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Understanding spatial and temporal processes of urban growth: cellular automata modelling

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Abstract. An understanding of the dynamic process of urban growth is a prerequisite to the prediction of land-cover change and the support of urban development planning and sustainable growth management. The spatial and temporal complexity inherent in urban growth requires the development of a new simulation approach, which should be process-oriented and have a strong interpretive element. In this paper the authors present an innovative methodology for understanding spatial processes and their temporal dynamics on two interrelated scales—the municipality and project scale—by means of a multistage framework and a dynamic weighting concept. The multistage framework is aimed at modelling local spatial processes and global temporal dynamics by the incorporation of explicit decisionmaking processes. It is divided into four stages: project planning, site selection, local growth, and temporal control. These four stages represent the interactions between top-down and bottom-up decisionmaking involved in land development in large-scale projects. Project-based cellular automata modelling is developed for interpreting the spatial and temporal logic between various projects that form the whole of urban growth. Use of dynamic weighting is an attempt to model local temporal dynamics at the project level as an extension of the local growth stage. As nonlinear function of temporal land development, dynamic weighting can link spatial processes and temporal patterns. The methodology is tested with reference to the urban growth of a fast growing city—Wuhan, in the People's Republic of China—from 1993 to 2000. The findings from this research suggest that this methodology can be used to interpret and visualise the dynamic process of urban growth temporally and transparently, globally and locally.

1 Introduction

An understanding of urban development processes is crucial in urban development planning and sustainable growth management. The urban development process involves many actors and types of behaviour and various policies, resulting in spatial and temporal complexity. The nonlinear dynamics inherent in these growth processes opens up the possibility for 'emergencies' (sudden changes) that are difficult or impossible to predict. Owing to the hidden complexity of reality, our science has become less orientated to prediction and more an aid to understanding in order to structure debate (Batty and Torrens, 2001). Orjan (1999) argued that without a proper understanding of the recent past we are in no position to comprehend—let alone predict—emerging patterns and processes. Couclelis (1997) first put forward the idea of a spatial understanding support system (SUSS). Horita (2000) reported a new SUSS for representing community disputes. Limited by existing sciences and techniques, understanding-oriented modelling is orientated more to practicability than to prediction. To achieve a reasonable understanding we need reliable information sources and models. Successful models should have a strong interpretive element and an interactive environment to simulate 'what-if' scenarios. Consequently, they require an innovative simulation approach.

The first step in such decisionmaking is to identify the process of decisionmaking. This is the same as in the area of information management, where we need to recognise the data flowchart and model before establishing any operational information system.

Remote sensing and geographical information systems (GIS) have proven to be effective means for extracting and processing varied resolutions of spatial information for monitoring urban growth (Masser, 2001). However, they are still not adequate for process-oriented modelling as they lack social and economic attributes, particularly at a detailed scale. In developing countries, acquisition and integration of socioeconomic data still have a long way to go. In such a situation, local knowledge (expert opinions, historical documents), albeit only qualitative or semiquantitative, can be very valuable in assisting us in understanding processes such as urban growth patterns, driving forces, and the major actors involved. Hence, local knowledge should be incorporated into simulation modelling at certain stages and in certain ways.

The use of cellular automata (CA), a technique developed recently, has been receiving more and more attention in urban and GIS modelling because of its simplicity, transparency, strong potential for dynamic spatial simulation, and innovative bottom-up approach. When applied to real urban systems, CA models have to be modified by including cell multistates, by relaxing the size of the neighbourhood with distance-decay effects, probabilistic rules, and by linking them to complexity theory. In fact, many—if not all—urban CA bear little resemblance to the formal CA model (Torrens and O'Sullivan, 2001). The literature in the field of urban CA modelling includes at least two classes of successful applications at various spatial and temporal scales. One class concentrates on the study of artificial cities to test the theories of complexity and urban studies (Batty, 1998; Benati, 1997; Couclelis, 1997; Wu, 1998a). The other class focuses on real cities to provide decision support to urban planners at the regional, municipal, and town levels (Besussi et al, 1998; Clarke and Gaydos, 1998; Silva and Clarke, 2002; Ward et al, 2000; White and Engelen, 2000; Wu, 2002; Yeh and Li, 2001). These studies have revealed that urban CA-like models are effective in simulating the complexity of urban systems and their subsystems, from emergence, feedback, and self-organisation. Nevertheless, the interpretation of transition rules, which is highly important for urban planners, still receives little attention in urban CA modelling, particularly in providing a link to the process of urban planning.

Moreover, previous studies of urban CA models ignore the fact that urban growth is a dynamic process rather than a static pattern. For example, the urban growth model of Clarke and Gaydos (1998) has attracted a lot of attention regarding urban growth prediction (Silva and Clarke, 2002). Their CA model controls the evolution of city growth by means of five coefficients (diffusion, breed, spread, slope, and roads). The diffusion factor determines the overall outward dispersive nature of the distribution. The breed coefficient specifies how likely it is that a newly generated detached settlement will begin its own growth cycle. The spread coefficient controls how much diffusion expansion occurs from existing settlements. The slope resistance factor influences the likelihood of settlement extending up steeper slopes. The road gravity factor attracts new settlements toward and along roads. This is a successful simulation model of patterns, focusing principally on spontaneous, organic, spread, road-influenced, and diffusive patterns. It still lacks the ability to interpret causal factors in a complete process model because similar patterns from the final output of CA simulation do not indicate similar processes. Thus, the transition rules validated are not evidence to explain the complex spatial behaviour behind the process. Therefore, process-oriented rather than pattern-oriented simulation should be the main concern of urban growth CA modelling. This point has been supported and recognised recently in some journals (Torrens and O'Sullivan, 2001). Dragicevic et al (2001) apply fuzzy spatiotemporal interpolation to simulate changes that occurred between 'snapshots' registered in a GIS database. The main advantage of their research lies in its flexibility to create various temporal scenarios of urbanisation processes and to choose the desired temporal resolution. Dragiceivc et al also declared that the approach does not explicitly provide causal factors; thus it is not an explanatory model.

