Different Method to find Optimum Training Data in Artificial Neural Network (ANN) for Urban Growth Modeling Case Study: Sanandaj City in IRAN

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Paper Reference Number: 07-89-5301
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Abstract

Different approaches have been attempted in spatial modeling. Artificial Neural network (ANN) models are knowledge-based models and fit within the regression type models of land use changes. ANNs are powerful tools that use a machine learning approach to quantify and model complex behavior and patterns. In this research we use artificial neural networks and our case study is Sanandaj .We use Landsat imagery, taken in 2000 - 2006.Our parameters in this study are: distance to principle roads, distance to residence region, Elevation, Slope, distance to faults, distance to facilities, distance to downtown and the number of urban pixels in an neighborhood with radius of 1 pixel. Finally we predict land us change for 2012.

Key words: Artificial Neural Network, Urban Growth Modelling

1. Introduction

Urban growth boundaries, or UGBs, are planning tools used by local governments to constrain urban development to a fixed area (Calthorpe et al, 2001). Urban growth modeling aims to understand the dynamic processes, and therefore interpretability of models is becoming crucial (Zhiyong Hu a et al, 2007). Local governments that implement UGBs need to estimate the amount of urban land required in the future given anticipated growth of housing, business, recreation and other urban uses required within the boundary. The boundary most frequently occurs across several local government units, and as such, is considered to be a regional planning tool (American Planning Association, 2002). Urban growth is a complex process that encounters a number of sophisticated parameters that interact to produce the urban growth pattern (Zhiyong Hu, 2007). In urban growth, (Pijanowski et al., 2002) integrate both the artificial neural network and geographic information systems for the purpose of forecasting the change in land use.

2. Data and Material

Remote sensing techniques and the availability of free to less expensive data sources of satellite imagery and their temporal frequency has greatly enhanced the potential for monitoring urban growth (Im, J.,2008, Goodchild, M.F.2000), urban land use dynamics

(Herold, M,2003), landscape pattern analysis (Li, X,2004), and urbanization (Weng, Y,2007). The study area in this research is the city of Sanandaj, Iran. Data used in our research, come from two satellite images related to years 2000 and 2006 from land set satellite and are from TM & ETM$^+$ sensors which, they have Earth pixel size of 28.5 meters. The main road map, attractive areas (such as Parks), Faults, Slope, Elevation, Land use maps and others also are formatted in Shape file, using software Arc GIS 9.3 ESRI. All processes on satellite images are done using software ENVI 4.7. Distance to main road, distance to attractive areas (such as Parks), distance to Faults, Slope, Elevation, distance to downtown, distance to residence region will be normalized before using them.

