INT. J. GEOGRAPHICAL INFORMATION SCIENCE, 2002
VOL. 16, NO. 4, 323–343

Research Article

Neural-network-based cellular automata for simulating multiple land use changes using GIS

XIA LI[†‡] and ANTHONY GAR-ON YEH[†]

[†]Centre of Urban Planning and Environmental Management, The University of Hong Kong, Pokfulam Road, Hong Kong SAR, P.R. China;
e-mail: lixia@graduate.hku.hk; hdxugoy@hkucc.hku.hk
[‡]Guangzhou Institute of Geography, Guangzhou, P.R. China;
e-mail: xlib@gis.sti.gd.cn

(*Received 20 April 2000; accepted 2 September 2001*)

Abstract. This paper presents a new method to simulate the evolution of multiple land uses based on the integration of neural networks and cellular automata using GIS. Simulation of multiple land use changes using cellular automata (CA) is difficult because numerous spatial variables and parameters have to be utilized. Conventional CA models have problems in defining simulation parameter values, transition rules and model structures. In this paper, a three-layer neural network with multiple output neurons is designed to calculate conversion probabilities for competing multiple land uses. The model involves iterative looping of the neural network to simulate gradual land use conversion processes. Spatial variables are not deterministic because they are dynamically updated at the end of each loop. A GIS is used to obtain site attributes and training data, and to provide spatial functions for constructing the neural network. The parameter values for modelling are automatically generated by the training procedure of neural networks. The model has been successfully applied to the simulation of multiple land use changes in a fast growing area in southern China.

1. Introduction

There are numerous studies on the detection of land use change using remote sensing and GIS (Howarth 1986, Jensen *et al.* 1995, Li and Yeh, 1998). However, there is a general lack of studies on the simulation of land use changes because of their complexities. It is possible to project future land use patterns using empirical data. The generic paths of change can be identified, such as the typical sequences of land use changes found across tropical regions (Lambin, 1997). Most economic modelling on land use changes originates from land rent theories of von Thünen and Ricardo (Mertens and Lambin, 2000). Any parcel of land, given its attributes, is assumed to be allocated to the use that earns the highest profit. Land uses compete against each other in biding for a favourable location. Multivariate spatial models can be developed to predict possible land use conversions (Mertens and Lambin, 2000). Another example of predicting land use changes is based on the Markov

International Journal of Geographical Information Science
ISSN 1365-8816 print/ISSN 1362-3087 online © 2002 Taylor & Francis Ltd
http://www.tandf.co.uk/journals
DOI: 10.1080/13658810210137004

analysis (Hathout, 1988). However, this method only produces the prediction of land use categories without spatial details.

Recently, there are increasing studies on simulating urban growth using cellular automata (CA) techniques (White and Engelen, 1993, Batty and Xie 1994, Wu, 1998). The application of CA in urban modelling can give insights into a wide variety of urban phenomena. Urban CA models have better performance in simulating urban growth than conventional urban models because they are much simpler than complex mathematical equations, but produce results that are more meaningful and useful with intuitive results (Deadman *et al.* 1993, White and Engelen 1993, Wu 1998). Temporal and spatial complexities of urban systems can be well modelled by properly defining transition rules in CA models. CA simulation provides important information for understanding urban theories, such as the evolution of forms and structures.

Simulation of land use changes is important for a variety of planning and management issues as well as for academic research. It can provide the baseline growth scenario to show the future land development pattern when the current land development process continues into the future. The baseline growth can be used to identify future urban development problems. It can also be used to compare with the improvements that could be made by different urban development plans and policies. Such simulation provides useful information about locations, types, scale, amount and density of land conversion that will probably take place. The simulation of land use changes can help to assess development impacts, prepare land use plans, and seek optimal land use patterns. It can forecast the consequences of specific human behaviour and land use policies. It can also identify the possibility of severe land use problems, such as the encroachment on important environmental areas, including croplands and wetlands. Strict land use zoning may be required to prevent the potential land use problems identified by the simulation. The simulation of land use changes will enable rural and urban planners to provide the public with necessary facilities and services to sustain the development (Hathout 1998).

The simulation of multiple land use changes using CA is much more difficult than the simulation of urban growth which is normally done on a binary basis, i.e. land is either assigned or not assigned for urban development. When multiple land uses are presented, the transition rules of urban CA models become substantially more complicated because the simulation involves the use of a much larger set of spatial variables and parameters and more complex model structures. In this paper, a neural-network-based CA model is developed to simulate multiple land use changes. The integration of a neural network with the cellular automata should be a much better approach to simulation of complex land use systems because neural networks are very good at coping with wrong and poor data and capturing non-linear complex features in modelling processes.

2. Urban CA models and calibrations

In general GIS modelling, land use changes are predicted according to the independent spatial variables that are generated from standard GIS analysis tools (Mertens and Lambin 2000). These independent variables are usually deterministic and unchanged during the modelling process. An example is the California Urban Futures (CUF) model that is specified for metropolitan growth simulation (Landis 1995). The revised CUF model includes multiple land uses for more realistic GIS modelling (Landis and Zhang 1998). Land use changes are considered as a path-dependent and discrete approach. Land use changes are estimated by using a multinomial logit procedure in the revised CUF model. GIS modelling can also be used to simulate idealized growth patterns by applying various types of constraints (Yeh and Li 1998).

Another type of approach for modelling cities and land use is based on cellular automata (CA) techniques. CA models are bottom-up approaches as local (neighbourhood) interactions give rise to the formation of complex global patterns. CA models have become very attractive to urban simulation because they can generate interesting results. They provide a useful tool to understand cities that are regarded as evolutionary and complex systems. In a self-organizing city, land development is a historically dependent process in which development in the past affects the future through local interactions among land parcels (Wu and Webster 1998). In CA simulation, the outcome at the previous iteration has important effects on the outcome at the next iteration. Complex global patterns can be formed after many iterations of a simulation. Some unexpected features can even emerge during the simulation by properly defining transition rules (Wu 1998).

CA models have better modelling capability than general GIS in the simulation of urban growth and land use changes. Spatial variables in CA models are dynamically updated during iterative looping so that the results are not deterministic. Some realistic and new features can emerge during the processes of simulation, e.g. formation of new aggregate centres (Wu 1998) and fractal properties (White and Engelen 1993). Complex global patterns can emerge from local interactions during CA simulation (Batty and Xie 1994). In contrast, general GIS models have difficulties in simulating complex urban dynamics without using local rules and iterative looping. and they usually use static spatial variables in the simulation. It is also hard to capture non-linear features that are presented in many geographical phenomena. It is not easy to explain the theoretical and intuitive meaning when the urban simulation is purely based on GIS modelling. The algorithms of GIS modelling are also much more complicated and the simulation time is much longer than with CA.