Wu (1998b) developed a CA model driven by an analytical hierarchy process (AHP) to simulate the spatial decisionmaking process of land conversion (AHPs were originated by Saaty, 1980). In AHPs pair-wise comparisons are used to reveal the preferences of decisionmakers and are an ideal means for calculating weight values from the qualitative knowledge of local experts. This CA model is, in essence, a dynamic multicriteria evaluation (MCE) as a dynamic neighbourhood (updated during model runs) is treated as an independent variable. This model is successful in linking explicit decisionmaking processes to CA. The adjustment of factor weights allows one to generate distinctive scenarios. Hence, this model has a strong interpretive element. However, an AHP-driven decisionmaking process is not spatially and temporally explicit as the weight values are fixed for the whole study area and period modelled. They cannot be used to model processes, especially temporal dynamics. The incorporation of spatially and temporally explicit decisionmaking processes into CA models has not been reported to date.

In summary, we need to develop a new methodology based on present urban CA that allows one to model and interpret spatial process and temporal dynamics and also incorporate local knowledge to interpret these processes. With this in mind, we have organised this paper into four sections. In the next section we introduce the concepts that we meet in trying to understand urban growth: processes and dynamics, global and local. We also discuss in detail a proposed methodology, that comprises mainly a multistage framework and a dynamic weighting concept. The framework incorporates explicit decisionmaking processes into the modelling of local spatial processes and global temporal dynamics. The dynamic weighting concept allows the modelling of local temporal dynamics by representing the dynamic interaction between pattern and process at a lower level. CA-based simulation is developed to support and implement each method. The mathematical foundations are described step by step. In section 3 we focus on the implementation of the methodology by undertaking a case study of Wuhan City, People's Republic of China. In section 4 we end the paper with further discussion and conclusions regarding model calibration and validation, the visualisation of processes, and process modelling.

2 Methodology

2.1 Complex processes and dynamics

Urban growth can be defined as a system resulting from complex interactions between urban social and economic activities, physical ecological units in regional areas, and future urban development plans. This interaction is an open, nonlinear, dynamic, and local process, which leads to the emergence of global growth patterns. The urban growth process is a self-organised system (Allen, 1997).

The term 'process' generally refers to a sequence of changes in space and time—spatial processes and temporal processes, respectively. It should be noted that, strictly speaking, spatial and temporal processes cannot be separated precisely, as any geographical phenomenon is bound to have both a spatial and a temporal dimension. An understanding of change through both time and space should, theoretically, lead to an improved understanding of change and of the processes driving change (Gregory, 2002). However, a spatial process is much more than a sequence of changes. It implies a logical sequence of changes being carried out in some definite manner that lead to a recognisable result (Getis and Boots, 1978). To sum up, the key components of a process are change and logical sequence. 'Change' is defined by a series of patterns, and 'logical sequence' implies an understanding of process. In contrast to pattern, process contains a dynamic component.

An urban growth system consists of a large number of new projects on various scales. Large-scale projects are characterised by dominant functions, heavy investment, long-term construction, and the involvement of a number of actors; examples include the construction of airports, industrial parks, and universities. In contrast, small-scale projects are characterised by a single function, rapid construction, light investment, and few actors; examples may be the construction of a private house or a small shop. The project, as the basic unit of urban development, is the physical carrier of complex social and economic activities.

The spatial and temporal heterogeneity of social and economic activities creates massive flows of matter, people, energy, and information between new projects and also between the projects and the other systems (developable, developed, and planned). They are the sources of the complex interactions inherent in urban growth. As such, the urban growth process consists of a spatial and temporal logic between various scales of land development projects. The spatial and temporal organisation of projects is the key to understanding these processes and dynamics. This understanding can be based on two scales: the municipal (global) scale and the project (local) scale. For instance, on the global scale, in space, projects can be organised into clustered or dispersed patterns, 'clustering' implying a self-organised process, and 'dispersal' a stochastic process. In time, projects can be organised into quick or slow patterns. The term 'local process' refers to spatial growth at the project level. The term 'global dynamics' refers to the temporal logic between the projects forming urban growth as a whole, and the term 'local dynamics' the temporal logic between only the spatial factors or elements within a project.

The research reported in this paper has two specific objectives in terms of gaining a systematic understanding of the spatial and temporal process of urban growth:
(1) to understand the local spatial process at the project level and the global temporal dynamics with use of a multistage framework;
(2) to understand local temporal dynamics at the project level with use of the dynamic weighting concept.

2.2 A conceptual model of global dynamics

The complexity of the urban growth process can intuitively be projected onto decision-making processes and their spatial and temporal dimensions. The decisionmaking process involves multiple actors and types of behaviour. The spatial and temporal dimensions involve various spatial and temporal heterogeneities. Or, we can say, the decisionmaking process is a cause, the spatial and temporal dimensions the effect and projection. In consequence, we must start with the decisionmaking process in order to understand the spatial and temporal processes of urban growth.

