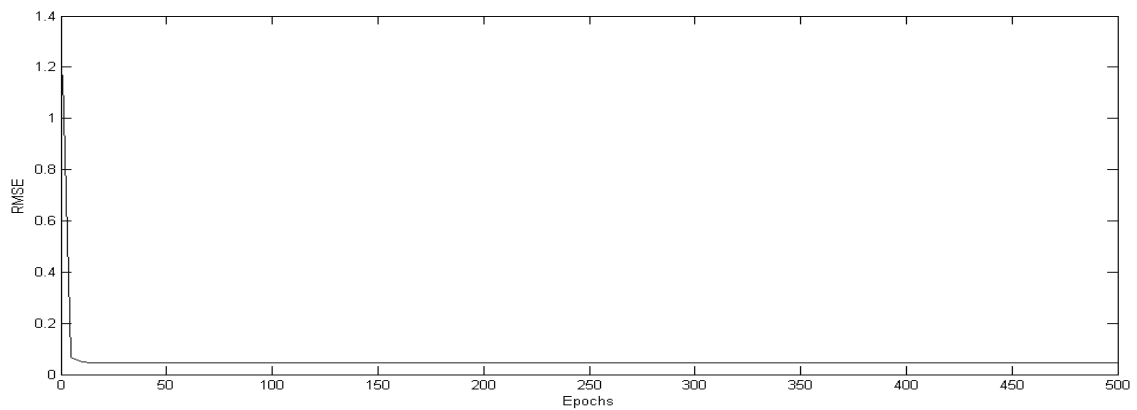
**Table 2.** *Accuracy totals (2006)*

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Water Body	118	147	117	99.15	79.59
Built-up Area	176	177	175	99.43	98.87
Highland Area	243	214	213	87.65	99.53
Vegetation	87	86	86	98.85	100
Total	624	624	591		

URBAN GROWTH MODELLING WITH ARTIFICIAL NEURAL NETWORK AND LOGISTIC REGRESSION. CASE STUDY: SANANDAJ CITY, IRAN



**Figure 6.** Normalized dataset parameters



**Figure 7.** Training error for ANN

**RESULTS AND ANALYSIS**

**Percent Correct Match (PCM)**

A way to evaluate models of urban development is PCM. In fact, this method only considers the special case of the comparison matrix as follows: 1) Urban development has taken place and model has been able to predict urban development; 2) Urban development has not occurred and model has been modelled correctly. This method compares only the parameters of the original diameter of the A and D matrices (Table 3). The Percent Correct Match (PCM) is calculated based on the Confusion matrix (Table 3) (Pontius and Schneider, 2001) using the equation below.

**Table 3.** 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

$$PCM = \frac{A + D}{A + B + C + D}$$

**Figure of Merit**

The Figure of Merit is another method to evaluate resemblance between two maps. It was first suggested by Pontius (2008). In land use change modelling, the Figure of Merit has been used for exhibiting resemblance between actual and simulated maps and was defined as a ratio, where the numerator is the number of pixels truly modelled as changes and the denominator is the union of changed pixels that are observed or predicted. If the simulated map has a high goodness of fit to the actual map, the Figure of Merit will be high and vice versa. The accuracy of land use changes is compared with the sum of land use changes that are only simulated, only in the actual data, or simulated and in the actual data.

- 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

$$Figure\ of\ Merit = \frac{b}{a + b + c + d}$$

Coefficients of the logistic regression are shown in Table 4. Covariance between parameters is shown in Table 6. Considering these factors, it can be claimed that the bigger the coefficient for a variable, the more important variable is in modelling and vice versa. In other words, urban development depends heavily on the accessibility.

**Percent Area Match (PAM)**

We also used a percent area match (PAM) metric to evaluate the Urban Growth Model (UGM). PAM compares areas that are predicted correctly to change according to the proposed UGM with areas that are converted to new areas in the observed map (Pontius and Millones, 2011):

$$Percent\ Area\ Match = \frac{Area\ predicted\ to\ change}{Actual\ area}$$



URBAN GROWTH MODELLING WITH ARTIFICIAL NEURAL NETWORK AND LOGISTIC REGRESSION. CASE STUDY: SANANDAJ CITY, IRAN

PAM is expressed as a percentage. Values less than 100 indicate that the model underestimates the size of the urban area; values greater than 100 indicate that the model overestimates the urban area.

**Table 4. Results of Logistic Regression**

Variable	Coefficient	Standard error
Distance to Residence region	8.205	0.943
Distance to Facility	-5.479	0.528
Elevation	0.314	0.231
Slope	-0.398	0.189
Distance to Main Road	13.492	0.971
<b>Constant</b>	<b>-21.476</b>	<b>0.900</b>

**Table 5. Description of parameters**

Variables	Description
Input 1	Distance to Residence Region
Input 2	Distance to fault
Input 3	Elevation
Input 4	Slope
Input 5	Distance to Main Road