Although CA have many advantages, a major problem is how to determine their parameter values. In the past, CA models mainly concentrated on the simulation of urban growth from rural to urban land use. It is relatively easy to simulate urban growth which only deals with the binary state—urbanized or not. CA models become considerably more complex when there are multiple land use types, such as vacant, residential, commercial, housing and transportation land uses (Batty *et al.* 1999). When dealing with competing multiple land uses, the number of factor weights substantially increases and the structure of CA models becomes more complicated. There are numerous parameters which need to be determined to reflect a particular urban system being simulated and the range of possible model types is enormous (Batty *et al.* 1999).

The simulation of multiple land use changes involves the use of numerous spatial variables. The contribution of each spatial variable to the simulation is quantified by its associated weight or parameter. There are thus numerous parameters to be defined before the simulation can be executed. Parameter values have great effects on the results of simulation. Different combinations of parameter values will lead to a totally different urban form (Batty *et al.* 1999, Yeh and Li 2001).

In most situations, calibration of CA models is needed to ensure that the simulation can generate the results close to the reality. The calibration is extremely difficult when the conversion takes place among multiple land use types. There are two major types of calibration methods for CA simulation. One type is based on statistical methods. For example, logistic regression can be used to calibrate CA models to obtain parameter values for urban simulation (Wu 1998). This type of models is only concerned with the binary conversion of land uses—urbanized or not. General statistical methods may have some limitations when spatial factors and model structures are too complicated. They are invalid when spatial factors correlate with each other. They also have difficulties in handling poor and noisy data.

Another type of calibration is based on trial and error approaches. No strict mathematical methods are required for such calibration. A simple method is to compare the simulation results visually using various combinations of parameter values (Clarke *et al.* 1997, Ward *et al.* 2000). The 'best' set of parameter values is determined from a visual comparison. However, it is difficult to define the combinations when there are many variables, and to assess the results visually because the patterns are usually very complex. White *et al.* (1997) also propose an intuitive method by means of a trial and error approach to obtain a parameter matrix for urban simulation. Their models have used as many as $21 \times 18 = 378$ parameters for simulating competing urban land uses. The method is not based on strict mathematical methods and fine-tuning the calibration to get the matrix might take too much time. Clarke and Gaydos (1998) develop a relatively robust method for calibrating CA models based on computer comparison. It calculates the fits between the observed historical data and various simulation results. The suitable set of parameter values is found based on the 'best' outcome of the various trials. The calibration is very computation-intensive although it seems to be sound in the search algorithms. The calibration needs a high-end workstation to run hundreds of hours before finding the 'best' outcome.

Another problem with CA models is how to define transition rules and model structures. Transition rules and model structures are usually application-dependent. Although some CA models have been argued to be generic in nature (White *et al.* 1997, Wu 1998, Batty *et al.* 1999), these models are substantially different in their forms. The variations are due to the existence of many possible ways of defining the transition rules and model structures. For example, Batty and Xie (1994) use nested neighbourhood space and a distance decay function from the seed of development to determine transition probability. Wu and Webster (1998) define transition rules based on multicriteria evaluation (MCE) methods. A predefined parameter matrix can be used to control development probability instead (White and Engelen 1993). Li and Yeh (2000) propose a grey-cell-based model to accommodate gradual urban conversion process. A series of constraints can be used to define transition rules for generating idealized urban forms (White *et al.* 1997, Li and Yeh 2000). Planning objectives and options can be embedded in CA models to produce alternative plans (Yeh and Li, 2001). CA models can also accommodate neo-classical urban theory by properly defining transition rules (Wu and Webster 2000). In these models, substantially different forms of CA models in terms of transition rules and model structures have been proposed to satisfy various objectives and specifications. There is a dilemma in how to choose a suitable CA model because too many choices are presented.

3. Neural-network-based CA model for simulating multiple land use changes

This paper presents the results of an experiment on simulating land use dynamics by using neural networks. The simulation has to deal with the complex relationships of land use conversion (figure 1). For a total of N land use classes, there can be

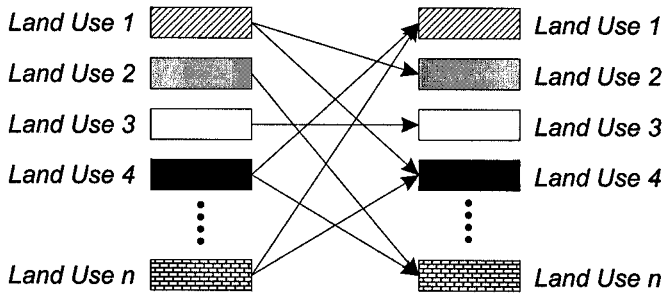

Figure 1. Complex relationships of land use conversion.

$N \times N$ types of possible conversions. Neural networks seem to be most suitable for the simulation of the complex relationships.

Artificial neural networks (ANNs) consist of layers and neurons which simulate the structure of human brains. The layers and neurons allow ANNs to have the learning and recall abilities like human, especially for non-linear mapping. ANNs can be well trained by using back-propagation learning algorithms. ANNs have been quite successfully employed to the analysis and modelling problems of geography (Openshaw and Openshaw 1997, Openshaw 1998). It is generally accepted that neural networks can achieve results of greater accuracy in modelling (Wang 1994, Zhou and Civco 1996).

The proposed ANN-CA model is devised using multiple output neurons for simulating multiple land use changes. The output layer of the network determines the transition probabilities of multiple land uses by using multiple output neurons. The parameters that are required for the simulation are automatically determined by a training procedure of neural networks. No explicit transition rules are required in the ANN-CA model. The only task is to train the neural network to obtain parameter values based on empirical data.

The structure of the ANN-CA model is very simple and virtually unchanged because it is using neural networks. The model can deal with the complex relationships among variables because ANNs have excellent non-linear mapping abilities. The integration is especially useful when there are many parameters to define in the simulation of complex systems, e.g. multiple land uses.

Traditionally, a neural network can be used to classify a set of observations, $\mathbf{X} = [x_1, x_2, x_3, \ldots, x_n]^T$ which is of n different variables. The architecture of a simple three-layer neural network with multiple output neurons is shown in figure 2. A neural network consists of one input layer, one output layer, and no or some hidden layers between them. Neurons or nodes which are the basic units to process signals are arranged in layers. In the first (input) layer, each neuron accepts a single value which corresponds to an element in $\mathbf{X}$. Then each neuron generates an output value and the output value may be used as the input for all the neurons in the next layer. Weights are used to address the strengths of network interconnection between associated neurons.