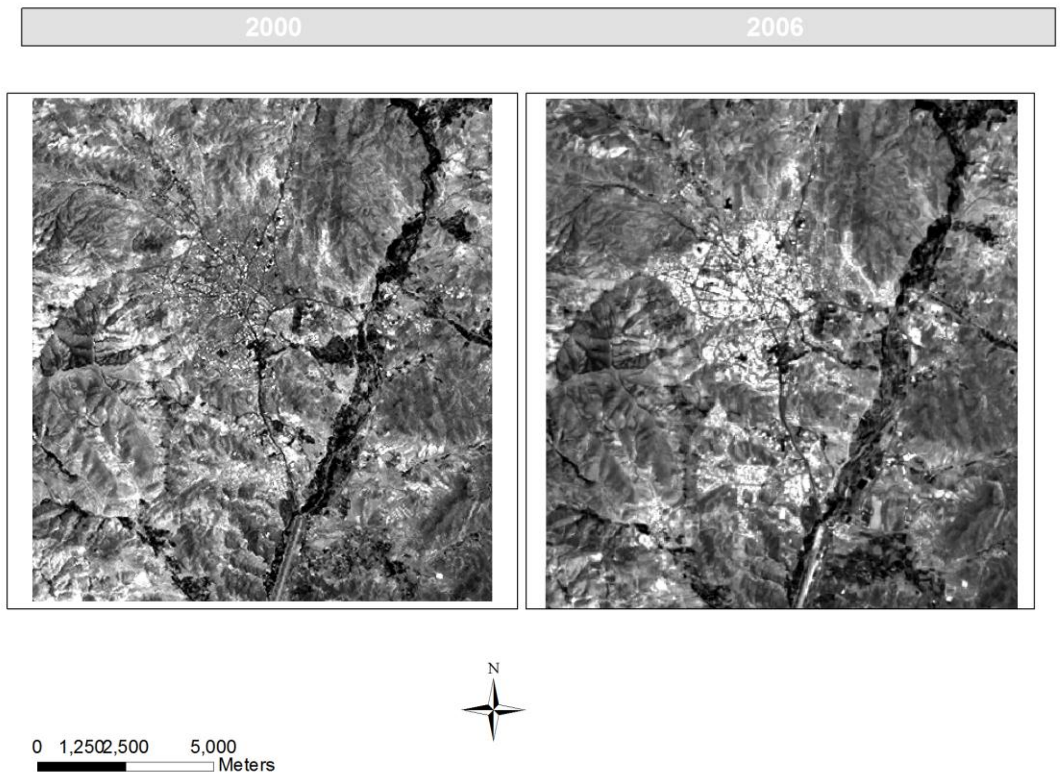

Fig.1 Satellite images of Sanandaj in 2000 and 2006,respectively

2.1 Artificial Neural Network (ANN)

ANN is composed of many non-linear processing units that are connected to each other and collectively perform a single task. One of the main properties of an ANN is the ability to learn 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. During learning, known input-output pairs (e.g. historical data), 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 (Zhang et al, 1998, Padmanaban, R.C, 2012) (Fig2). Artificial Neural network due to the possibility of learning, is an appropriate tool for environmental modeling. These networks are composed of three layers: 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.

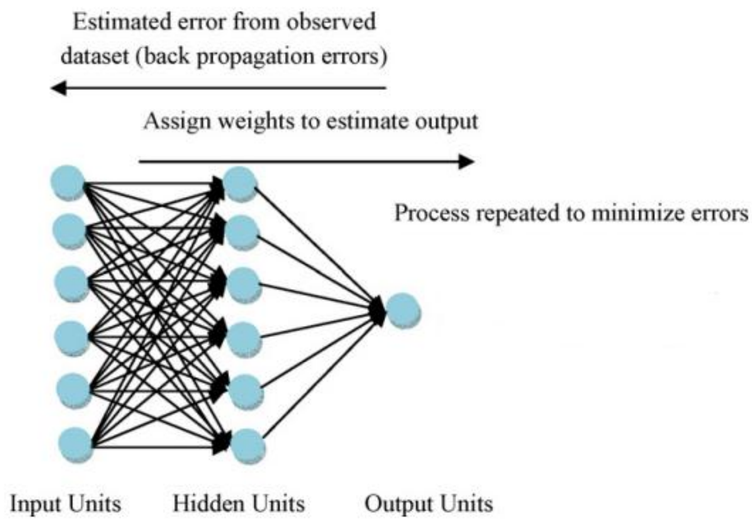

Fig2. A typical architecture of feed-forward back propagation ANN.(Tayyebi, 2011)

3. Research Methodology

In urban growth modeling, one of the most important problem that we deal with is large volume of data and limited performance of computers. If we use all of data, that is time consuming and as a result, we must descend volume of input data for solving this problem. In this study we use random selection method for input data. We choose pixels randomly in space of map. 19500 pixels (10% of data) for learning our network and other pixels (90% of data) for checking will be used. The input of the neural network for modeling urban development, are 8 parameters that we mentioned them and output parameter is being urban or non-urban.

4. Results and Analysis

4.1 Kappa Statistics

Kappa coefficient, a statistical method for evaluating models of urban development in general is widely used in spatial issues. This coefficient shows the rate of compatibility between simulated and reality. In other words, this factor can be used to measure the spatial distribution of the amount of similarities between the two maps. It is generally considered that 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 (Pijanowski et al., 2005). The calculation of Kappa is based on contingency table (Monserud et al, 1992) (Table 1).

		Model					Total
	Class	1	2	…	c		
Reality	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

$$P(A) = \sum_{i=1}^{c} P_{ii} \quad (3)$$

$$P(E) = \sum_{i=1}^{c} P_{iT}.P_{Ti} \quad (4)$$

$$KS = \frac{P(A) - P(E)}{1 - P(E)} \quad (5)$$

Table1.The Contingency Table

4.2 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 is as follows.1) In fact, urban development has taken place and model been able to predict urban development. 2) In fact urban development has not occurred and model has been modeled correctly. This method compares only the parameters of the original diameter of the A and D matrices are used to assess the shortcomings of this method is considered. The Percent Correct Match (PCM) is calculated based on Confusion matrix (table2). (Pontius et al, 2001)

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

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

Table2.Confusion Matrix

The simulation of 2006 from the 2000 was executed for the 6 years period. The simulated 2006 map was validated with the actual map of 2006, by comparing the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) matches using both maps. The overlay map of the simulated and actual 2006 maps is presented in Figure 3. A performance matrix derived from the result shown in Figure 3 is given in Table 3.

