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

SASSAN MOHAMMADY[1], MAHMOUD R. DELAVAR[2], BRYAN C. PIJANOWSKI[3]

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$^+$ 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

[1] GIS MSc. student, Dept. of Surveying and Geomatic Eng., College of Eng., University of Tehran, Tehran, Iran
E-mail: Sassanmohammady@ut.ac.ir
[2] Assistant Professor, Ph.D., Center of Excellence in Geomatic Eng. in Disaster Management, Dept. of Surveying and Geomatic Eng., College of Eng., University of Tehran, Tehran, Iran
E-mail: mdelavar@ut.ac.ir
[3] Professor, Ph.D., Dept. of Forestry and Natural Resources, College of Agriculture, Purdue University, West Lafayette, IN 47907, USA
E-mail: bpijanow@purdue.edu

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).

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

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.

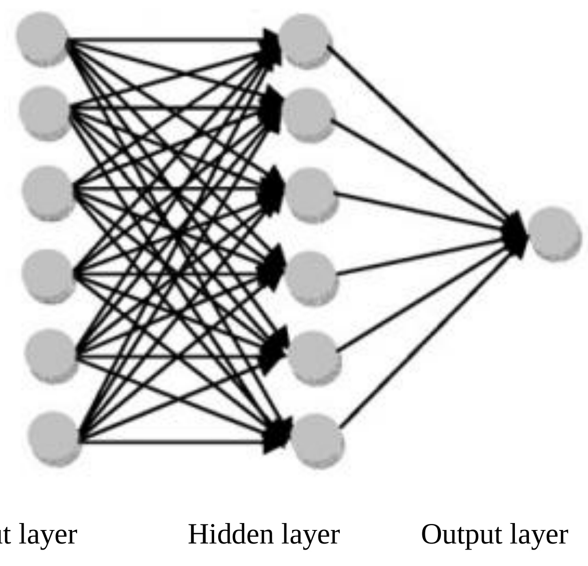


Figure 1. *A typical feed-forward back-propagation neural network*

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 35º 18' 40"N and 46º 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.