The algorithms to quantify the above signal collection and activation processes are quite simple. For neuron j in the receiver layer, the *net* input from the collection process is calculated by:

$$net_j = \sum_i w_{i,j} I_i \tag{1}$$

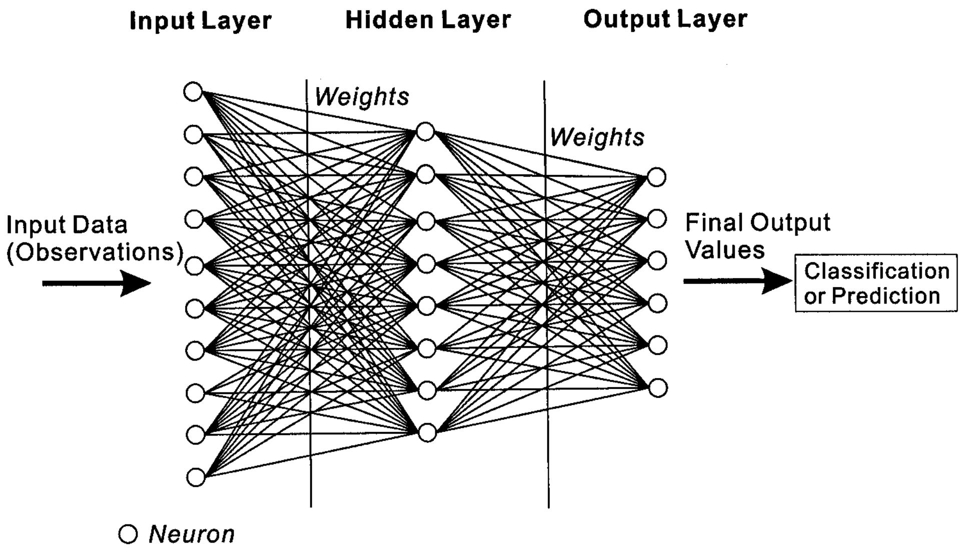

Figure 2. Basic structure of an artificial neural network with multiple output neurons.

where I_i is the signal from neuron i of the sender layer, net_j is the collection signal for receiver neuron j, and $w_{i,j}$ is the parameter or weight to sum the signals from different input neurons.

The receiver neuron creates activation in response to the signal net_j. The activation is usually created in the form of sigmoid function:

$$\frac{1}{1+e^{-net_j}} \tag{2}$$

The activation becomes the inputs to the next layer. Equations (1) and (2) can be used to process the signals again. The collection and activation processes continue until the final signals are obtained by the output layer.

A neural network can be used for pattern recognition or classification. Each neuron in the output layer is associated with a class. When a case is presented to the network, each output neuron will generate a value that indicates the similarity between the input case and the corresponding class. An input case can be classified into the class that is associated with the neuron of the highest activation level.

The determination of weights is critical to successful applications of neural networks. A set of training data has to be used to obtain the optimal weights based on a back-propagation learning algorithm. The algorithm is quite robust because it iteratively minimizes an error function over the network outputs and desired outputs based on a training data set (Rumelhart *et al.* 1986, Foody 1996). When the set of weights has been obtained, the network is ready for classification or prediction.

The simulation of multiple land use changes needs to deal with numerous complex spatial variables. These variables may correlate with each other and the relationships between them are quite complex. Traditional CA methods have difficulties in handling complex variables and determining parameter values. A neural-network-based CA model seems to be most suitable for the simulation of multiple land uses. The flowchart of the proposed model is presented in figure 3. The model is divided into two parts—training and simulation. The network structure remains the same for the two parts.

The first step is to define the inputs to the network for the simulation. The simulation is cell-based and each cell has a set of n attributes (variables) as the inputs to the neural network. It is assumed that these site attributes decide land use conversion probabilities. These variables can be conveniently obtained by using general GIS buffer and overlay analyses. They can be expressed by:

$$X = [x_1, x_2, x_3, ..., x_n]^T \tag{3}$$

where x_i is the ith site attribute and T is transposition.

Each variable is associated with a neuron in the input layer. It is more appropriate to convert input data into the range of [0,1] for neural networks (Gong 1996). The transformation may be similar to data normalization by using the minimum and maximum values in scaling the original data set. Scaling each variable treats them as equally important inputs to neural networks and makes them compatible with the sigmoid activation function that produces a value between 0 and 1. The transformation is carried out by:

$$x'_i = (x_i - \text{minimum})/(\text{maximum} - \text{minimum}) \tag{4}$$

The architecture of the neural network should be designed as simply as possible because the simulation is of many loops. The proposed neural network only has three layers—the input layer, a hidden layer and the output layer for simplicity. The input layer receives the scaled attributes, x'_i. Studies indicate that the network with one or more hidden layers can approximate any continuous function, given sufficient hidden neurons (Zhou and Civco 1996). Sometimes difficult learning tasks can be simplified by increasing the number of hidden layers, but a three-layer network can form any decision boundaries (Gong 1996).

In the hidden layer, the signal received by neuron j from the input layer for cell k at time t is calculated by:

$$net_j(k, t) = \sum_i w_{i,j} x'_i(k, t) \tag{5}$$

where $net_j(k, t)$ is the signal received by neuron j in the hidden layer, $w_{i,j}$ is the parameter or weight between the input layer and the hidden layer, and $x'_i(x, t)$ is the ith scaled site attribute associated with neuron i in the input layer with regard to cell k and time t.

The activation of the hidden layer to the input signal is calculated by:

$$\frac{1}{1 + e^{-net_j(k,t)}} \tag{6}$$

The output layer has a total of N neurons corresponding to N classes of land uses. The lth neuron in the output layer generates a value that represents the conversion probability from the existing type to the lth (target) type of land use. A higher value means that the conversion probability from the existing type to the lth type of land use is greater. Conversion probabilities are calculated by the following formula according to the output function of neural networks:

$$P(k, t, l) = \sum_j w_{j,l} \frac{1}{1 + e^{-net_j(k,t)}} \tag{7}$$

where $P(k, t, l)$ is the conversion probability from the existing to the lth type of land use for cell k at time t, and $w_{j,l}$ is the parameter or weight between the hidden layer and the output layer.

A stochastic disturbance term is usually incorporated in CA simulation to generate more plausible results (White and Engelen 1993). The disturbance can lead the simulation to produce fractal properties that are found in real urban systems and land use patterns. The error term (RA) can be defined as (White and Engelen 1993):

$$RA = 1 + (-\ln \gamma)^{\alpha} \tag{8}$$

where γ is a uniform random variable within the range of 0 to 1, and α is the parameter to control the size of the stochastic perturbation. α can be used as a dispersion factor in the simulation.

The disturbance is incorporated in the neural-network-based CA model for more realistic simulation. The conversion probability is then revised as:

$$\begin{aligned} P(k, t, l) &= \mathrm{RA} \times \sum_j w_{j,l} \frac{1}{1 + e^{-net_j(k,t)}} \\ &= (1 + (-\ln \gamma)^{\alpha}) \times \sum_j w_{j,l} \frac{1}{1 + e^{-net_j(k,t)}} \end{aligned} \tag{9}$$

A loop-based neural network is designed to simulate land uses. At each iteration, each neuron in the output layer generates a conversion probability from existing type to another type of land use. Different types of land uses compete against each other for a given cell (e.g. more than two types of land uses can be suitable for a cell simultaneously according to the suitability). The competition can be better explained by a neo-classical bid-rent model (Webster and Wu 1999). In our simulation, land use conversion is decided by comparing the values of conversion probabilities. Land use will convert from the existing type to the type that is associated with the highest value of conversion probability. If the same type of land use has the highest conversion probability, the state of the cell remains unchanged. The simulation of land uses is carried out by running the neural network iteratively until some constraints are satisfied, e.g. the total amount of available land for urban uses.