Decisionmaking in urban growth is related to plans, policies, and projects. Projects consist of special land-use or development proposals usually by various types of actors such as investors, planners, developers, landowners, and work units. They evolve in the context of various levels of policy and plans. The project development process is a dynamic, spatially nested, hierarchy of multiple decisionmaking procedures, from the municipal to the building level, and vice versa. The global dynamics of urban growth results from the interactions between the top-down and bottom-up processes of decision-making. Top-down decisionmaking includes allocation of financial resources, master planning, and the time schedule of projects; bottom-up decisionmaking includes building style, building density, and plot ratios.

Global patterns can be described as having a cumulative and an aggregate order that results from numerous locally made decisions involving a large number of intelligent and adaptive agents. At the municipal scale, the decisionmaking process can fall into four stages: project planning, site selection, local growth, and temporal control, as illustrated in figure 1.

The first (project-planning) stage answers the questions 'how many large-scale projects were planned in previous periods?' and 'how much area was constructed in each project?' This stage is a typical top-down decisionmaking process based on a systematic consideration of physical and socioeconomic systems. Municipalities need to plan land consumption according to their social and economic demand for development. When land consumption is projected onto the physical land-cover system one observes different scales of new projects. Land-development projects can be divided into spontaneous and self-organisational types (Wu, 2000). 'Spontaneous projects' correspond to small-scale or sparse developments that may contain more stochastic disturbance and involve lower-level actors such as individuals or organisations. 'Self-organisational projects' represent larger-scale projects with a dominant land use and higher level actors. Such projects are the main concern at this project planning stage. The project here can be called an 'agent', which is a spatial entity linking with distinct actors and spatial and temporal behaviour. In this sense, the project-based approach proposed here is also a kind of agent-like modelling.

The first stage belongs to nonspatial modelling, resulting in proposals for development projects. These new developments will be projected along their spatial and temporal dimensions. Spatial complexity can be considered from two aspects: the location of the site and the spatial interaction between sites. 'Site location' concerns the issue of spatial site selection or location, leading to the second stage. 'Spatial interactions' relate to the issue of local growth or the control of development density and pattern, the third stage

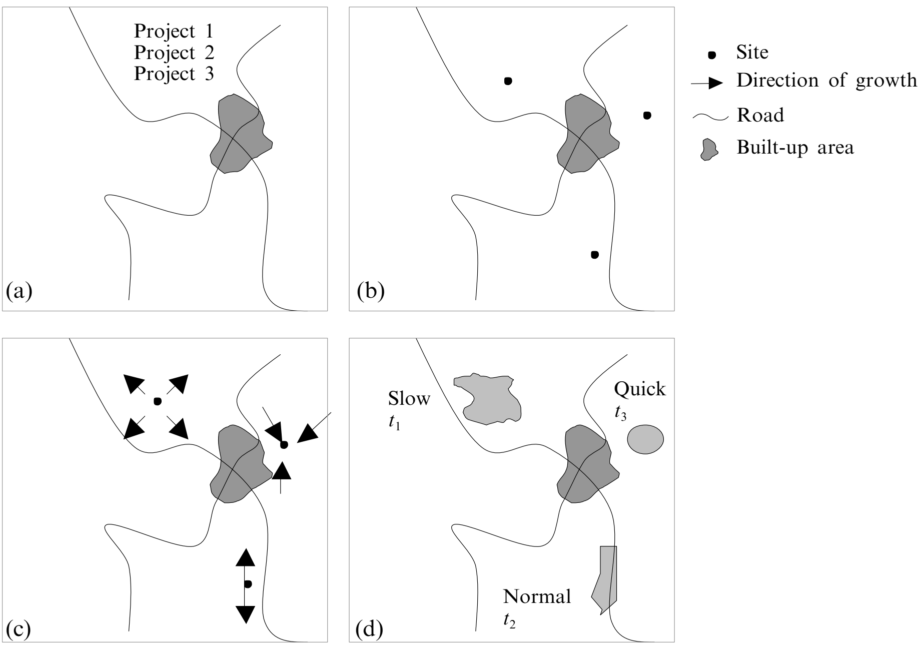


Figure 1. A conceptual model of the decisionmaking process: (a) project planning, (b) site selection, (c) local growth, and (d) temporal control.

of the framework. Temporal complexity, which is typically indicated by temporal heterogeneity or the timing of local growth, will be described in the fourth stage.

The second (site-selection) stage deals with the question 'where were the various sizes (or scales) of the projects to be located?' This stage is a typical spatial decision process involving municipal decisionmakers. The aim is systematically to optimise and balance the spatial distribution of socioeconomic activities as each project has specific socioeconomic functions planned. This stage can be seen as the static projection of the projects planned during the first stage. The rules of site selection are represented by multiple physical, socioeconomic, and institutional factors, incorporating various global and local constraints. Rules are delineated to differentiate between the various planned projects in terms of influential factors, weights, and constraints. To some extent, this stage provides growth boundaries and seeds for the next (local growth) stage and results in a number of potential spatial subsystems through the top-down process.

