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SMART CITIES
RESEARCHES, PROJECTS AND GOOD PRACTICES FOR BUILDINGS

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THE SPATIO-TEMPORAL
MODELING OF URBAN GROWTH

CASE STUDY: MAHABAD, IRAN

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ABSTRACT

The simulation of urban growth can be considered as a useful way for analyzing the complex process of urban physical evolution. The aim of this study is to model and simulate the complex patterns of land use change by utilizing remote sensing and artificial intelligence techniques in the fast growing city of Mahabad, north-west of Iran which encountered with several environmental subsequences. The key subject is how to allocate optimized weight into effective parameters upon urban growth and subsequently achieving an improved simulation. Artificial Neural Networks (ANN) algorithm was used to allocate the weight via an iteration approach. In this way, weight allocation was carried out by the ANN training accomplishing through time-series satellite images representing urban growth process. Cellular Automata (CA) was used as the principal motor of the model and then ANN applied to find suitable scale of parameters and relations between potential factors affecting urban growth. The general accuracy of the suggested model and obtained Fuzzy Kappa Coefficient confirms achieving better results than classic CA models in simulating nonlinear urban evolution process.

1   INTRODUCTION

The irregular expansion of urban land use can be considered as one of the biggest problems for urban managers and policy makers in different fields. Nowadays investigating the trend of converting of noun-urban land use to urban land use and determining the parameters which influence this trend are of great importance in long-term decision making and planning. In this way, exploring the rules and relations which are effective in changing lands into urban area and also the predicting the trend of city development in the future through reliable and efficient methods have received significant attention in urban researches. Land use change models are considered to be among the tools for identifying land use change (Onishi and Braimoh, 2007). Also land use change models are not only considered as approaches for the purpose of improving the quality of change identification and predicting the regimes dominating development patterns (Turner, 1994; Bockstael et al., 1995), but are also of use when it comes to analyzing the factors affecting land use change and choosing the most suitable development strategy (Erfu and Shaohong, 2005). Moreover, spatial models are useful tools for the purpose of a better perception of urban development and are also of use as tools assisting policy making, urban management, and tools providing information for evaluating environmental effects (He et al., 2008).

Urban growth and its management are considered to be a multi-dimensional problem. Cities emerge as complex dynamic systems, with non-linear processes, which are unexpected and self-organizing (Allen, 1997; Portugali et al.1997; Batty, 2007). Additionally, most of the methods which have embarked on model making for cities have traditionally been static, linear, centralized, and based on simple systems theory with a top-down approach. Recent, improvements happened in urban simulation have been because introducing new approaches (techniques) such as CA Multi-agent Systems, Micro Simulation, and Connectionist Models. These all have turned the urban model making into a powerful tool to be used for the purpose of analyzing the complex structures of urban systems. In this paper, efforts have been taken to determine the dynamic land use change in the dimensions of time and space through the use of Non-linear modeling in hope of achieving the closest simulation to reality. Multi temporal images and zoning maps are among the main data of this study. GIS has been used in order to extract the spatial factors and analyze the data. Additionally, ANN algorithm has been used to determine the influential factors and to find suitable values of simulation parameters that can best fit actual development. In other hand Neural network can be used to replace the transition rules used by classical CA models. Therefore CA has been applied as the main simulation engine .

2   CELLULAR AUTOMATION AND URBAN GROWTH MODELING

Cellular automation (CA) has attracted the attention of the researchers significantly in the past two decades (Alkheder, 2006). CA has found a wide range of applications in predicting land use change due to its simple structure in modeling. CA is a discrete dynamic system in which the situation of each cell is determined in the time of t+1, and according to the neighbourhood situations in the time of t, corresponding with already-defined transition rules. CA possessing time-space dynamics is capable of simulating changes in two-dimensional aspects. This method has been used widely for many application areas specifically for urban growth and land use change. In other words, CA is a dynamic modeling technique which produces global patterns from local cells through the use of the four main elements of cells, states, neighbourhood, and transition rules (Batty et al., 1999). In a CA system, space is divided into a regular network of cells with the same form and size and generally in the shape of squares. Each cell possesses a value equal to 0 or 1 or a range of values in a scale from 0.0 to 1.0 and finds certain values in accordance with different uses (AL-Ahmadi et al. 2009). In an urban CA the situations or states can be as: a) binary values (urban, non-urban), b) discrete values which represent different land uses, c) quantitative values which can, represent for instance population density, the level of development (Li and Yeh, 2002), the building cost (Cecchini and Rizzi, 2001), or a vector (Santé et al., 2010) of a number of features. The

state for each cell includes a number of discrete time steps which are controlled by a set of transition rules. These rules are generally defined based on the initial state of the cell and the status of the neighbouring cells.

The competence and attractiveness of this approach can be considered to be because of CA's ability in showing, simulating, and realizing the patterns and behaviors of complex geographical phenomena and self-organizing systems through the use of a number of somewhat simple rules (Torrens and O'Sullivan, 2001; Wu and Webster,1998).