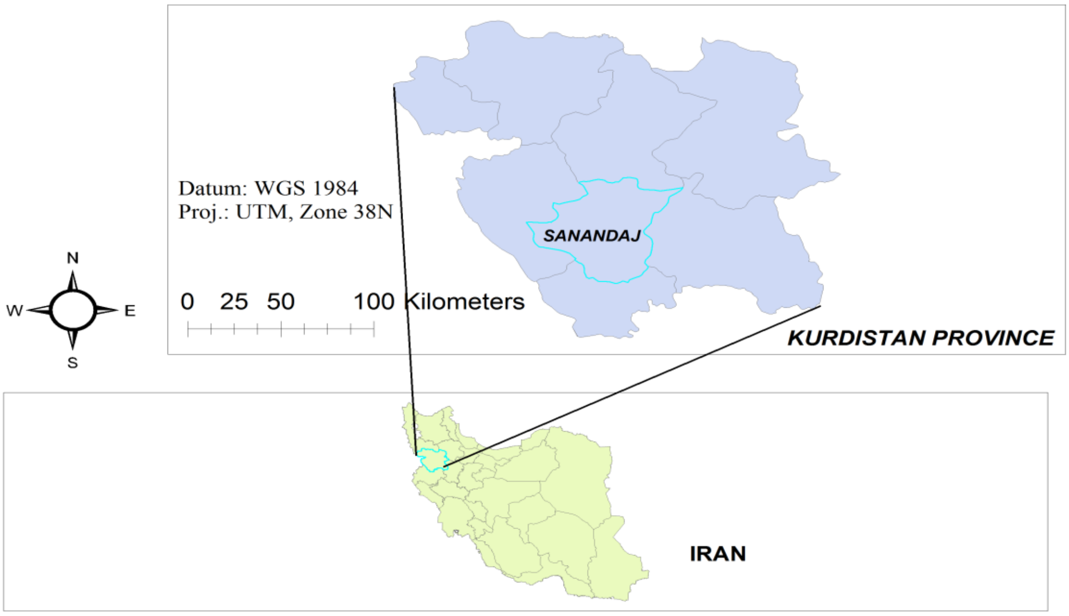


Figure 2. *Study Area*

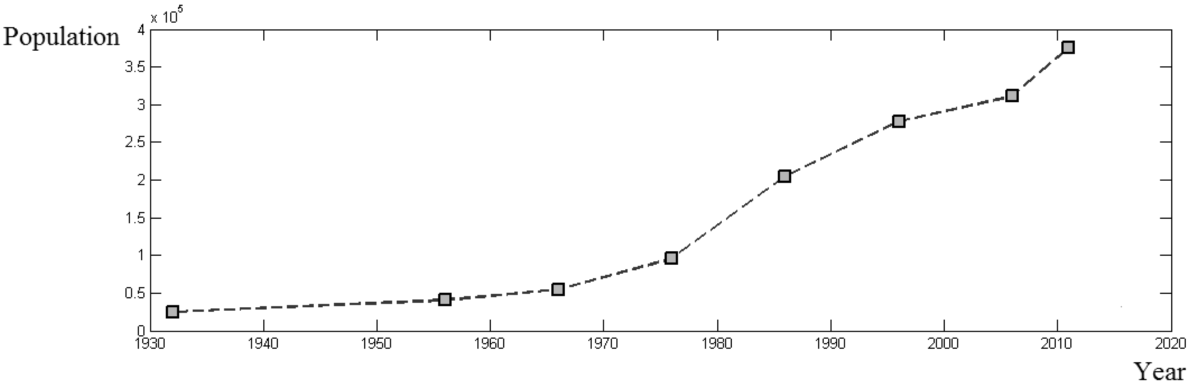


Figure 3. *Sanandaj's urban population growth*

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^+ 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.

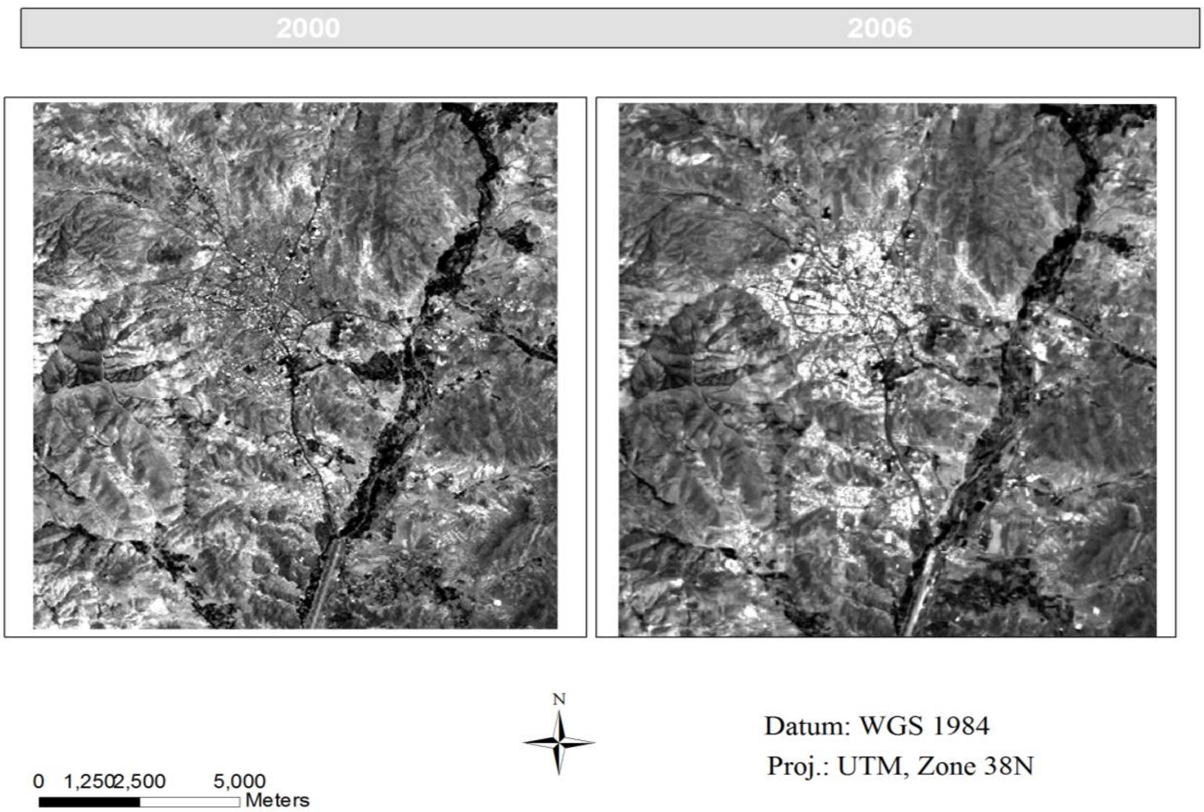


Figure 4. *Sanandaj satellite imageries*

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.