The third (local growth) stage addresses the question 'how did each project grow locally?' The answer to this question includes consideration of development density, intensity, and the spatial organisation of development units. After the spatial location has been agreed, each project is developed based on a more local type of decisionmaking involving landowners, investors, and individuals. This results in different spatial processes. The outcomes of these local growth processes can be concentric, diffusive, road influenced, and leapfrog in nature. They are affected by numerous factors, which change their influential roles spatially and temporally. Spatial heterogeneity (heterogeneity in a spatial context means that the parameters describing the data vary from place to place) suggests that spatial processes are locally varied. In spatial statistics, global analysis is being complemented by local area analyses such as local indicators of spatial association (LISA: Anselin, 1995) and geographically weighted regression (GWR): Fotheringham and Rogerson, 1994). As for understanding local urban growth, its spatial process depends mostly on local conditions such as physical constraints and socioeconomic circumstances. Using CA we are able to explore the dominant causal factors locally. This stage is dominated by the bottom-up approach.

The last (temporal-control) stage answers the question 'how fast did each project grow temporally?' This stage shifts to managing the local growth speed from a global perspective. The image of the whole urban growth process comprises the temporal sequences of all projects. For example, we can define such patterns as being quick, basic or normal, or slow local growth, representing three identifiable timing modes. The rate of local growth is governed by numerous factors resulting from top-down and bottom-up decisionmaking. For example, top-down decisionmaking includes allocation of financial resources from higher level organisations, and master and land-use planning control. Bottom-up decisionmaking includes manpower allocation and facility supply. The temporal land-demand amount decided at this stage should be input for use as a guide or constraint at the local growth stage. Hence, the stage is primarily a top-down procedure for controlling local temporal patterns and is conditioned by a bottom-up procedure.

It should be noted that each stage described above involves interactions between top-down and bottom-up decisionmaking. For example, although the land demand of each project is planned by municipal organisations, actual consumption is influenced by a number of local constraints. The whole process of urban growth should contain numerous feedback loops between these at various spatial and temporal scales. As the focus of our research aspects of top-down socioeconomic decisionmaking at various stages of the decisionmaking process will be treated as the exogenous variables.

The framework described in this paper has been designed primarily for understanding the dynamic processes of urban growth. When used for planning support, the first question will become 'how many large-scale projects will be planned in the coming years?' In this case, the socioeconomic model for determining the land consumption of projects should be included at this stage. Other questions arising at various stages will be similarly modified. Such a multistage framework can offer a transparent and friendly environment for constructing various scenarios for plans.

2.3 Land-transition models

The multistage framework discussed above conceptually breaks down the global dynamics of the whole urban growth process into the local land-conversion processes that result from large-scale projects. These local processes consist of complex spatial and temporal interactions, which can be simulated by the urban CA approach. The identification of large-scale projects and their functions is of importance for understanding the spatial behaviour of relevant actors. The term 'large-scale' has two meanings, from a spatial and a socioeconomic perspective, respectively. The spatial interpretation refers to a certain scale of spatial clustering of new development units. A project defined in this way may have no definite socioeconomic implications as it is not planned as a complete spatial entity. This definition allows one to look at relative spatial division. The socioeconomic interpretation refers to larger-area land development with special socioeconomic functions, such as the construction of a car manufacturing centre. A project defined in this way may have no ideal spatial agglomeration as the building density may be low. In this paper, we wish to focus on the socioeconomic interpretation as it provides a link to the underlying socioeconomic activities. However, it should be noted that spatial interpretations are also significant and necessary in some spatial process modelling.

In the following, small-scale projects with mixed functions are merged into one class conceptually. To identify large-scale projects, it was necessary to examine historical documents and to carry out interviews with local planning organisations. Last, as the process of CA modelling is identical in each project, as an example we refer only to project d in the following description; the other projects are followed through the same procedure.

2.3.1 *Project planning*

The simulated area of land for development from the starting time $t = 1$ up to time $t = n$, $\mathrm{L}(t)$, is given as follows:

$$\mathrm{L}(t)|_{t=n} = L_d , \tag{1}$$

where L_d is the actual (or planned) area for land-development project d (from stage 1) over the whole period ($t = 1$ to $t = n$). L_d in principle should be the output from traditional top-down socioeconomic models (for example, White and Engelen, 2000). Here, it is assumed to be an exogenous variable (of known value from previous urban growth analysis). For example, if a shopping centre is known to have occupied 5 ha from 1993 to 2000 then $L_d = 5$ ha for that period. $\mathrm{L}(t)$ is the simulated are of land-development project d up to time t, so L(1996) is the simulated land-transition area from 1993 to 1996. Calculation of $\mathrm{L}(t)$ is described in section 2.3.4.

2.3.2 *Constraint-based site-selection model*

The constraint-based site-selection model is defined as follows:

$$S = N\mathrm{Centre}(x, y) , \tag{2}$$

where

$$\mathrm{Centre}(x, y) = \prod_{i=1}^{I} \gamma_i \, . \tag{3}$$

Here, S, the site selected for a project, includes a central starting point, Centre(x, y), and its surrounding area or neighbourhood, N. The location of the centre is determined by various critical constraints γ_i. As in other research (Ward et al, 2000; Yeh and Li, 2001), constraints operate at the local, regional, and global levels. Global constraints taking an account of the whole study area include physical aspects (for example, ecological protection zones, accessibility to transport infrastructure, and city centres and subcentres), economic aspects (for example, investment, and land value), social aspects (for example, population density), and institutional aspects (such as master planning). Regional constraints are defined by the availability of developable or developed land and its density in a neighbourhood. It should be noted that the regional level has a varied spatial extent as the sizes of neighbourhood vary from project to project. In some cases, we have to define multilevel regions (for example, Batty et al, 1999). Local constraints refer to the physical conditions of a site or pixel, such as slope, soil quality, and geological condition. Each of the criteria at each of the three levels varies from project to project, and from case to case, so that one is able to interpret the specific spatial behaviour of the actors involved in each project. For example, slope does not take effect in a flat city. Equation (2) is based on the assumption that site selection depends on a limited number of equally weighted constraints [equation (3)] as, in practice, the decisionmaking process is primarily qualitative and simple for decisionmakers. This stage is implemented by GIS analysis based on spatial operations (for example, 'find distance', 'neighbourhood statistics', and 'map calculation') and by the use of heuristic rules (for example, if rule 1 and rule 2, then do ...) based on visual programming. GIS visual functions can help modellers to test their systematic thinking; that is, whether a particular rule can create ideal sites for a planned project.