3   ARTIFICIAL NEURAL NETWORKS AND URBAN GROWTH MODELING

One of the applications of Artificial Intelligence (AI), which has been studied in this study, is using AI techniques in optimizing urban growth modeling, specifically CA. Artificial Neural Network (ANN), as one of the components of computational intelligence has a structure including non-linear processing elements known as neurons which model the neural networks of human brain with connected weights. This network is a non-parametric algorithm and has characteristics such as learning, parallel processing, and the ability to generalize without needing an initial knowledge of the statistical distribution of data (unlike conventional statistical methods), which, This property is significant importance in space-time modeling.

Additionally, ANN is capable of recognizing and classifying patterns through training and learning urban growth processes. Therefore, ANN can be used as a simple and effective replacement for the Transition Rules from the classic CA models (Yeh and Li, 2001).

Capability and ability of applying ANN algorithm in urban development researches, is recently attracted some researches and scholars attention to itself. On the other hand, ANN are synthetically applied with other artificial intelligence techniques for urban modeling. Bilanowskia and his colleague assimilated an ANN with GIS to anticipate the earth control changes (Bilanowskia et al, 2002).

In this model, the role of ANN was learning of development patterns in the region and capacity test and the ability of anticipating model. Multi-Layer Perceptron (MLP) which be created by Ramelhart and his colleges (1986), are the most applicable ANN that be used. MLP was formed of three layers, input, hidden and output layers (Fig 1). As these nets are three-layers, there is the possibility of recognition of nonlinear communications existing in nature (Mahini and others, 2010).
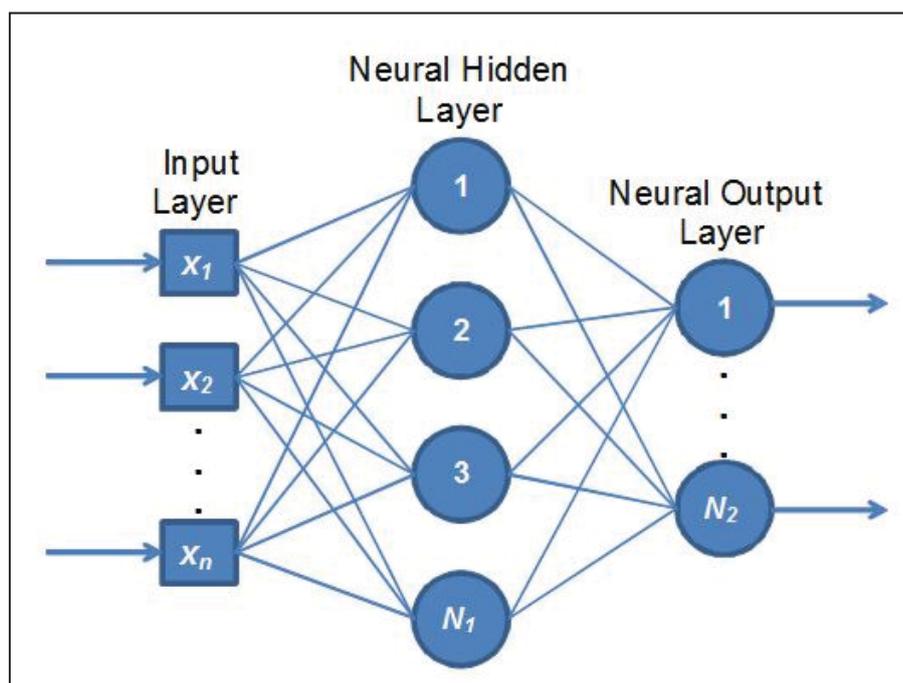

Fig.1 The architecture of 3 layer MLP Network

4   CALIBRATING THE CA MODEL USING ANN

Urban CA models are considered as tools highly capable of developing applied models for producing real urban patterns, hence it is possible to gain better comprehension of urban dynamics and theories. The majority of studies conducted on urban simulation through CA in the past three decades have focused on extracting or defining transition rules. In most of the cases, transition rules have been defined heuristically based on the realm of science and priority of the expert.

Therefore, one of the key points in simulating urban growth is calibrating the model in order to find the proper weights for the simulating parameters. It is obvious that in the process of simulation, calibration calls for finding those weights of the simulating parameters which can have the highest level of conformity with real development. However, after several decades of the application of this method in urban planning and the efforts of researchers in finding a globally applicable model for the purpose of predicting urban complexities, one can still feel some shortcomings in the calibration of the CA model.

In order to point to some studies conducted on the calibration of the CA model, one can mention the efforts of Wu and Webster (1998) in using multi criteria evaluation (MCE), Li (2006) in using the hierarchical analysis (AHP), Wu (2002) in regression logistics, AL-Ahmadi (2009) in fuzzy logic, and Li et al. (2008) in genetic algorithm, and Li and Yeh (2004) in decision making tree where CA produced different results.