**Table 6. Covariance between parameters**

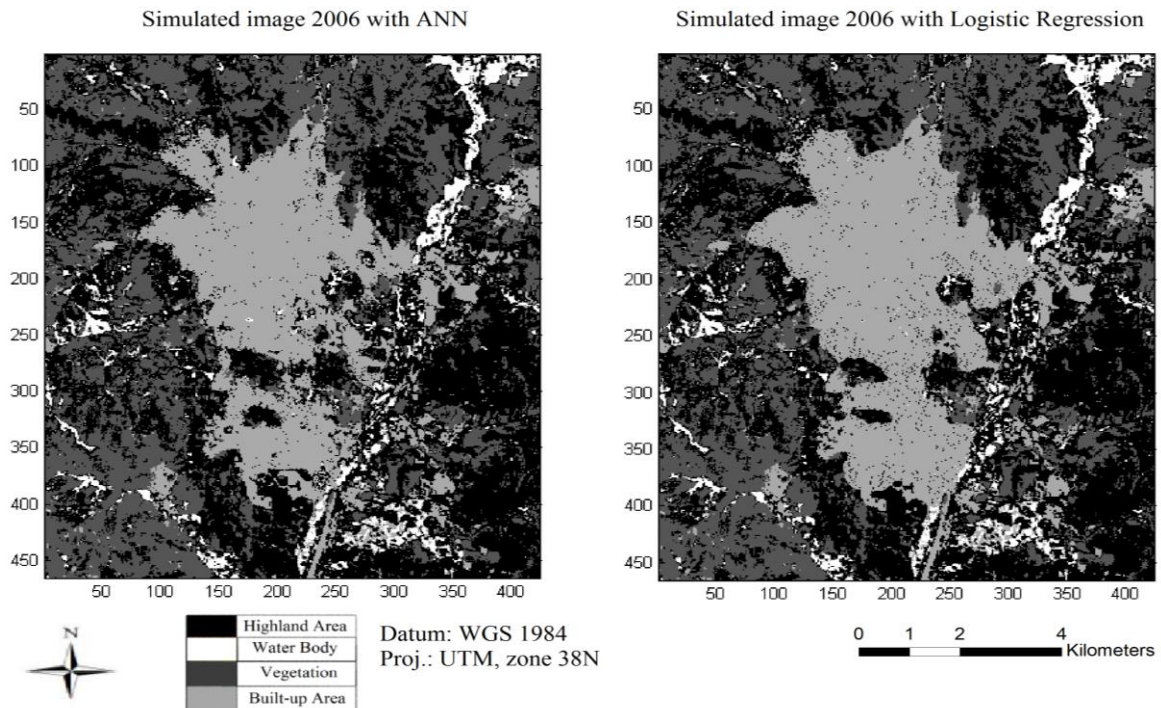
Variables	Input 1	Input 2	Input 3	Input 4	Input 5
Input 1	1	-.363	-.047	.051	-.241
Input 2	-.363	1	-.146	.041	-.430
Input 3	-.047	-.146	1	-.293	.071
Input 4	.051	.041	-.293	1	-.007
Input 5	-.241	-.430	.071	-.007	1

**Table 7. Results of ANN and Logistic Regression**

Method	PCM (%)	Figure of Merit (%)
ANN	91.33	59.07
Logistic Regression	90.84	57.07

**Table 8. PAM values for different methods**

Method	PAM	Area actually transitioning (km <sup>2</sup> )	Area predicted to change (km <sup>2</sup> )
ANN	90.47%	14.4124	12.8596
Logistic Regression	88.91%	14.4124	12.6386



**Figure 8.** Results of modelling using ANN and logistic regression

## DISCUSSION

In Iran, policy makers, urban planners and natural resource managers have begun to propose the use of Urban Growth Boundaries (UGBs), both locally and nationally (Tayyebi *et al.*, 2001). Recently, policies related to land use and urban growth intend to support efficient use of land and natural resources (Tayyebi *et al.*, 2001). Thus, Urban Growth Models (UGMs) are powerful tools for urban planners and decision makers to manage and analyse the expansion of cities.

Combination of Geospatial Information Systems tools and remote sensing data has the potential to support such models by providing data and analytical tools for the study of urban planning. This combination can be a useful method for analysing and modelling environmental phenomena such as urban growth.

## CONCLUSIONS

This paper presented two methods to simulate the urban growth modelling and it presented the models ANN and Logistic Regression, employed in order to predict dynamic urban growth in Sanandaj city, Iran. Dataset included distance to main roads, distance to residence region, elevation, slope, and distance to green space. There was no huge covariance between parameters and as a result we used all the proposed parameters for modelling urban growth for Sanandaj city.

There was no huge covariance between these inputs and it was assumed that they were independent parameters. The coefficients obtained from LR method showed that distance to main road had the biggest impact on urban growth in this area and, on the other hand, elevation had the minimum impact.

We used multi factor to evaluate our results. The accuracy of results of modelling with ANN for PAM, PCM and the Figure of Merit were 90.47%, 91.33%, and 59.07%, respectively, and for Logistic Regression were 88.91%, 90.84%, and 57.07%, respectively. In other words, ANN had a better performance than LR in modelling urban growth in this area.

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URBAN GROWTH MODELLING WITH ARTIFICIAL NEURAL NETWORK AND LOGISTIC  
REGRESSION. CASE STUDY: SANANDAJ CITY, IRAN

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