In most situations, land use changes take place only by a small percentage within a short period. CA simulation usually involves many iterations to decide whether a cell is converted or not. A predefined threshold value should be used to control the rate of conversion so that land use changes take place step-by-step. If the highest conversion probability is less than the threshold value, the cell remains unchanged. The threshold value may range from 0 to 1. Experiments show that a relatively large value of threshold (e.g. 0.90) can be used to prevent land use from changing too fast in the simulation. The smaller the value, the more cells will be converted at each iteration. A relatively large value of threshold (e.g. 0.90) is useful for obtaining the fine patterns of simulation.

4. Implementation and simulation results

4.1. *Monitoring land use changes from remote sensing*

The proposed ANN-CA model was tested by applying it to the simulation of multiple land use changes in a real city, *Dongguan*, in the Pear River Delta in southern China. The study region consists of a city proper and 29 towns with a total area of 2465 km^2. It was mainly an agricultural area. Tremendous land use changes have occurred in the 1990s due to the fast economic development (Li and Yeh 1998). An urban planning CA model was developed to generate urban growth pattern that could minimize agricultural land loss and achieve compact development (Li and Yeh 2000). Like most urban CA models, it only dealt with the conversion between the binary states–urbanized or not. In order to predict what will happen if the current urban development pattern continues, there is a need to develop a CA model that can simulate future urban growth. More ideally, the model should be able to provide detailed information about the conversion between multiple land uses for planning and management purposes. In this study, the simulation involves six types of land uses—cropland, orchards, development sites, built-up areas, forest and water.

Empirical data should be used to calibrate CA models when the simulation is for real cities. Empirical data usually include the information of location, type and amount of land use conversion. This type of information can be conveniently obtained from satellite images by employing land use change detection methods. There is a lot of research on land use change detection using satellite images (Howarth 1986, Jensen *et al.* 1995). In this study, a method based on principal components analysis (Li and Yeh 1998) was employed to obtain the information of land use changes for the study area. The 1988 and 1993 TM images were used as empirical data to reveal the fast land use conversion in the region.

Table 1 is the land use conversion matrix obtained from these satellite images. Two major categories of land use changes can be observed—internal agricultural restructuring and urban encroachment on agricultural land. The table indicates that a large amount of cropland was converted into orchards due to market mechanism. The loss of agricultural land is significant because both cropland and orchards were converted into development sites at a large scale. Some of the existing development sites finally became built-up areas. The patterns of land use conversions can be clearly observed from satellite images. For example, the conversion from agricultural uses to urban uses is dominant along main transport corridors. Idle land uses associated with land speculations can be identified in many rural areas from satellite images. The conversion processes are rather complex in terms of the types, amounts and locations of land use changes. General linear regression analyses are unsuitable for revealing the complex relationships because it is hard to capture non-linear characteristics.

4.2. *The GIS database for site attributes and training data*

A GIS database which contains both raster and vector data was built to provide the basic spatial information for the simulation. It contains the raster information of historical land use changes that were detected from satellite images and soil types. It also contains other vector layers of spatial information, such as topography, urban centres, roads, and administrative boundaries. Standard GIS buffer and overlay analyses were carried out to retrieve site attributes and training data from the database. Although the original database contains both vector and raster data, they need to be converted into a raster format for the simulation. All the data were converted into a raster format with each cell representing an area of $50\,\mathrm{m} \times 50\,\mathrm{m}$ on the ground for the simulation. Like other CA models, this model is also cell-based. Each cell is represented by a set of site attributes. These attributes are passed through the network for getting the output values—conversion probabilities. Land use conversion can be predicted based on site attributes although the relationships may be quite complex.

Table 1. Conversion matrix of multiple land use changes in Dongguan in 1988–93 (in hectares).

		1993						
		Cropland	Construction sites	Orchard	Built-up areas	Forest	Water	Total (1988)
	Cropland	62 602.4 (64.9%)	1737.8 (1.8%)	31 945.8 (33.1%)	103.2 (0.1%)			96 389.2 (100%)
	Construction sites		0.3 (0%)		2115.3 (100%)			2 115.6 (100%)
	Orchard		19 432.0 (29.7%)	45 987.9 (70.3%)	9.3 (0%)			65 429.2 (100%)
1988	Built-up areas				16 235.8 (100%)			1635.8 (100%)
	Forest					41 462.1 (99.7%)		41 462.1 (100%)
	Water		1442.9 (8%)		3.4 (0%)		16 590.4 (92.0%)	18 036.7 (100%)
	Total (1993)	62 602.4	22 613.0	77 933.7	18 467.0	41 462.1	16 590.4	239 668.6

A total of twelve spatial variables were chosen for the simulation of multiple land use changes. They include various distance-based variables, neighbourhood functions and physical properties (table 2). Studies have shown that these variables are closely related to urban development and land use changes (White and Engelen 1993, Wu and Webster 1998, Li and Yeh 2000). They are usually used as independent variables for urban and land use simulation. However, the simulation will be more precise when the distances are measured from existing urban areas rather than from urban centres because growing urban areas will generate more infrastructure and additional centres to support further urban growth.

Land use conversion is usually dependent on a series of spatial variables in terms of accessibilities or proximities, e.g. distances to urban centres, town centres and transportation lines. An example is to simulate urban growth according to a linear weighted combination of a series of spatial factors, e.g. distances to urban centres and transportation lines, and the developed quantity in the neighbourhood (Wu and Webster 1998, Wu 1998). In this study, the *Eucdistance* function of *ARC/INFO GRID* was used to obtain the three distance variables that were used for the simulation.

Neighbourhood functions are central to the CA models. The *Focal* functions of *ARC/INFO GRID* were used to obtain the site attributes of neighbourhood properties. Besides location variables, land use conversion is also dependent on the amount of land use types in the neighbourhood. Usually, the presence of a larger amount of

Table 2. Spatial variables for simulating multiple land use changes in the neural network.