2.3.3 *Local growth model*

Through this model we seek the major spatial determinants of local spatial processes with use of bottom-up CA simulation. CA are dynamic discrete space and time systems. A CA system consists of a regular grid of cells, each of which can be in one of a finite number of possible states, updated synchronously in discrete time steps according to a local, identical interaction rule. In this model, the cell state is binary (1 indicates a land-cover transition from nonurban to urban; 0 indicates no such transition), limited to the cellular space of each project, CA simulation is carried out by dynamic evaluation and by updating the development probabilities for each cell in the cellular space. The cells selected at each iteration will be changed from 0 to 1. The development potential of each cell j at time t, $\mathrm{P}_j(t)$, is defined as follows:

$$\mathrm{P}_j(t) = \sum_{i=1}^{k} \mathrm{W}_i(t)\mathrm{V}_{ij}(t) \prod_{i=k+1}^{I} \omega_i \, , \tag{4}$$

where $\mathrm{W}_i(t)$ is the weight of constraint (or factor) i at time t, $\mathrm{V}_{ij}(t)$ is the standardised score of constraint (or factor) i for cell j at time t, and ω_i is a restriction relating to constraint i.

It is assumed that I constraints $(1 \leqslant i \leqslant I)$ are considered, comprising k nonrestrictive and $I-k$ restrictive constraints. When $(k+1) \leqslant i \leqslant I$, ω_i is a binary variable (taking a value 0 or 1) representing restrictive constraints at the local, regional, and global levels: $\omega_i = 0$ indicates that a cell is absolutely restricted from transition to urban use in relation to constraint i (for example, it may be at the centre of a large lake). When $1 \leqslant i \leqslant k$, i is a nonrestrictive constraint and may be referred to as a factor in order to distinguish it from a restrictive constraint, ω_i. These factors are complementary in contributing to the development potential of a cell.

The potential for transition depends on a linear weighted additive sum of development factors. $W_i(t)$, the relative weight value of factor i, is calibrated from data. Largely, $W_i(t)$ can be seen as representing the causal effects of the local growth process. In the case of global temporal dynamics, $W_i(t)$ is treated temporally as a constant, W_i. The function $W_i(t)$ will be discussed in detail in section 2.3.4, on local temporal dynamics.

$V_{ij}(t)$ is the standardised score (falling within the range 0 to 1) of factor i for cell j at time t according to the following:

$$V_{ij}(t) = \frac{X_{ij}(t) - \min[X_{ij}(t)]}{\max[X_{ij}(t)] - \min[X_{ij}(t)]}, \qquad 0 \leqslant V_{ij}(t) \leqslant 1, \quad 1 \leqslant i \leqslant k, \tag{5}$$

and

$$X_{ij}(t) = \exp(-\phi d_{ij}), \tag{6}$$

where $X_{ij}(t)$ is the value of factor i for cell j at time t; $\min[X_{ij}(t)]$ and $\max[X_{ij}(t)]$ are, respectively, the minimum and maximum values of $X_{ij}(t)$ among the cells to be evaluated in relation to factor i; ϕ is a distance-decay parameter; and d_{ij} is the distance from cell j to any spatial element defined in factor i, such as a major road network.

In urban growth, frequently considered factors include: (1) transport accessibility, (2) accessibility to urban centres and subcentres, (3) suitability, (4) planning input, and (5) the presence of dynamic neighbourhoods (Clarke and Gaydos, 1998; Ward et al, 2000; White et al, 1997; Wu, 1998b). In this paper, suitability analysis is applied at the stage of site selection. The other four factors are used to evaluate $P_j(t)$ at this stage. The quantification of master planning will be explained in section 3.

Accessibility measurement, such as accessibility to a major road, is a very active field in GIS and modelling. Numerous methods have been published (see, for example, Miller, 1999). In this study, a negative exponential function [equation (6)] is employed to quantify the distance-decay effect. Urban modellers making use of economic theory (Muth, 1969) and discrete choice theory (Anas, 1982) have made widespread use of the negative exponential function. Previous research on the same case-study city (Cheng and Masser, 2003) confirmed its effectiveness, although the inverse power function has also frequently been successfully employed for quantifying the distance-decay effect (Batty and Kim, 1992).

In this paper, ϕ is the parameter controlling the distance-decay effect. Usually, we can assume $0 < \phi < 1$, and ϕ varies with factor i. A higher value of ϕ means that the influence on land transition will decrease more rapidly. The parameter ϕ can be determined by means of a global exploratory data analysis of urban growth patterns (Cheng and Masser, 2003), where ϕ is the slope of the log–linear relationship between the probability of transition and distance d_{ij}. From equation (6) we calculate the potential for land conversion contributed from proximity factors. In this study, accessibility factors are fixed or static during the modelling period as the spatial factors (such as road networks) are not updated temporally, so $V_{ij}(t) = V_{ij}$.