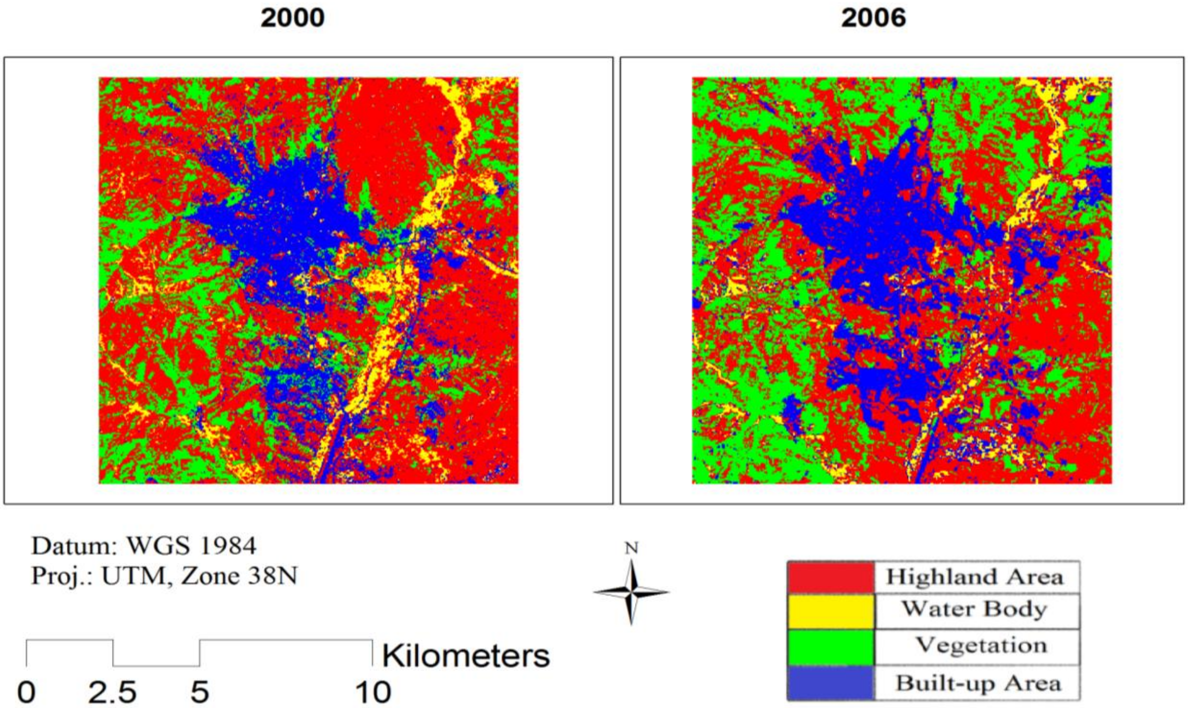


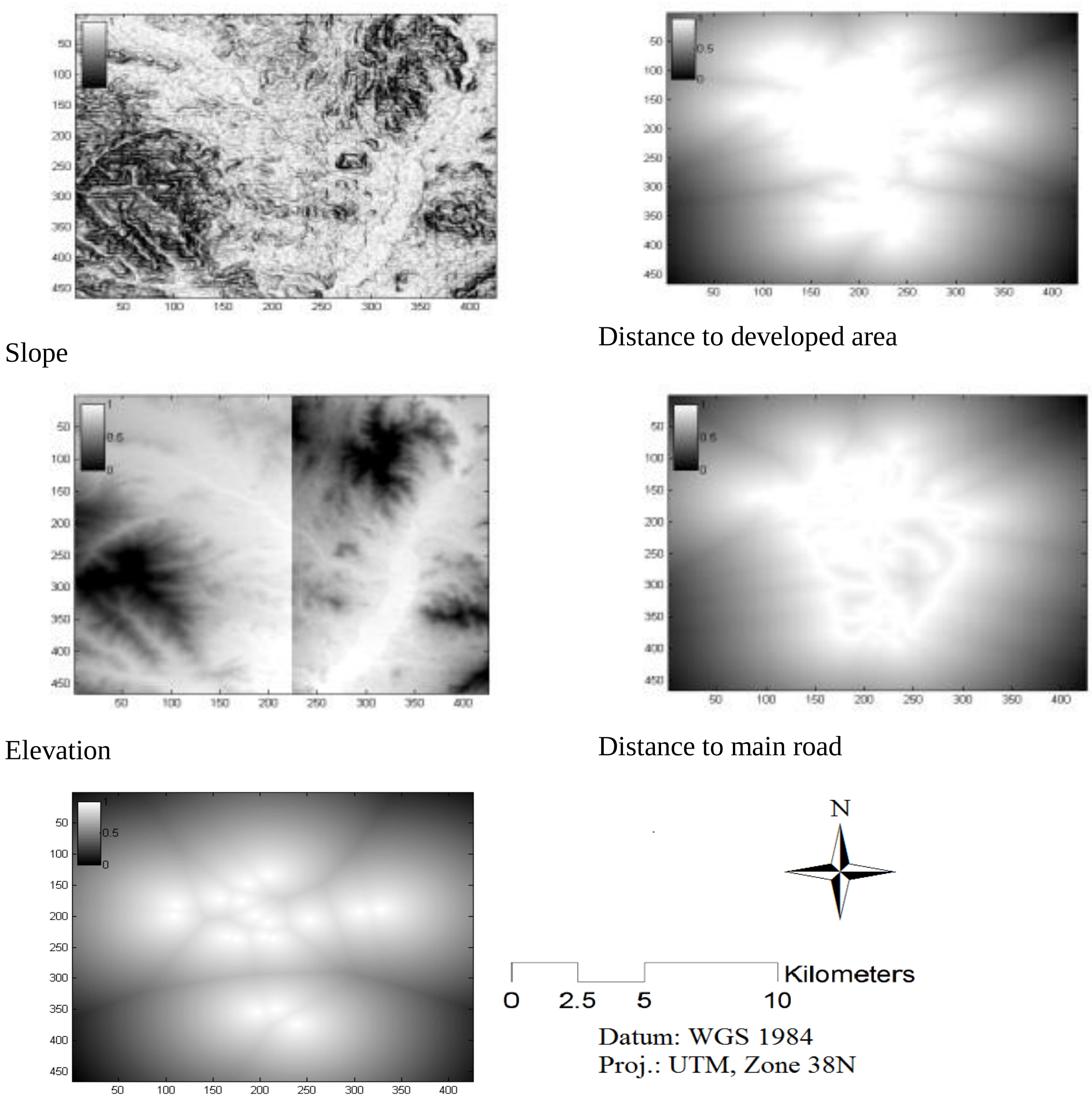
Figure 5. *Classified images*

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		



Distance to Green space