The values of the effective parameters in simulation are determined by holding other parameters constant. Calibration and validation of CA models are the key to their successful implementation due to the fact that the quality of the urban CA model depends on the adequacy of the transition rules which usually include a number of parameters to be calibrated (Wu, 2002; Straatman et al., 2004). Moreover ANN has been used to recognize the patterns in different studies such as pictures analysis (Fukushima et al., 1983), weather forecast (Drummond et al., 1998), classification feature of the land (Brown et al., 1998), remote sensing (Atkinson & Tantall, 1997) and earth control changes (Pijanowski et al., 2002).

Based on these points and due to the non-linear and self-organizing nature of urban systems, the use of ANN for the purpose of calibrating the CA model has been examined in this paper.

5   CALIBRATING CA MODEL THROUGH ANN

Urban CA models are considered as tools highly capable of developing applied models for producing real urban patterns, hence it is possible to gain better comprehension of urban dynamics and theories.

The majority of studies conducted on urban simulation through CA in the past three decades have focused on extracting or defining transition rules. In most of the cases, transition rules have been defined heuristically based on the realm of science and priority of the expert.

Therefore, one of the key points in simulating urban growth is calibrating the model in order to find the proper weights for the simulating parameters. It is obvious that in the process of simulation, calibration calls for finding those weights of the simulating parameters which can have the highest level of conformity with real development. Calibrating CA model can be done in two ways (Li & Yeh, 2002).

A method is in base of statistical data such as Logistic Regression operation which is presented by WU (2002) and techniques such as genetic algorithm which is represented by Alkhadar (2008). The other method is calibrating in base of trial and error method such as visual tests (Clarke et al., 1997; Ward et al., 2000) computer simulation comparison (Clarke and Gaydos, 1998). Because of the absence of similar structures and objects, however, in these models, there is no popular method to calibrate CA model (Straatman et al., 2004).

In this paper, we were exploited from ANN algorithm to calibrate CA model. After calibrating, a set of optimized values have been allocated to simulator parameters (Fig 2).
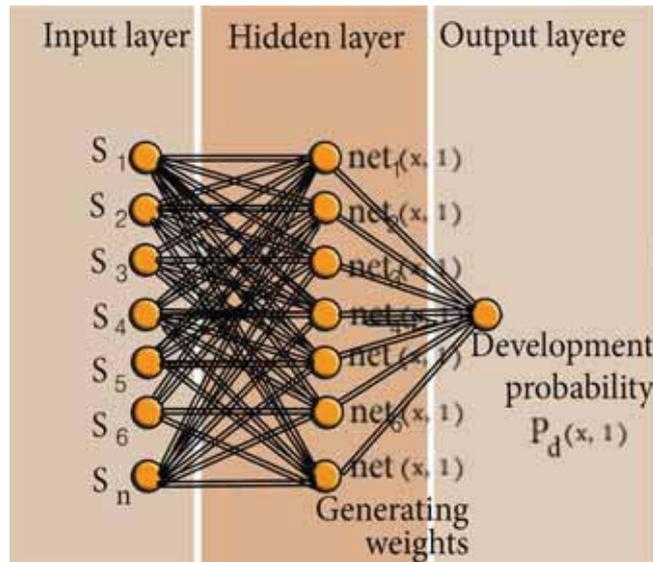
Fig. 2 Generating Weights and Development probability based on ANN

CA simulation is designed in base of ANN algorithm. At each of iteration of CA, ANN will recognize the development, which is subject to the input of site attributes and weights. A cell may be had n characteristic:

$$(s_1, s_2, s_3, s_4, s_5, s_6 \dots, s_n) \qquad (1)$$

A neural network can be designed to estimate the probability of development in each period of CA iteration. In the ANN, three layers have been recognized: input layer, hidden layer and output layer.

Input layer has n neurons in base of characteristics of site. Hidden layer may also have n neurons, while in output layer; there is just one neuron which calculates the probability of development.

In each period, iteration of the characteristics of site for each cell is as the first layer input and ANN recognize the probability of development unto that layer.

Most of the basic data before entering in model as the ANN input, are scaled into domain of $[0,1]$. Scaling gives each cell same significance and creates the same numerical value in input data and causes the compatibility of these data with activation function:

$$s_i' = (s_i - min)/(max - min) \qquad (2)$$

The algorithm which is incorporated with CA model consists of a simple three-layer net. In ANN, received signal has been calculated by the neuron j hidden layer of the first input layer for each cell as follow:

$$net_j(x, t) = \sum_i w_{i,j}\, s_i'(x, t) \qquad (3)$$

Where x is a cell and net_j is received signal by neuron j belonging to x cell in time, and $s_i'(x,t)$ is the characteristics of the slightly site for parameter (neuron) i.

Activation function of the hidden layer is:

$$\frac{1}{1+e^{-net_j(x,t)}} \qquad (4)$$

Probability of development (P_d) also defines for each x cell as:

$$P_d(x, t) = \sum_j W_j \frac{1}{1+e^{-net_j(x,t)}} \qquad (5)$$

The simulation is loop-based. In each iteration period, probability of development has calculated by the ANN in base of the characteristics of the site attributes. Probable perturbation (error net) is an expression which can be applied for representation of unknown errors during simulation, that it seems necessary to generate patterns coincident to reality, the probability of variation each cell has recognized by the probability of development.