Spatial variables	Creation method	Original data range	Scaled range
1. *Distance variables*			
Distance from the cell to the major (city proper) urban areas (x_1);	GIS Buffer Analysis using the *Eucdistance* function of *ARC/INFO GRID*	0∼30 km	0∼1
Distance from the cell to the closest sub-urban (town) areas (x_2);		0∼5 km	0∼1
Distance from the cell to the closest road (x_3).		0∼3 km	0∼1
2. *Neighbourhood functions*	Focal functions in a 7×7 window using *ARC/INFO GRID*		
Amount of cropland (x_4);		0∼49 pixels	0∼1
Amount of orchards (x_5);		0∼49 pixels	0∼1
Amount of construction sites (x_6);		0∼49 pixels	0∼1
Amount of built-up areas (x_7);		0∼49 pixels	0∼1
Amount of forest (x_8);		0∼49 pixels	0∼1
Amount of water (x_9).		0∼49 pixels	0∼1
3. *Physical properties*			
Slope (x_{10});	TIN Model; Converted into *ARC/INFO GRID*	0∼75 °	0∼1
Soil types (x_{11});	Conversion from vector to raster	1∼7 categories	0∼1
Existing type of land use (x_{12}).	Remote sensing classification & simulation	1∼6 categories	0∼1

a certain type of land use in the neighbourhood will increase the probability of the conversion to that type of land use. For example, there is a higher chance for a cell to be developed if it is surrounded by more developed cells. The relationships may be more complicated in the case of multiple land uses. However, neural networks are quite appropriate to deal with the complex relationships.

The physical properties for each cell will also affect the land use changes. These properties include soil types, slope and existing type of land use. Soil types and slope should be important constraints for land use conversion. The existing type of land use at time t is also an important input for estimating conversion probabilities. These physical properties were retrieved from the GIS database and converted into the raster format of *ARC/INFO GRID*.

The model has a total of twelve input neurons to receive these variables (site attributes) for each cell at time t. The first three neurons are specified to represent three main types of distance variables. The next six neurons are used to count the amount of each land use type in the neighbourhood of 7×7 window. The last three neurons are assigned to express the physical property of a cell.

Table 2 lists the details of the spatial variables that are used by the model. Although these original data had different scales, they were normalized into the range of [0, 1] before inputting to the network according to the equation (4). There is little concern about correlated variables and data redundancy because neural networks are good at dealing with these problems.

Unlike general GIS modelling, the distance and neighbourhood variables are dynamically updated during the simulation. GIS data and functions can be directly used for the updating because the model was built within a GIS. The updated attributes are used as the inputs to the neural network at each loop.

4.3. *The architecture of neural network*

Various studies have been carried out to test the effects of neural-network structures, which are determined by the numbers of layers and neurons, on modelling performance (Openshaw and Openshaw 1997, Paola and Schowengerdt 1997). It is considered that there is no universal optimal structure for all applications. The principle is to use as few layers and neurons as possible. A three-layer neural network has been commonly used because of its simplicity and effectiveness. 2–3 hidden layers may sometimes be useful if the function being modelled is extremely complex, noisy or discontinuous (Openshaw and Openshaw 1997). Determining the optimal number of layers is usually a matter of experimentation. A useful approach to the experiment is to start with one hidden layer and then add a second if the level of performance is unsatisfactory.

This study used a three-layer neural network for the simulation of multiple land uses (figure 3). More layers will significantly prolong the simulation time. Kolmogorov's theorem indicates that any continuous function ϕ: $X^n \rightarrow R^c$ can be implemented by a three-layer neural network which has n neurons in the input layer, $(2n+1)$ neurons in the single hidden layer, and c nodes in the output layer (Hecht-Nielsen 1987). In this model, there were twelve neurons in the input layers corresponding to the number of spatial variables (site attributes). Six neurons were specified to represent six classes of land uses in the output layer. Each output neuron produces a conversion probability corresponding to one target type of land use.

There is a need to determine the number of neurons in the hidden layer. According to Kolmogorov's theorem, the use of $2n+1$ hidden neurons can guarantee the perfect

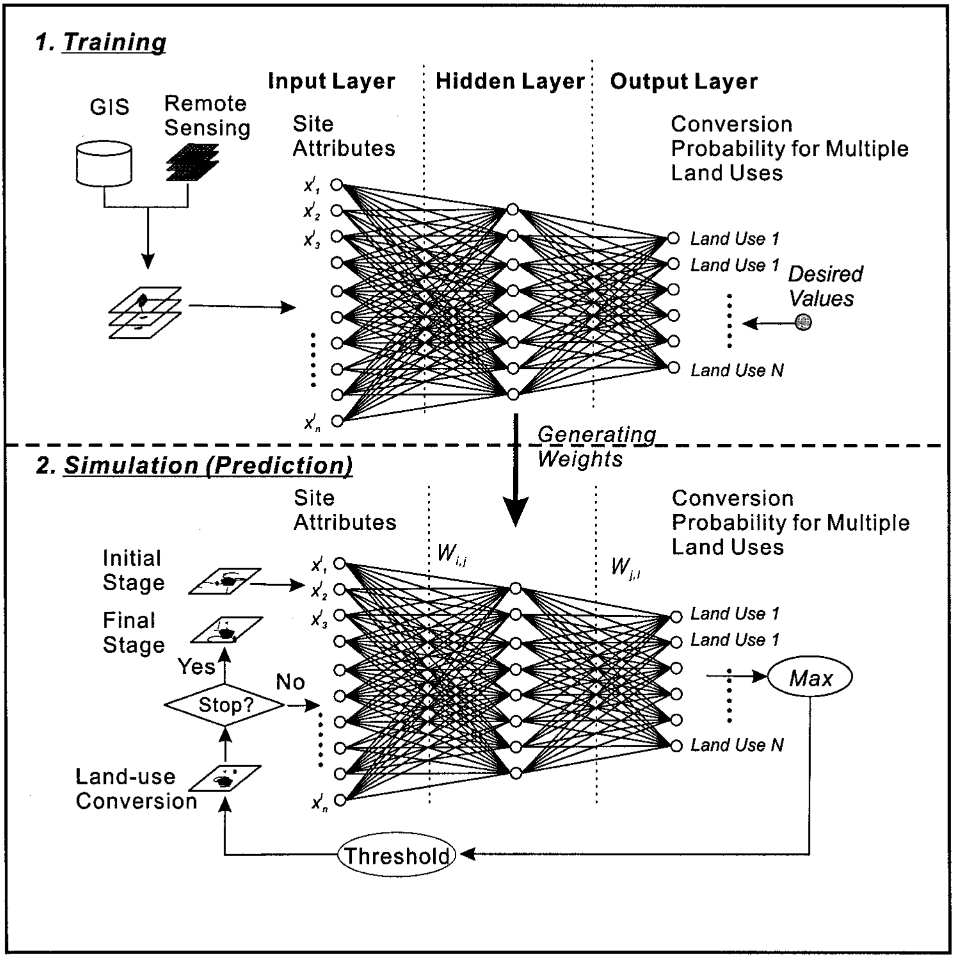

Figure 3. The flowchart of the neural-network-based CA model for simulating multiple land use changes.

fit of any continuous functions and reducing the number of neurons may lead to lesser accuracy. However, experiments indicate that $2n+1$ hidden neurons may be too many in applications (Wang 1994). $2n/3$ hidden neurons can generate results of almost similar accuracy but requires much less time to train. In this model, eight hidden neurons were used in the network to ensure a balance of both accuracy and simulation speed.