Figure 6. *Normalized dataset parameters*

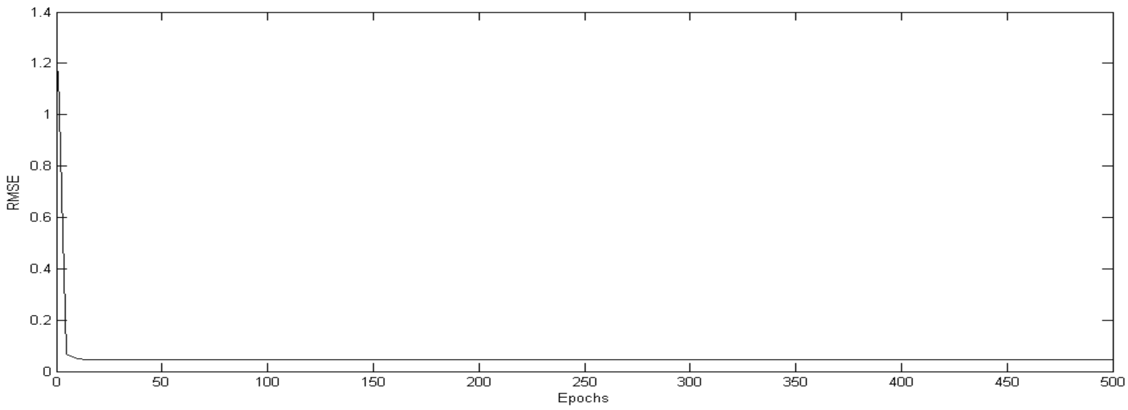


Figure 7. *Training error for ANN*

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):