Error net (RA) has been determined by:

$$RA = 1 + (-Ln\gamma)^{\alpha} \qquad (6)$$

Where γ is uniform random variable in domain of {0,1}, and α is a parameter to control the probable deviation scale and also can be used as dispersion factor in this simulation.

In this base, the probability of development function has been modified as:

$$P_d'\ (x,t) = RA \sum_j W_j \frac{1}{1+e^{-net_j(x,t)}} \qquad (7)$$

$$= (1 + (-Ln\gamma)^{\alpha}) \times \sum_j W_j \frac{1}{1+e^{-net_j(x,t)}} \qquad (8)$$

The probability of urbanizing of each cell is more probable in higher weight than probability of development during simulation process.

A threshold value is also defined by each cell before starting the process in order to accept the alteration. If a cell has higher probability of development than threshold value, the cell will change and expand. The number of expanded cell in defined neighborhood recalculates and the characteristics of site updates at the end of each iteration period. Simulation has maintained as long as the amount of total altered cells equal to amount of consumed land (Yeh And Li, 2002).

6   STUDY AREA AND DATA PREPARATION

The city of Mahabad in Western Azarbayjan province, Iran has been selected as the case study to simulate urban growth process. According to census, its population was 201,104, in 41,000 families. The city's population is predominantly Kurdish, with the city lying south of Lake Uremia in a narrow valley 1,300 meters above sea level in Iranian Kurdistan (fig. 3).
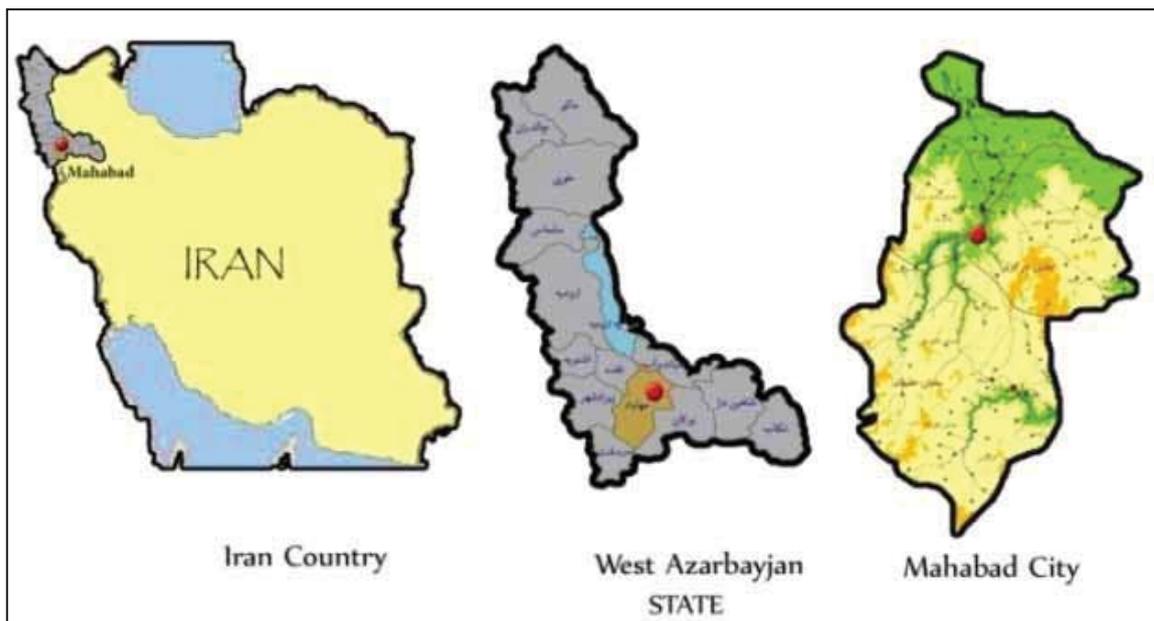

Fig. 3 Case study area, City of Mahabad.

Mahabad with the area of 2'541 square kilometers is the fifth county of this province.

Historical studies show that Mahabad is not a very old city and it was founded at the beginning of Safavi epoch.

Mahabad which was called Mokri Savojbolaq in the past, started to grow since the beginning of this century and then was developing following the permanently settling the tribes and establishing modern organizations and gradually was added to the new districts.

After the Islamic Revolution (1978), it was faced with rapid unplanned development as the consequence of political and social transformation.

The city's visage changed completely. At that time, eastern and southern areas of the city were developed irregularly. In 1989, Mahabad had an area of 591 hectares which is three times bigger than its area in 1966.

Between 1989 to 2005, city's area reached to 1'434 hectares that is two times of its area in 1989. In fact Mahabad is considered as one of very fast growing urban region of the country (fig. 4).