Table3**.** Performance matrix

	Reference Data 2006	
	Developed	**Undeveloped**
Simulated Data 2006		
Developed	**18709 (TP)**	**4368 (FP)**
Undeveloped	**6240(FN)**	**148546 (TN)**

The computed Kappa statistics is 0.7447, and PCM is 94.04%. Based on the earlier work (Pijanowski, et al., 2005) Kappa values calculated for simulated land use map seems very good.

5. Conclusions

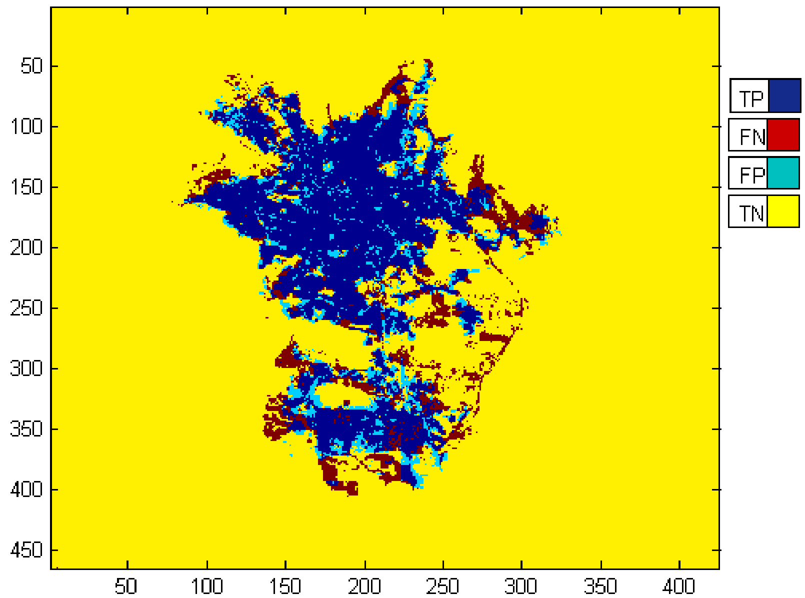

Fig 3. Simulation result of 2006.

In this paper, we simulated urban growth modeling for Sanandaj city in Iran. The computed kappa statistics and PCM was 0.7447 and 94.04% respectively. And we can say our simulation results have a very good agreement with our reference data (according to Pijanowski, et al., 2005). Urban growth map for 2012 are shown in Fig.4.

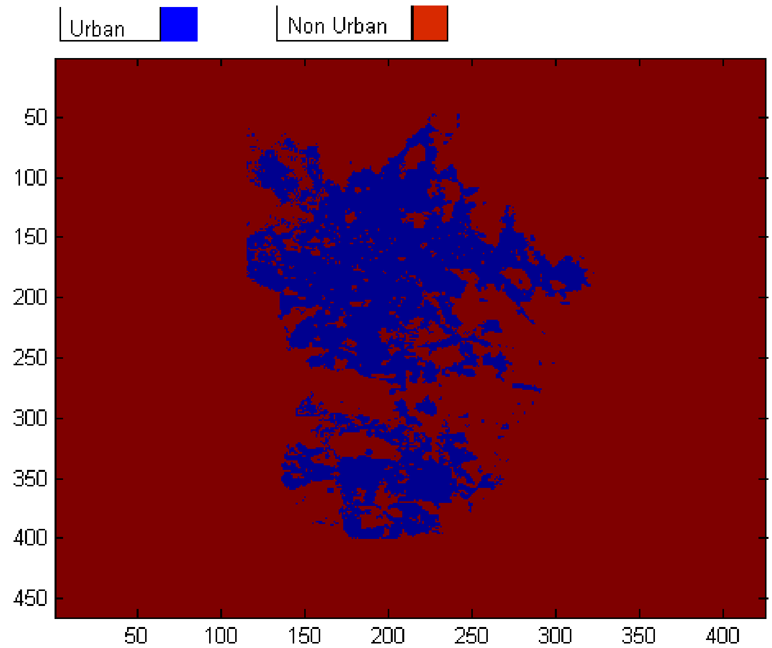

Fig 4.Prediction for 2012

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