4.4. *Training the network*

Training the neural network is essential to the simulation of realistic land use patterns. The parameters of CA models have to be obtained through calibration procedures. It is rather convenient to obtain parameter values if they are based on neural networks. The information of land use changes was obtained by the classification of remote sensing images. The results of change detection were then overlaid with the site attributes obtained from GIS analysis. This produced the data set that could reveal the relationship between land use conversion probabilities and site attributes.

Data encoding is carried out to prepare the final training data set. Each output neuron is associated with a target land use. The network will calculate the conversion probabilities for each target land use based on site attributes. The calculated probabilities are compared with desired values for the training. The desired values are obtained from historical data. A neuron will be assigned with the desired value of 1 when there was land use conversion for its associated target land use. Otherwise, the neuron will be assigned with the desired value of 0. The calculated value is expected to be as close as possible to the desired value by automatically adjusting the weights in the learning process.

The calculated value is within the range from 0 to 1, which represents the conversion probability for the target land use. A calculated value closer to 1 indicates a higher conversion probability to the target land use and vice versa. The learning process can effectively let the network estimate conversion probabilities based on a set of site attributes.

It is unwise to use the whole data set for training because the data volume is huge. There is still a common problem of spatial autocorrelation for most spatial variables. Random sampling is a common way to solve these problems. Random sampling procedure can be improved by using stratified sampling (Congalton 1993). This is better than purely random sampling which may leave out some smaller categories. Proportional stratified sampling was used in the study. A total of 3000 samples were proportionally randomly selected from different land use types. Only 50% of the total samples were used as the training data set and the rest were treated as the test data set to verify the training results.

The parameter values were automatically determined by a learning process which was based on the back-propagation algorithm (Rumelhart *et al*. 1986, Foody 1996). The algorithm iteratively minimized an error function over the network (calculated) outputs and desired outputs based on the training data set. The training process was carried out outside the simulation model by using a neural network package, *THINKS PRO*. The package contains sophisticated algorithms and convenient interfaces for effective training and visualization. During the training, the prediction error decreased steadily at the beginning (figure 4). However, the decrease became minor soon and insignificant after many iterations. In this study, the training process was terminated at 1000. These parameter values were then imported to the model for further simulation.

4.5. *Simulation*

The neural-network-based CA model was written in *ARC/INFO GRID*'s Arc Macro Language (*AML*). There are two advantages for programming within the GIS. First, GIS data layers can be directly read by the neural network as data input without any data conversion. Secondly, the powerful spatial analysis functions of GIS, such as the *Eucdistance* and *Focal* functions of *ARC/INFO GRID*, can be conveniently used in the programming.

The output layer has six neurons, each representing the conversion probability from the existing type to a target type of land use. There are six types of land uses—cropland, orchards, construction sites, built-up areas, forest and water. When a set of site attributes is passed through the network, each output neuron produces a conversion probability for a target type of land use. Land use conversion at a cell

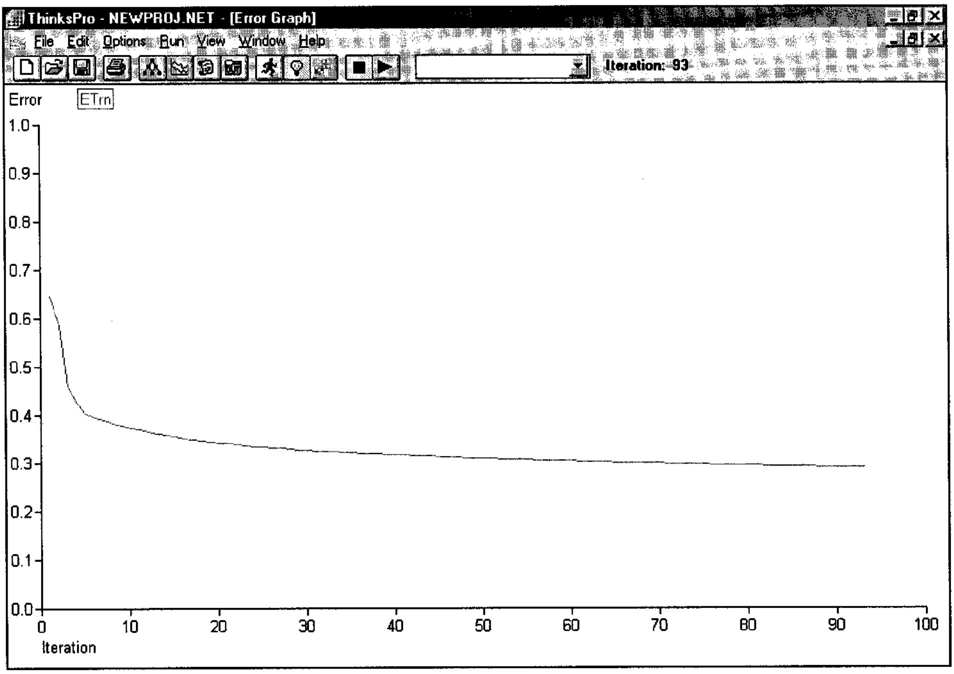

Figure 4. Training time and prediction error.

is decided by the competition between different types of land uses. At each iteration, a cell will be converted from one type to another type of land use that is associated with the highest conversion probability. Land use remains unchanged if it is converted to the same type of land use.

The simulation was executed by using the land use in 1988 as the initial grid. A mask was used to confine the simulation within the study area. Land use changes outside the study area were masked out. Figure 5 shows the results of simulating multiple land uses in the period of 1988–2005 by using the neural-network-based CA model. It first simulated the land uses in 1993. The goodness of fit was evaluated by comparing the simulation results with the actual land uses that are obtained from remote sensing. Table 3 shows the confusion matrix between the simulated and the actual land uses in 1993 based on overlay analysis. The simulation is quite acceptable with overall accuracy of 83%.

The next step was to simulate future land use patterns in 2005, assuming the continuation of the current trend and dynamics of urban development. The same parameter values were used for the network to simulate the future land use changes. Table 4 shows the simulated land use changes by categories. It is found that the future urban growth will lead to a large amount of agricultural land loss if the current land use development process continues. According to the simulation, the built-up areas will increase by 163% while the cropland will drop by 70% in 2005. The prediction of future land use pattern provides useful information for land use planning and management. Potential impacts of land use changes can be further estimated by GIS analysis (Li 1998). Sustainable land development plans can be formulated to mitigate the negative impacts (e.g. control the scale and extent of the land development) before they actually take place.

5. Conclusion

This paper has demonstrated that neural networks can be conveniently integrated with cellular automata for simulating multiple land use changes. The proposed method can overcome some of the shortcomings of the currently used CA models in simulating complex urban systems and multiple land use changes by significantly reducing the tedious work in defining parameter values, transition rules and model structures. Training data from the GIS can be easily used to obtain parameter values by calibrating the model. The model has the advantages of handling incomplete and erroroneus input data. The prediction surface is distinctly non-linear which is much superior to the linear surface of the popular regression models (Lloyd 1997). In many geographical phenomena, spatial variables are usually correlated with each other. Traditional methods, such as multicriteria evaluation (MCE) techniques, are inadequate in providing correct weights for correlated variables. In the neural-network-based CA model, spatial variables are not necessarily required to be independent of each other.