Over the past two decades, rapid urbanization has threatened the agricultural land and ecologically sensitive landscapes located around Mahabad (fig. 5). The rapid un- planned growth of Mahabad during recent decade makes it a suitable case for model growth.
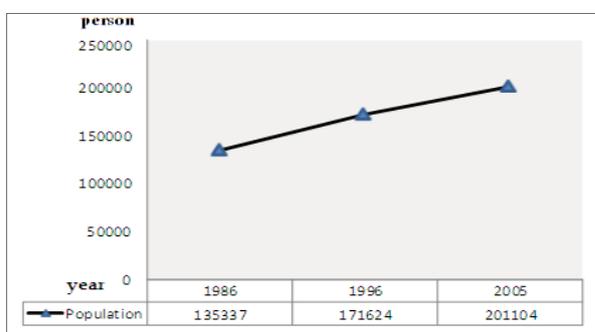
Fig. 4 The population growth of Mahabad 1986-2005.

	Pasture	Orchard	Urban	Water
1989	172666000	16024300	5911780	7429660
2000	172482000	13627600	10261500	5368050
2005	153070000	18480700	14348600	8669090
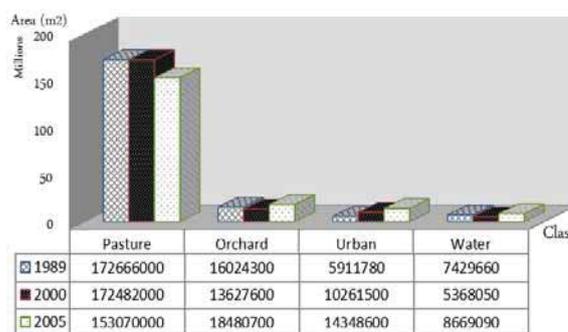
Fig. 5 The land use change statistics of Mahabad.

In this study, remote sensing and GIS techniques were used to provide spatial parameters and land use data, to characterize the relationships exist between site attributes and urban growth. Satellite Images were acquired on 1989 (TM), 2000 (ETM+), and 2005 (ETM+).

The Minimum Distance Supervised Classification (MDSC) approach was employed for land use classification (fig.6).
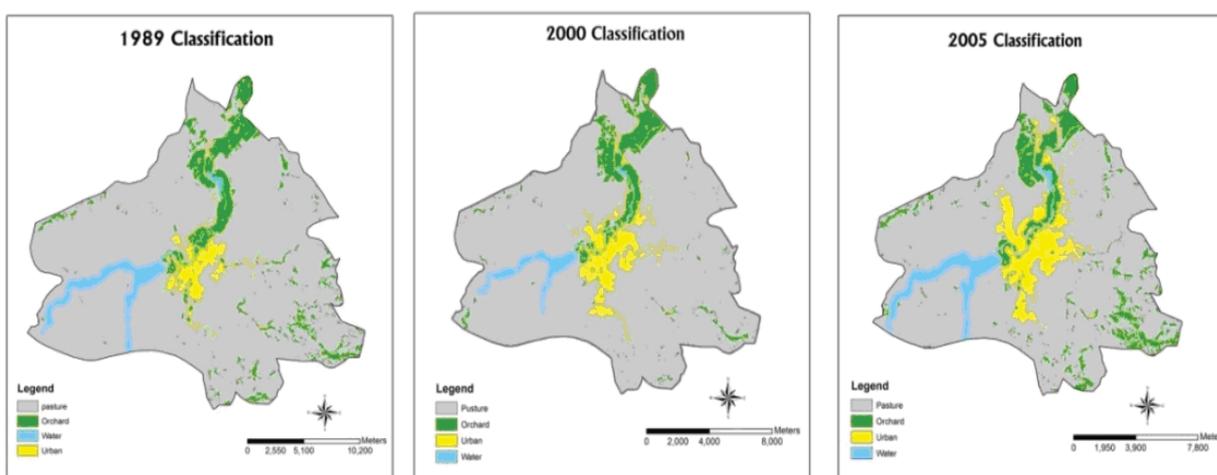
Fig. 6 The classification of satellite images of 1989, 2000, 2005.

To extract the land use layers, fuzzy logic was used for classifying images. For this purpose, fuzzy toolbox of MATLAB package was used.

The Mamdani's Fuzzy Inference method was applied to classify the images. Spatial parameters were calculated by use of Euclidean Function in Spatial Analyst Toolbox of ESRI ArcGIS9.3 (fig. 7).

To get target samples for the ANN training/learning process, the time-series land-use data of Mahabad City in 1989, 2000, and 2005 were used.

The neighborhood level of growth level was measured basing on the number of developed cells in the neighborhood of 10×10 cells adjacent to the central cell. The growth area of initial neighborhood of the model was computed using of binary image of 1989.