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

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
Constant	**-21.476**	**0.900**

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 (km2)	Area predicted to change (km2)
ANN	90.47%	14.4124	12.8596
Logistic Regression	88.91%	14.4124	12.6386

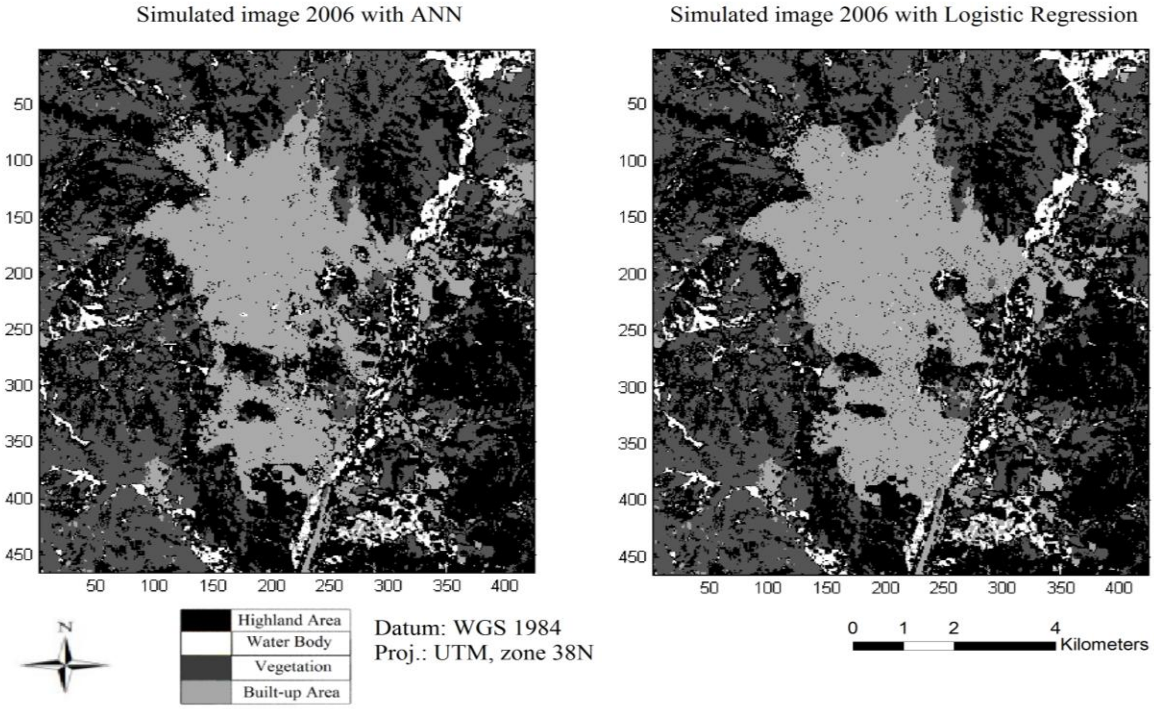


Figure 8. *Results of modelling using ANN and logistic regression*

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.

REFERENCES

AGUILERA, F., VALENZUELA, L. M., BOTEQUILHA-LEITÃO, A. (2011), Landscape metrics in the analysis of urban land use patterns: A case study in a Spanish Metropolitan area, *Landscape and Urban Planning*, 99, pp. 226–238.

ANTROP, M. (2005), Why landscapes of the past are important for the future, *Landscape and Urban Planning*, 70, pp. 21–34.

AYAD, Y.M. (2005), Remote sensing and GIS in modelling visual landscape change: a case of the northwestern arid coast of Egypt, *Landscape and Urban Planning*, 73 (4), pp. 307–325.

BHATTA, B., SARASWATI, S., BANDYOPADHYAY, D. (2009), Urban growth is a spatial and demographic process and refers to the increased importance of towns and cities as a concentration of population within a particular economy and society, *Applied Geography*, 30, pp. 96–111.

CHENG, J., MASSER, I. (2003), Urban growth pattern modelling, a case study of Wuhan, P.R.China, *Landscape and Urban Planning*, 62(4), pp. 199-217.