It is extremely difficult to calibrate CA models when there are multiple land uses. Traditional calibration methods are not robust because they are mainly based on trial and error approaches. These approaches involve the test of many possible combinations of parameter values for seeking the best fit. They are very computation-intensive because there are numerous possible combinations. The calibration algorithms are also application-dependent. Neural networks are quite robust and convenient in calibrating simulation models by using common back-propagation algorithms. In this study, the training process of neural network automatically determines the parameter values. These values are then imported to the model for simulation of multiple land use changes. The method significantly reduces the time of calibration.

The model structure is very simple by using a three-layer network with multiple output neurons to generate conversion probabilities. The model structure is generic and widely applicable to many applications of land use simulation. The users do not need to define the parameter values, detailed transition rules and model structures but just need to supply the training data. For other types of CA models, transition rules and model structures are not unique because different CA models usually adopt different transition rules and model structures.

The neural-network-based CA model is directly developed in a GIS environment by using *ARC/INFO GRID AML*. The GIS provides both data and spatial analysis functions for constructing the neural network. Real data are conveniently retrieved from the GIS database for calibrating and testing the model. The GIS functions are also used for the neural network calculations. The neural network has multiple output neurons to generate conversion probabilities at each iteration. Land use conversion is decided by comparing the conversion probabilities. The model is carried out by iteratively looping the neural network for simulating multiple land use changes. Site attributes are dynamically updated at the end of each iteration. Complex global patterns can be generated from local interactions through the neural network. The simulation results are not deterministic because a stochastic variable is used and site attributes are dynamically updated at the end of each loop.

The model has been successfully applied to the simulation of a fast growing region in southern China using a real data set from satellite images. The accuracy of the simulation of 83% is quite acceptable. The simulation of future base-line multiple land use development can help planners and policy makers to understand

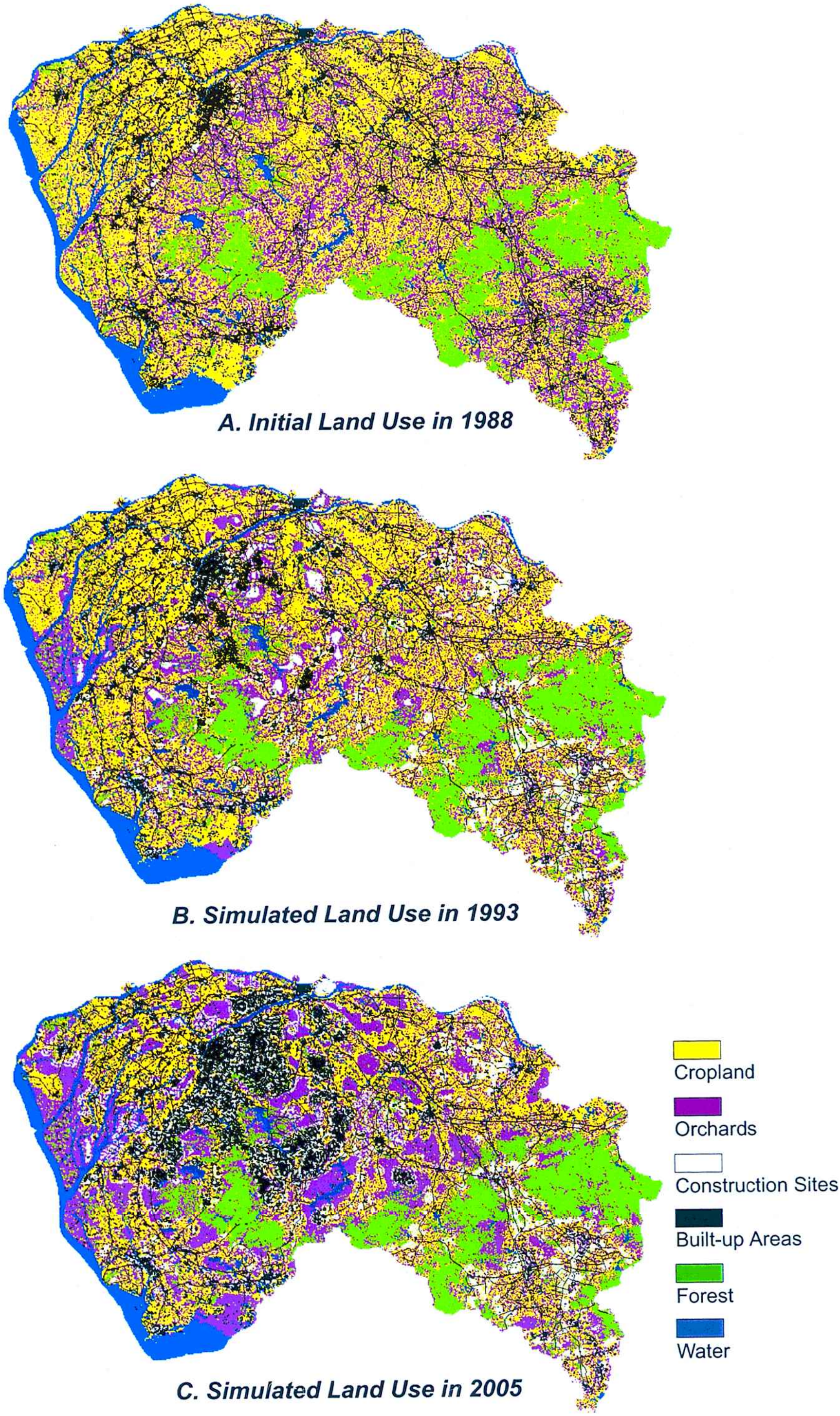

Figure 5. Simulation of multiple land use changes using the neural-network-based CA model.

Table 3. Confusion matrix between the actual and the simulated land uses in 1993 (in percentage).

		Simulated						
		Cropland	Construction sites	Orchard	Built-up areas	Forest	Water	Total
Actual	Cropland	89.3	3.3	7.3	0.1	0.0	0.0	100.0
	Construction sites	8.4	57.2	9.6	14.3	0.0	10.5	100.0
	Orchard	4.3	8.6	83.1	3.7	0.3	0.0	100.0
	Built-up areas	0.0	8.6	0.9	79.1	9.6	1.7	100.0
	Forest	0.2	0.0	0.6	1.1	96.4	1.8	100.0
	Water	0.0	0.8	0.0	0.0	4.3	94.9	100.0

Table 4. Simulated land use changes by categories (in hectares).