In our model, neighbourhood size is not globally universal but locally parameterised and varies for different projects, as each project has distinguishing social and economic functions. The neighbourhood effect ('action-at-distance') is represented as a nonrestrictive factor in equation (4), which indicates the spatial influences of developed cells on land conversion in surrounding sites. Developed cells come from the cells previously transited or the old urban area. Strictly speaking, the further development of cells that have already undergone a transition reflects the local spatial self-organisation of land conversion in each project as a dynamic variable that is updated in each iteration [that is, $V_{ij}(t) \neq V_{ij}$]. The development of old urban area depends on existing global urban activities as a fixed spatial factor. These two types of development are treated as two independent factors in this research.

In practice, restrictive and nonrestrictive constraints are relative classifications and vary temporally. For example, ponds may have constituted a restrictive constraint in 1950 but may become nonrestrictive in 2000 as no large quantity of developable land may be available in the later period. We may write:

$$P_j'(t) = [1 + \ln(\xi)^{\alpha}]P_j(t), \tag{7}$$

and

$$\Delta L(t) = L(t) - L(t-1), \qquad L(0) = 0, \tag{8}$$

where $P_j'(t)$ is the development potential of cell j at time t; $\Delta L(t)$ is the demand for land from time $t-1$ to time t; ξ is a random variable taking values in the range 0 to 1; and α is a parameter controlling the size or strength of the stochastic perturbation.

Principally, land conversion is allocated according to the highest score of the potential; however, practically, this is subject to stochastic disturbance and imperfect information. To generate patterns that are closer to reality, a stochastic disturbance is introduced, as $1 + \ln(\xi)^{\alpha}$ (Li and Yeh, 2001). As in other CA applications (Ward et al, 2000; White et al, 1997; Wu and Webster, 1998), $P_j'(t)$ in equation (7), representing the probability of land transition at cell j at time t, is the major driving force of local growth.

Whether or not a cell is to undergo transition over time $t-1$ to time t depends on the probability $P_j'(t)$ at each iteration. Selection will start from the maximum of $\{P_j'(t)\}$ until it reaches the required number of cells—that is $\Delta L(t)$ for the iteration between time $t-1$ and time t. The demand for land consumption $\Delta L(t)$ in equation (8) will be calculated at the temporal control stage, as $L(t)$ is the cumulative amount of land development up to time t.

2.3.4 *Temporal control model*

Previous studies suggest that the urban development process represented by $L(t)$ in equations (1) and (8) follows a logistic curve over time (Herbert and Thomas, 1997). For example, Sui and Hui (2001) simulated the expansion trend of the desakota regions between 1990 and 2010 by using a logistic equation, where the total number of converted urban pixels was a logistic function of year. Here, the same principle is applied for the temporal control of each project. A standard logistic curve is defined as follows:

$$L(t) = \frac{a}{1 + b\exp(-ct)}, \tag{9}$$

where a, b, and c are unknown parameters, t (where $t = 1, ..., n$) is the time step, and $L(t)$ the amount of land development up to time t. If it is assumed that

$$L(0) = L_0 = \frac{a}{1+b} = 1, \tag{10}$$

and

$$L(n) = L_n = \frac{a}{1 + b\exp(-cn)} = L_d, \tag{11}$$

then n and L_d are as defined in equation (1). Equation (9) can then be revised as follows. If

$$z = \frac{L_d[\exp(-cn) - 1]}{L_d \exp(-cn) - 1}, \tag{12}$$

then

$$\mathrm{L}(t) = \frac{z}{1 + (z - 1)\exp(-ct)}. \tag{13}$$

In equations (12) and (13) z implies the long-term limit of $\mathrm{L}(t)$ behaviour. The shape of the logistic curve usually represents the speed of project development over time, which is controlled by the parameters c, n, and L_d. Here, for simplicity, temporal control is classified into three types—slow growth, normal growth, and quick growth—providing three distinguishing scenarios. If it is assumed that

$$\mathrm{L}(t) = \frac{L_d}{\lambda}, \qquad \text{for } t = \frac{n}{2}, \tag{14}$$

then

$$c = \frac{2}{n}\ln\left(\frac{L_d - \lambda}{\lambda - 1}\right). \tag{15}$$

Further, $L(t)$ may be a function of both time t and parameter λ when n and L_d are fixed. Consequently, the value of λ will determine the shape of the logistic curve. As such, we can define slow, normal, and quick growth according to λ:

$$\lambda = \begin{cases} \frac{4}{3}, & \text{quick growth;} \\ 2, & \text{normal growth;} \\ 4, & \text{slow growth.} \end{cases} \tag{16}$$

Of course, we can define more classes, such as 'very slow' or 'very quick' by assigning λ values differently.