Fig. 7 The spatial parameter of simulation

7   TRANING

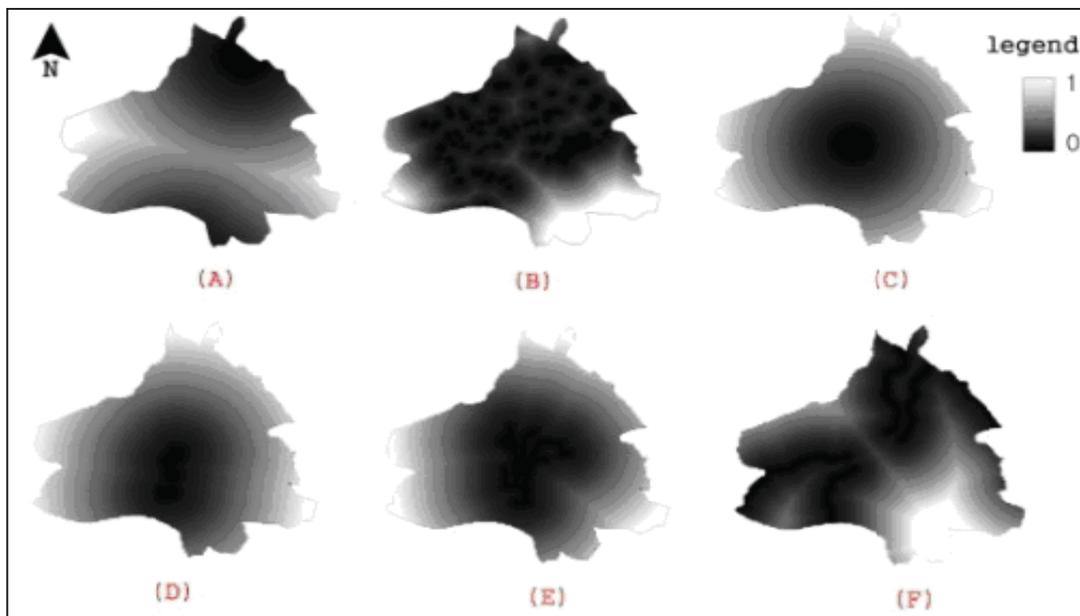In order to use the ANN for prediction purposes, the ANN must be taught the characteristics of the dataset being processed. The training dataset consists of input values and the desired output values corresponding to these input values. The desired output values can be obtained from field, remote sensing data and other secondary sources (Maithani, 2009).

Training data for urban growth in case study area were obtained from satellite images including TM and ETM+ for time between 1989-2005. Although the ANN can be trained using a number of training algorithms, in the present study, the Back Propagation (BP) learning algorithm proposed by Rumelhart et al. (1986) was used for training the ANN due to its simplicity and wide applicability.

The training data can be used to calibrate the network to produce the realistic simulation of the study area. It is inappropriate to use the whole data set for training because the size is too large and the data may have spatial correlation. As mentioned above, a certain number of sample data is needed for the training/learning process of the ANN. So, a random-sampling method was applied to reduce the time and volume of computation.

Some 3'360 training samples were selected from urban growth maps belonged to 1989 to 2005 using ERDAS IMAGINE package.

The selection of samples was similar heuristic method of Kavzoglu and Mather (2003) which is as follow:

$$60N_i(N_i + 1) \qquad (9)$$

where N_i is number of input neurons.

In this study, four groups of data relating to physical attribute, accessibility and neighborhood and zoning as well as land use data for the period of 1989-2005 were manipulated (Table 1).

Factor	Parameters
Physical attribute	Slope of the area altitude model
Accessibility and Neighborhood	Accessibility to local road Accessibility to main road Accessibility to CBD Accessibility to local centers Accessibility to business and community centers
Zoning	Planed area Protected area
Data related to land use	Land use classes: Urban, arid, green, water

Table. 1 The explanation of the spatial factors and corresponding driving forces.

8   SIMULATION OF URBAN DEVELOPMENT

The final step of modeling was prediction of urban growth. Based on the parameters and results of model validation, the prediction of future urban growth for 2025 was predicted (fig. 8).