COSKUN, H. G., BAYRAKTAR, O., YILMAZ, L. (2006), Monitoring of protected bands of Terkos drinking water reservoir of metropolitan Istanbul near the Black Sea coast using satellite data, *International Journal of Applied Earth Observation and Geoinformation* 8, pp. 49-60.

CLARKE, K.C., GAYDOS, L. (1998), Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington-Baltimore, *International Journal of Geographical Information Science*, 12, pp. 699–714.

DEWAN, A. M., YAMAGUCHI, Y. (2009), Land use and land cover change in Greater Dhaka, Bangladesh: using remote sensing to promote sustainable urbanization, *Applied Geography*, 29, pp. 390–401.

DING, H., WANG, R. C., WU, J. P., ZHOU, B., SHI, Z., & DING, L. X. (2007), Quantifying landuse change in Zhejiang Coastal Region China using multi-Temporal temporal Landsat TM/ETM+ images, *Pedosphere*, 17, pp. 712–720.

FAN, F. L., WENG, Q. H., WANG, Y. P. (2007), Land use and land cover change in Guangzhou, China, from 1998 to 2003, based on Landsat TM/ETM+ Imagery, *Sensors*, 7, pp. 1323–1342.

FANG, S., GERTNER, G. Z., SUN, Z., ANDERSON, A. A. (2005), The impact of interactions in spatial simulation of the dynamics of urban sprawl, *Landscape and Urban Planning*, 73, pp. 294–306.

FISCHER, G., SUN, L. X. (2001), Model based analysis of future land-use development in China, *Agriculture, Ecosystems and Environment*, 85, pp. 163–176.

FISHER, M. M., ABRAHART, R. J. (2000), Neurocomputing – tools for geographers, In: Openshaw S., Abrahart R.J. (eds), *Geocomputation*, Taylor & Francis, New York, pp. 187-217.

GLP (Global Land Project) (2005), *Science plan and implementation strategy*, IGBP Report No. 53/IHDP Report No. 19., IGBP Secretariat, Stockholm, 64 p.

GOODCHILD, M. F. (2000), Spatial analysis: Methods and problems in land use management,In: Hill, M. J., Aspinall, R. J. (eds.), *Spatial Information for Land Use Management*, Gordon and Breach Science Publishers, Singapore, pp. 39-50.

HAN, J., HAYASHI, Y., CAOB, X., IMURA, H. (2009), Application of an integrated system dynamics and cellular automata model for urban growth assessment: A case study of Shanghai, *Landscape and Urban Planning*, 91, pp. 133-141.

HEROLD, M., GOLDSTEIN, N., CLARKE K. (2003), The spatio-temporal form of urban growth: Measurement, analysis and modelling, *Remote Sensing of Environment*, 85, pp. 95–105.

HU, Z, LO, C. P. (2007), Modelling urban growth in Atlanta using logistic regression, *Computers, Environment and Urban Systems*, 31, pp. 667–688.

HUANG, J, TU, Z, LIN, J. (2009), Land use dynamics and landscape pattern change in a coastal gulf region, southeast China, *International Journal of Sustainable Development and World Ecology*, 16(1), pp. 61-66.

IM, J., JENSEN, J., TULLIS, J. (2008), Object-based change detection using correlation image analysis and image segmentation, *International Journal of Remote Sensing*, 29, pp. 399-423.

IRWIN, E. G., GEOGHEGAN, J. (2001), Theory, data, methods: developing spatially explicit economic models of land use change, *Agriculture, Ecosystems and Environment*, 85, pp. 7–24.

KOLMOGOROV, A. N. (1957), On the Representation of Continuous Functions of Several Variables by Superposition of Continuous Functions of one Variable and Addition, *Doklady Akademii. Nauk SSSR*, 114, pp. 679-681.

LAMBIN, E. F., GEIST, H. (eds.) (2006), *Land-use and land-cover change: Local Processes and global impacts*, Springer, New York.

LANDIS, J., ZHANG, M. (1998), The second generation of the California urban futures model, *Environment and Planning B: Planning and Design*, 25, pp. 795–824.

LI, X., YEH, A. G. (2001), Calibration of cellular automata by using neural networks for the simulation of complex urban systems, *Environmental and Planning*, A 33, pp. 1445–1462.

LI, X., YEH, A. G. (2004), Analyzing spatial restructuring of land use patterns in a fast growing region using remote sensing and GIS, *Landscape and Urban Planning*, 69, pp. 335-354.