In figure 2 we provide an example of three modes, where $L_d = 500$, $n = 30$, and where λ is 4/3, 2, and 4, respectively, for the three (quick, normal, and slow) patterns. However, iteration time t ($t = 1, ..., n$) in simulation is different from the real time τ in

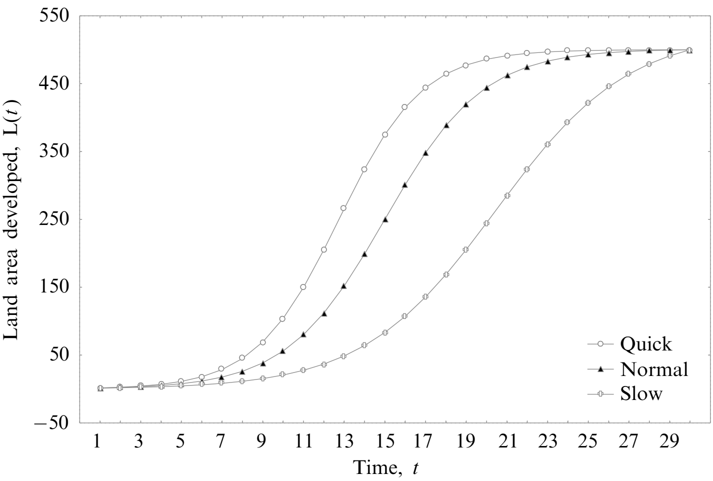


Figure 2. An illustration of temporal development patterns.

years (1, ..., m) where the base year may be 1993 ($\tau = 0$) and the seventh year ($\tau = 7$) 2000. Let $L_i(\tau)$ denote the total growth of project i up to year τ, a transition from $L_i(t)$ to $L_i(\tau)$ may be established as follows:

$$L_i(\tau) = h[L_i(t)], \qquad \tau = 1, 2, ..., m; \quad t = 1, 2, ..., n; n > m. \tag{17}$$

In previous research on CA applications, a linear function is applied, that is, $t = \Delta\tau$. Here, Δ is assumed to be a constant, which implies an equal growth rate. For example, if when $\tau = 5$ years, t corresponds to 20 iterations this can be defined, in the case of linear relationship, as $t = 4\tau$. So, $L(\tau)|_{\tau=1} = \sum L(t)$, $0 < t < 5$. In reality, function h may be a nonlinear function of iteration number t, which may be tested experimentally through qualitative understanding and visual exploration of the difference between actual and simulated processes.

2.4 A conceptual model for local temporal dynamics

The multistage method can be used to understand the global temporal dynamics of the whole study area rather than the local dynamics of each project. An understanding of local dynamics requires a different perspective focusing on more detailed aspects of spatial and temporal processes.

Heterogeneity in a temporal context means that the parameters describing any geographical phenomena vary from phase to phase over the whole period studied. For example, Wu and Yeh (1997) applied logistic regression methods for modelling land-development patterns in two periods (1979–87 and 1987–92) based on parcel data extracted from aerial photographs. They found that the major determinants of land development have changed from distance from the city centre to closeness to the city centre; from proximity to intercity highways to proximity to city streets; and are more rather than less related to the physical condition of the sites. This suggests that the roles of various factors are changing in the process of land development. Likewise, if we shrink a longer period (1979–92) to a shorter period, such as 1993–2000, and reduce the spatial extent, from looking at the whole city to looking at a smaller part such as a large-scale project, the same principle should be working as well. Therefore, temporal heterogeneity results in complex spatial and temporal processes, which need to be identified in modelling. As similar patterns can result from numerous different processes, the understanding of process is more important than the understanding of pattern. Pattern is only a phenomenon but process is the essence.

In figure 3 we give an example of a spatial pattern and the processes involved in urban growth. T_1, T_2, and T_3 indicate time series of land development with T_1 the earliest, and T_3 the latest. The shading represents the temporal order of land development: the darker the shading the later the development. The same spatial pattern results from three (in reality, more) distinct spatiotemporal processes that reflect the spatial and temporal interactions between road-influenced and centre-based local

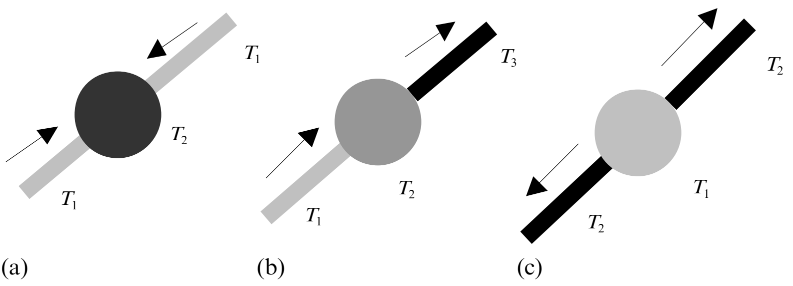


Figure 3. Different spatiotemporal processes: (a) convergence, (b) a sequence, and (c) divergence. Note: T_1, T_2, and T_3 are time sequences, from T_1, the earliest, to T_3, the latest.

growth patterns. The arrows indicate the trend of temporal development, from which we can define them as three different processes (convergence, sequence, and divergence).

The basic principle behind the phenomena is that various physical factors such as roads and centres play various roles over time during the course of local growth. In figure 3(a), relating to convergence, at T_1, the road is more important than the centre, but it is less important at T_2. This means that local growth occurs first along the road and then moves to the centre. In figurer 3(c) we see the opposite effect. If we use L to denote the total amount of local growth, L_l for the lower part along road, L_u for the upper part along road, L_c for the centre part, and L_t for the cumulative development amount up to time t, we may write:

$$L = L_l + L_u + L_c \,, \tag{18}$$

and

$$\mathrm{W}_i(t) = \mathrm{f}_i(L_t), \qquad i = \mathrm{c, r}\,. \tag{19}$$

where W_r and W_c represent the weights of spatial factors 'road' and 'centre' respectively. The rules detected are listed in table 1. The three cases imply that temporal dynamics can be represented and understood through dynamic weighting concepts. Dynamic weighting means that the factor weight is not a constant but is a function of development amount over time [equation (19)].