The CA-ANN model using calibrated with the actual urban growth pattern between 1989 and 2005, and then used to predict urban growth in 2025.
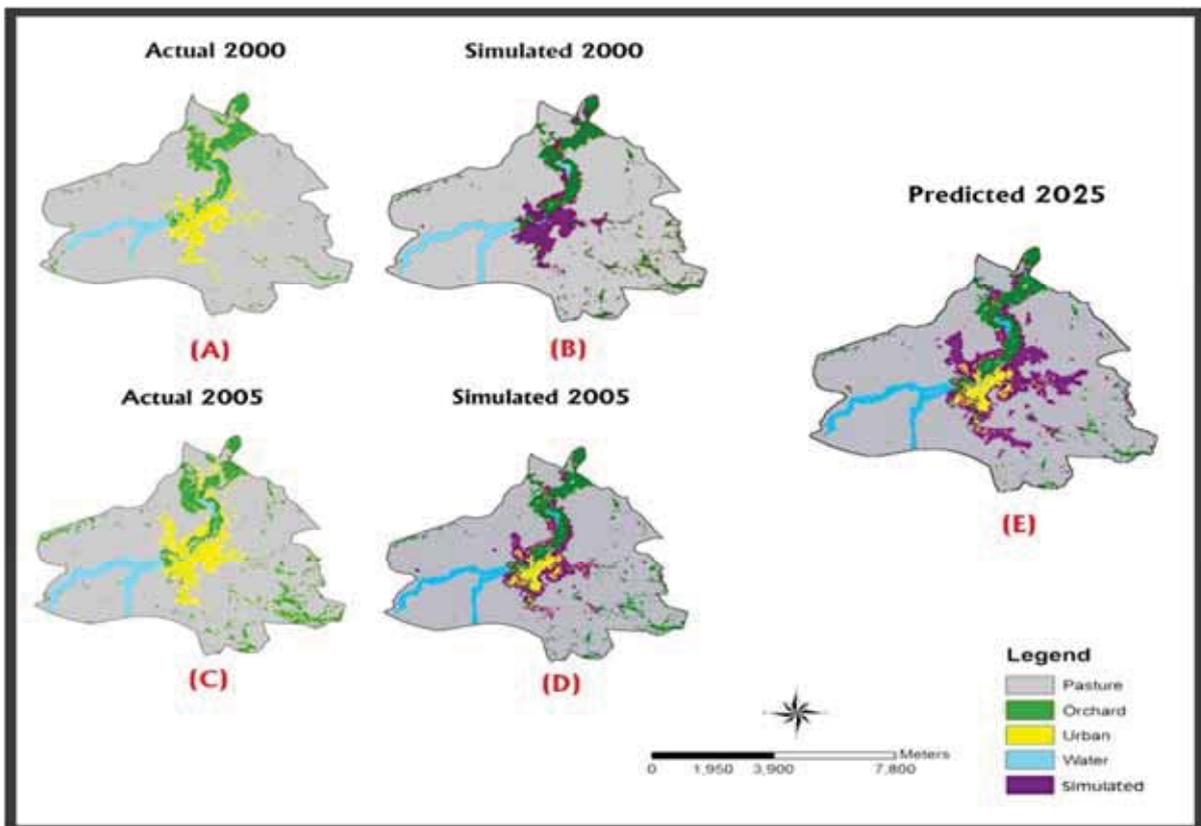

Fig. 8 (A) Actual urban land use in 2000, (B) simulated urban land use, (C) actual urban land use in 2005, (D) simulated urban land use in 2005 and (E) predicted urban land use in 2025.

9   DISCUSSIONS AND CONCLUSION

The result of the study showed that urban growth modeling through CA-ANN is an effective and useful way to analyze complex processes of urban evolutions. While classic CA model is associated with fixed transition rules and complicated calculation, this study was based on the growth of a procedure which calibrated the initial global probability surface from sequential land use data and then modifies the global probability with the local probability that was updated at each of iterations.

The applied approach of this study, integration of CA with ANN offers an easier and more flexible way instead. Because of the flexibility of the model with non-liner systems and uncertainty caused by spatial data, a higher level of confidence is achievable comparing to classic statistical model. In other hand, taking the advantage of ANN's capacity of dealing with nonlinear systems, this ANN-CA model can be calibrated without heavy computing overhead and subjective human interference.

This model can be considered as a helpful tool for policy making and planning. In fact, the results of this study can provide planners and decision-makers with influential information about alternative urban growth under various scenarios. Further, it can be easily combined with environmental models in hope of impact assessment. The model is reputable in other urban contexts using related data and circumstance.

This study can be improved in several ways. Since land use transformation is a multifaceted process, improving transition rules would enhance the classification accuracy and running efficiency.

Furthermore, if the CA simulation is calibrated through the desired pattern of changes, then the desired relationship can be incorporated into future growth evaluation for the purpose of simulating alternative scenarios. Furthermore, unsteadiness of the calibration process basing on ANN may bring superfluous parameters for the simulation model, which also points out the further research direction of this study.

REFERENCES

Berdini, P. (2008), *La città in vendita*, Donzelli, Roma.

Brenner, N. (2009), "A Thousand Leaves: Notes on the Geography of Uneven Spatial Development", in Keil, R., Mahon, R. (eds.), *Leviathan Undone? Towards a Political Economy of Scale*, UBC Press, Vancouver.

Brunet, R. (1996), "L'Europa delle reti", *Memorie geografiche*, n. 2, Società di Studi Geografici, Firenze.

Castells, M. (1996), *The Rise of the Network Society, The Information Age: Economy, Society and Culture,* Vol. I, *Blackwell, Oxford - Cambridge.*

Al-Ahmadi K; Heppenstall A; Hogg J; See L. (2009), A Fuzzy Cellular Automata Urban Growth Model (FCAUGM) for the City of Riyadh, Saudi Arabia. Part 1: Model Structure and Validation., Applied Spatial Analysis and Policy, 1, pp.65-83. doi: 10.1007/s12061-008-9020-6

Alkheder, SH. (2006), Urban growth modeling with artificial intelligence techniques. PhD Dissertation, Purdue University, USA.

Allen, PM. (1997), Cities and regions as self-organizing systems: models of complexity. Gordon and Breach Science, Amsterdam.