Land use	1988 (Initial)	1993 Actual	1993 Simulated	2005 (Future)
Cropland	100 400.3	77 839.3	84 229.6	57 047.0
Construction sites	2031.7	22 753.4	16 118.2	22 886.4
Orchard	63 512.6	62 458.9	59 608.8	70 281.0
Built-up areas	15 927.3	18 536.1	20 465.1	30 267.4
Forest	40 404.2	41 574.8	41 204.4	41 162.7
Water	17 392.5	16 506.1	18 042.5	18 024.2
Total	239 668.6	239 668.6	239 668.6	239 668.6

the environmental impacts and land use problems associated with the current trend of urban development. Alternative plans and policies can be formulated and compared with the simulated base-line growth to see what can be done to mitigate the negative impacts and control the scale and extent of the predicted land development.

There are some limitations for the model. Although it can be calibrated using empirical data, future changes in the transportation network cannot be easily forecasted and incorporated in the simulation. The changes of infrastructures can be regarded as exogenous factors rather than predicting these changes by the model itself. The calibration also assumes that the relationship can be extracted from empirical data. There is still a problem when the relationship is changing. More temporal data may be needed for the neural network to capture the changing features. These problems do not just apply to this neural-network-based model, but also to other CA and urban simulation models as well. Moreover, like other neural network models, it is essentially a black-box model. It does not provide explicit knowledge about the process of land use conversion. Further research is also needed to study the effects of different neural network structures on the simulation of land use changes.

Acknowledgements

This study is supported by the funding from the Croucher Foundation, Hong Kong. *ARC/INFO* and *ThinksPro* are trademarks of the Environmental Systems Research Institute, Inc. and Logical Designs Consulting, Inc, respectively.

References

Batty, M., and Xie, Y., 1994, From cells to cities. *Environment and Planning B: Planning and Design*, **21**, 531–548.

Batty, M., Xie, Y. C., and Sun, Z. L., 1999, Modelling urban dynamics through GIS-based cellular automata. *Computer, Environment and Urban Systems*, **23**, 205–233.

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: Planning and Design*, **24**, 247–261.

Clarke, K. C., and Gaydos, L. J., 1998, Loose-coupling a cellular automata model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science*, **12**, 699–714.

Congalton, R. G., 1991, A review of assessing the accuracy of classification of remotely sensed data. *Remote Sensing of Environment*, **37**, 35–46.

Deadman, P. D., Brown, R. D., and Gimblett, H. R., 1993, Modelling rural residential settlement patterns with cellular automata. *Journal of Environmental Management*, **37**, 147–160.

Foody, G. M., 1996, Relating the land cover composition of mixed pixels to artificial neural network classification output. *Photogrammetric Engineering & Remote Sensing*, **62**, 491–499.

Gong, P., 1996, Integrated analysis of spatial data from multiple sources: using evidential reasoning and artificial neural network techniques for geological mapping. *Photogrammetric Engineering & Remote Sensing*, **62**, 513–523.

Hathout, S., 1988, Land use change analysis and prediction of the suburban corridor of Winnipeg, Manitoba. *Journal of Environmental Management*, **27**, 325–335.

Howarth, P. J., 1986, Landsat digital enhancements for change detection in urban environment. *Remote Sensing of Environment*, **13**, 149–160.

Jensen, J. R., Rutchey, K., Koch, M. S., and Narumalani, S., 1995, Inland wetland change detection in the Everglades water conservation area 2A using a time series of normalized remotely sensed data. *Photogrammetric Engineering and Remote Sensing*, **61**, 199–209.

Lambin, E., 1997, Modelling and monitoring land cover change processes in tropical regions. *Progress in Physical Geography*, **21**, 375–93.

Landis, J. D., 1995, Imagining land use futures: applying the California urban futures model. *Journal of American Planning Association*, **6**, 438–457.

Landis, J., and Zhang, M., 1998, The second generation of the California urban futures model. Part 1: model logic and theory. *Environment and Planning B: Planning and Design*, **30**, 657–666.

Li, X., 1998, Measurement of rapid agricultural land loss in the Pearl River Delta with the integration of remote sensing and GIS. *Environment and Planning B: Planning and Design*, **25**, 447–461.

Li, X., and Yeh, A. G. O., 1998, Principal component analysis of stacked multi-temporal images for the monitoring of rapid urban expansion in the Pearl River Delta. *International Journal of Remote Sensing*, **19**, 1501–1518.

Li, X., and Yeh, A. G. O., 2000, Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *International Journal of Geographical Information Science*, **14**, 131–152.

Lloyd, R., 1997, *Spatial Cognition: Geographic Environments* (The Netherlands: Kluwer Academic Publishers).

Mertens, B., and Lambin, E. F., 2000, Land cover-change trajectories in Southern Cameroon. *Annals of the Association of American Geographers*, **93**, 467-494.

Openshaw, S., 1998, Neural network, genetic, and fuzzy logic models of spatial interaction. *Environment and Planning A*, **30**, 1857–1872.

Openshaw, S., and Openshaw, C., 1997, *Artificial Intelligence in Geography* (Chichester, England: John Wiley & Sons).

Paola, J., and Schowengerdt, R. A., 1997, The effect of Neural-network structure on a multispectural land use / land cover classification. *Photogrammetric Engineering & Remote Sensing*, **63**, 535–544.

Rumelhart, D. E., Hinton, G. E., and Williams, R. J., 1986, Learning representations by back-propagating errors. *Nature*, **323**, 533–536.

Wang, F., 1994, The use of artificial neural networks in a geographical information systems for agricultural land suitability assessment. *Environment and Planning A*, **26**, 265–284.

Ward, D. P., Murray, A. T., and Phinn, S. R., 2000, A stochastically constrained cellular model of urban growth. *Computers, Environment and Urban Systems*, **24**, 539–558.

Webster, C. J., and Wu, F., 1999, Regulation, land-use mix, and urban performance. Part 1: theory. *Environment and Planning A*, **31**, 1433–1442.

White, R., and Engelen, G., 1993, Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land use patterns. *Environment and Planning A*, **25**, 1175–1199.

White, R., Engelen, G., and Uijee, I., 1997, The use of constrained cellular automata for high-resolution modelling of urban land use dynamics. *Environment and Planning B: Planning and Design*, **24**, 323–343.

Wu, F., 1998, An experiment on the generic polycentricity of urban growth in a cellular automatic city. *Environment and Planning B: Planning and Design*, **25,** 103–126.

Wu, F., and Webster, C. J., 1998, Simulation of land development through the integration of cellular automata and multicriteria evaluation. *Environment and Planning B: Planning and Design*, **25**, 103–126.

Wu, F., and Webster, C. J., 2000, Simulating artificial cities in a GIS environment: urban growth under alternative regulation regimes. *International Journal of Geographical Information Science*, **14**, 625–648.

Yeh, A. G. O., and Li, X., 1998, Sustainable land development model for rapid growth areas using GIS. *International Journal of Geographical Information Science*, **12**, 169–189.

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

Zhou, J., and Civco, D., 1996, Using genetic learning neural networks for spatial decision making in GIS. *Photogrammetric Engineering & Remote Sensing*, **62**, 1287–1295.