MUNDIA, C. N., MURAYAMA, Y. (2010), Modelling spatial processes of urban growth in African cities: A case study of Nairobi city, *Urban Geography*, 31(2), pp. 259–272.

MOHAMMADY, S. (2013), *A Logistic Regression Method for Urban Growth Modelling. Case Study: Sanandaj City in IRAN*, 7th SASTech, Bandar-Abbas, Iran, March, 2013.

MOUSSAÏD, M., HELBING, D., GARNIER, S., JOHANSSON, A., COMBE, M., THERAULAZ, G. (2009), Experimental study of the behavioral mechanisms underlying self-organization in human crowds, *Proceedings of Biological Sciences/the Royal Society*, 276(1668), pp. 2755–2762.

MORRIS, J., PORTER, D., NEET, M., NOBLE, P. A., SCHMIDT, L., LAPINE, L. A., JENSEN, J. R. (2005), Salt and brackish marsh characterization at North Inlet, SC using LIDAR- derived elevation data and land cover extracted from multispectral imagery using a neural network, *International Journal of Remote Sensing*, 26, pp. 5221-5234.

OVERMARS, K. P., KONING, G. H. J., VELDKAMP, A. (2003), Spatial autocorrelation in multi-scale land use models, *Ecological Modelling*, 164, pp. 257–270.

OZCAN, H., CETIN, M., DIKER, K. (2003), Monitoring and assessment of land use status by GIS, *Environmental Monitoring and Assessment*, 87, pp. 33–45.

MCNELIS, P. D. (2004), *Neural Networks in Finance: Gaining Predictive Edge in the Market*, Academic Press Advanced Finance Series.

PANAGOULIA, D. (2006), Artificial neural networks and high and low flows in various climate regimes, *Hydrological Sciences Journal*, 51(4), pp. 563-587.

PIJANOWSKI, B. C., BROWN, D.G., SHELLITO, B. A., MANIK, G. A. (2002), Using neural networks and GIS to forecast land use changes: a land transformation model, *Computers, Environment and Urban Systems*, 26 (6), pp. 553–575.

PIJANOWSKI, B. C., ROBINSON, K. D. (2011), Rates and patterns of land use change in the Upper Great Lakes States, USA: A framework for spatial temporal analysis,*Landscape and Urban Planning*, 102, pp. 102–116.

PONTIUS Jr., R. G., SCHNEIDER, L. C. (2001), Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA, *Agriculture, Ecosystems & Environment*, 85(1-3), pp. 239-248.

PONTIUS Jr., R. G., BOERSMA, W., CASTELLA, J. C., CLARKE, K., DE NIJS, T., DIETZEL, C., ZENGQIANG, D., FOTSING, E., GOLDSTEIN, N., KOK, K., KOOMEN, E., LIPPITT, C. D., MCCONNELL,W., PIJANOWSKI, B., PITHADIA, S., SOOD, A. M., SWEENEY, S., TRUNG, T. N., VELDKAMP, A. T., VERBURG, P. H. (2008), Comparing the input, output, and validation maps for several models of land change, *Annals of Regional Science*, 42, pp. 11-47.

PONTIUS Jr., R. G., MILLONES, M. (2011), Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment, *International Journal of Remote Sensing*, in press.

PHAM, H. M., YAMAGUCHI, Y., BUI, T. Q. (2011), A case study on the relation between city planning and urban growth using remote sensing and spatial metrics, *Landscape and Urban Planning*, 100, pp. 223–230.

PICÓN-FELICIANO, A. J., VÁSQUEZ, R., GONZÁLEZ, J., LUVALL, J., RICKMAN, D. (2009), Use of remote sensing observations to study the urban climate on tropical coastal cities, *Revista Umbral*, 1, pp. 218–232.

QI ZHENG, X., ZHAO, L., XIANG, W. N., LI, N., LV, L. N., YANG, X. (2012), A coupled model for simulating spatio-temporal dynamics of land-use change: A case study in Changqing, Jinan, China, *Landscape and Urban Planning*, 106, pp. 51– 61.

RINDFUSS, R. R., WALSH, S. J., TURNER, B. L., FOX, J., MISHRA, V. (2004), Developing a science of land change: Challenges and methodological issues,*Proceedings of the National Academy of Sciences of the United States of America*, 101(39), pp.13976–13981.