Batty, M., Xie, Y., and Sun, Z., 1999, Modeling urban dynamics through GIS-based cellular automata. Computers, Environment and Urban Systems, 23: 205–233.

Bockstael, NR., Costanza, I., Strand, W., Boyton, K., Bell, S., and L. Wagner. (1995), Ecological economics modeling and evaluation of ecosystems. Ecological Economics: 14: 143–159.

Cecchini, A., Rizzi, P. (2001), The reasons why cellular automata are a useful tool in the working-kit for the new millennium urban planner in governing the territory. In: CUPUM 2001 Proceeding, Honolulu.

Erfu, D., and Shaohong, W. (2005), Modeling change-pattern-value dynamics on land use: an integrated GIS and artificial neural networks approach, In: Journal of Environmental Management, 36(2): 1–17.

Hagen, A. (2003), Fuzzy set approach to assessing similarity of categorical maps. In: International Journal of Geographical Information Science 01/2003; 17:235-249.

He, C., Okada N., Zhang Q., Shi P. and Li J., 2008. Modeling dynamic urban expansion processes incorporating a potential model with cellular automata, landscape and urban planning, 86: 79-91.

Kavzoglu, T., and Mather, PM. (2003), The use of back propagation artificial neural networks in land cover classification. In: International Journal of Remote Sensing, 24: 4097–4938.

Li, X., and Yeh, AGO. (2002), Neural network-based cellular automata for simulating multiple land use changes using GIS, In: International Journal of Geographical Information Science, 16(4): 323–343.

Li, X., Yang, Q., and Liu, X. (2008), Discovering and evaluating urban signatures for simulating compact development using cellular automata, In: Journal of Landscape and Urban Planning, 86: 177–186.

Li, X., and Yeh, AGO. (2004), Data mining of cellular automata's transition rules, In: International Journal of Geographical Information Science, 18(8): 723-744.

Mahini, AR., and Kamyab, A. (2010), Application of ANN in urban development, In: Journal of Iranian Human Geography, 76: 49-67.

Maithani, S. (2009), A neural network based urban growth model of an Indian city, In: Journal of Indian Society of Remote Sensing, 37: 363–376.

Onishi, T. and Braimoh, AK. (2007), Geostatistical techniques for incorporating spatial correlation into land use change models, In: International Journal of Applied Earth Observation and Geoinformation, 9: 438-443.

Portugali, J., Benenson, I., and Omer, I. (1997), Spatial cognitive dissonance and socio-spatial emergence in a self-organizing city, In: Environment and Planning B, 24: 263– 285.

Santé, I., Garcia, AM., Miranda, D., and Crecente, R. (2010), Cellular automata models for the simulation of real-world urban processes: a review and analysis, In: Journal of Landscape and Urban Planning, 96: 108-122.

Straatman, B., White, R. and Engelen, G. (2004), Towards an automatic calibration procedure for constrained cellular automata. Computers, Environment and Urban Systems, 28: 23-31.

Rumelhart, DE., McClelland, JL., and the PDP Research Group, (1986), Parallel Distributed Processing: Explorations in the Microstructure of Cognition. MIT Press, Cambridge.

Torrens, PM. and O'Sullivan, D. (2001), Cellular automata and urban simulation: where do we go from here? Environment and Planning B, 28: 163-168.

Turner, BL. (1994), Local faces, global flows: the role of land use and land cover in global environmental change, Land Degradation and Development, 5: 71-78.

Wu, F. (2002), Calibration of stochastic cellular automata: the application to rural-urban land conversions, In: International Journal of Geographical Information Science, 16: 795–818.

Wu, F., and Webster, CJ. (1998), *Simulation of land growth through the integration of cellular automata and multi-criteria evaluation*, Environment and Planning B, 25: 103–111.

Batty, M. 2007, Model cities. Centre for Advanced Spatial Analysis, University College London, working paper 113

Yeh, A., & Li, X. (2001), A constrained CA model for the simulation and planning of the sustainable urban forms by using GIS. Environment and Planning B: Planning and Design, 28(5), 733–753.

Ward D, Murray A, Phinn S (2000) A stochastically constrained cellular model of urban growth. Comput Environ Urban Sy 67.

Pijanowskia, B. C., Brown, D. G., Shellitoc, B. A., and Manikd, G. A. (2002). Using neural networks and GIS to forecast land use changes: a land transformation model. st 24:539–558

Clarke, K. C., Hoppen, S., and Gaydos, L. (1997). A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. Environment and planning B , 24:247– 261.

Clarke, K. C., and Gaydos, J. (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, 12:699–714.

Johny & Heng Li (2006), Application of the analytic hierarchy process (AHP) in multi- criteria analysis of the selection of intelligent building systems. Building and Environment, 43 (2006), 108–125

Al-kheder, S., Wang, J., Shan, J (2009). Fuzzy Inference Guided Cellular Automata Urban Growth Modeling Using Multi-temporal Satellite Images. International Journal of Geographical Information Science, Vol. 22, Nos. 11–12, 2008, pp. 1271–1293. Issue 11 & 12

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