SETO, K. C., KAUFMANN, R. K., WOODCOCK, C. E. (2000), Landsat reveals China's farm-land reserves, but they're vanishing fast, *Nature*, 406(13), p.121.

SAWAYA, K. E., OLMANSON, L. G., HEINERT, N. J., BREZONIK, P. L., BAUER, M E. (2003), Extending satellite remote sensing to local scales: Land and water resources monitoring using high-resolution imagery, *Remote Sensing of Environment*, 88, pp. 144–156.

TAN, M., LI, X., XIE, H., LU, C. (2005), Urban land expansion and arable land loss in China – A case study of Beijing-Tianjin-Hebei region, *Land Use Policy*, 22(3), pp. 187–196.

THEOBALD, D. M., HOBBS, N. T. (1998), Forecasting rural land use change: A comparison of regression- and spatial transition-based models, *Geographical & Environmental Modelling* 2(1), pp. 65-82.

THAPA, R. B., MURAYAMA, Y. (2009), Examining spatiotemporal urbanization patterns in Kathmandu valley, Nepal: remote sensing and spatial metrics approaches, *Remote Sensing*, 1, pp. 534–556.

TURNER, B. L., LAMBIN, E. F., REENBERG, A. (2007), The emergence of land change science for global environmental change and sustainability, *Proceedings of the National Academy of Sciences of the United States of America*,104(52), pp. 20666–20671.

TOBLER, W.R. (1970), A computer movie simulating urban growth in the Detroit region, *Economic Geography*, 46, pp. 234–240.

TAYYEBI, A., DELAVAR, M. R., YAZDANPANAH, M. J., PIJANOWSKI, B. C., SAEEDI, S., TAYYEBI, A. H. (2010), A Spatial Logistic Regression Model for Simulating Land Use Patterns: A Case Study of the Shiraz Metropolitan Area of Iran, *Advances in Earth Observation of Global Change*, pp. 27-42.

TAYYEBI, A., PIJANOWSKI, B. C., TAYYEBI, A. H. (2011), An urban growth boundary model using neural networks, GIS and radial parameterization: An application to Tehran, Iran, *Landscape and Urban Planning*, 100, pp. 35–44.

UNITED NATIONS (2007), World urbanization prospects. Department of Economic and Social Affairs, available at: http://esa.un.org/unpd/wup/index.htm.

WU, F., YEH, A. G. (1997), Changing spatial distribution and determinants of land development in Chinese cities in the transition from a centrally planned economy to a socialist market economy: a case study of Guangzhou, *Urban Studies*, 34(11), pp. 1851–1880.

WANG, F. (1994), The Use of Artificial Neural Networks in a Geographical Information System for Agricultural Land-suitability Assessment, *Environment and Planning A*, 26, pp. 265-284.

WENG, Q. H. (2002), Land Use change analysis in the Zhujiang Delta of China Using satellite remote sensing, GIS and stochastic modelling, Journal of Environmental Management, 64, pp. 273–284.

WEBER, C. (2001), Remote sensing data used for urban agglomeration delimitation, In: Donnay, J. P., Barnsley, M. J. & Longley, P. A. (eds.), *Remote Sensing and Urban Analysis*, Taylor and Francis, London and New York, pp. 155–167.

WENG, Y. (2007), Spatio-temporal changes of landscape pattern in response to urbanization, *Landscape and Urban Planning*, 81, pp. 341–353.

WHITE, R., ENGELEN, G., ULJEE, I. (1997), The use of constrained cellular automata for high resolution modelling of urban land use dynamics, *Environment and Planning* B, 24, pp. 323–343.

WHITE, R., ENGELEN, D., ULJEE, I. (2000), Modelling land use change with linked cellular automata and socio-economic models: a tool for exploring the impact of climate change on the island of St LUCIA, In: HILL, M. J., ASPINALL, R. J. (eds.), *Spatial Information for Land Use Management*, Gordon & Breach, Reading, pp. 189–204.

ZHANG, Q., SETO, K. C. (2011), Mapping urbanization dynamics at regional and global scales using multi-temporal DMSP/OLS nighttime light data, *Remote Sensing of Environment*, 115(9), pp. 2320–2329.

ZHANG, L., ZHEN, Y. (2006), An artificial neural network model of the landscape pattern in Shanghai metropolitan region, China, *Frontiers of Biology in China*, 1(4), pp. 463-469.