To some extent, equation (19) suggests a dynamic feedback between $\mathrm{W}_i(t)$ and L_t, representing the complex interaction between pattern and process. L_t indicates the temporal pattern in terms of area developed, and the process is described by the changing roles of multiple factors $\mathrm{W}_i(t)$; in fact, L_t is also impacted by $\mathrm{W}_i(t)$. In principle, the functions $\mathrm{f}_i(L_t)$ should be continuous, which can be a step linear or a more complicated nonlinear function, as in most cases $\mathrm{W}_i(t)$ is not negatively or positively linear with respect to L_t. For example, in the case of the sequence (table 1), W_r experiences a decrease from 1 to 0 over time and then an increase from 0 to 1 when t changes from T_1 to T_3. Apparently, W_r is a nonlinear function of L_t. When $\mathrm{f}_i(L_t)$ is constant in relation to t, $\mathrm{W}_i(t)$ also becomes constant over time, as in most CA applications. However, although this treatment is effective for gaining an understanding of global dynamics in section 2.3, it is not effective for looking at local dynamics at the project level such as those illustrated in figure 3. The design of function $\mathrm{f}_i(L_t)$ is critical. Empirical studies can be carried out based on a theoretical understanding of interaction. Higher temporal resolution, such as a series of the actual values of L_t, can

Table 1. Dynamics in the local spatiotemporal processes illustrated in figure 3.

Process	T_1	T_2	T_3
Convergence	$W_\mathrm{r} \to 1$, and $W_\mathrm{c} \to 0$, if $L_t < L_l + L_\mathrm{u}$	$W_\mathrm{r} \to 0$, and $W_\mathrm{c} \to 1$, if $L_t > L_l + L_\mathrm{u}$	Not applicable
Sequence	$W_\mathrm{r} \to 1$, and $W_\mathrm{c} \to 0$, if $L_t < L_l$	$W_\mathrm{r} \to 0$, and $W_\mathrm{c} \to 1$, if $L_t > L_l$, and $L_t < L_l + L_\mathrm{c}$	$W_\mathrm{r} \to 1$, $W_\mathrm{c} \to 0$, if $L_t > L_l + L_\mathrm{c}$, and $L_t < L$
Divergence	$W_\mathrm{r} \to 0$, and $W_\mathrm{c} \to 1$, if $L_t < L_\mathrm{c}$	$W_\mathrm{r} \to 1$, and $W_\mathrm{c} \to 0$, if $L_t > L_\mathrm{c}$, and $L_t < L$	Not applicable

Note: $\to$, 'approaching or close to'; L_l, L_u, L_c, local growth on the lower, upper, and centre part of the road, respectively; L_t, cumulative development amount up to time t; L, total amount of local growth; W_r, W_c, weights of spatial factors 'road' and 'centre', respectively; T_1, T_2, and T_3 are time sequences, where T_1 is the earliest, and T_3 the latest.

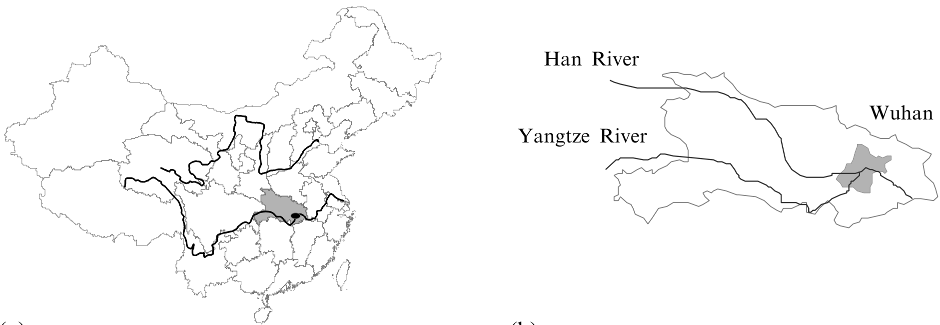
be used to calibrate the temporal rules $W_i(t)$. For simplicity, the functions $f_i(t)$ can be discretised. This implies that the whole period can be divided into a few phases, T_1 to T_N, for which various weight values are defined with the assistance of local knowledge or by calibration from data.

3 Implementation

A case study of Wuhan city, People's Republic of China, is used to test the methodology presented above for understanding the dynamic process of urban growth in a rapidly growing metropolitan region.

3.1 Wuhan context

As the capital of Hubei Province, Wuhan is the largest city in central China and in the middle reaches of the Yangtze River (figure 4). In 1999 it had an urban population of around 4 million people, four times that in 1949. During the past five decades, Wuhan has undergone rapid urban growth, from 3000 ha of builtup area in 1949 to 27 515 ha in 2000. As a result, Wuhan is a good case for gaining an understanding of the dynamic processes of urban growth in a fast-developing country. In this paper, the urban growth of Wuhan in the period 1993 – 2000 will be modelled based on the methodology discussed in section 2.



(a) (b)

Figure 4. Location of Wuhan municipality: (a) Hubei Province (shaded area), and (b) Wuhan (shaded area) in relation to Hubei Province.

Operational CA models need access to real databases for better simulation performance to be achieved (Li and Yeh, 2001). The imagery employed here includes SPOT PAN/XS for 2000, which covers the whole study area. The images are utilised as the primary data source for creating a land-cover-change map from 1993 to 2000. The topographic map (scale 1:10 000) of 1993 was used for imagery geocoding registration and also for producing the land-cover map for 1993. The secondary sources include planning scheme maps, traffic and tourism maps, street boundary maps, the population census, and the statistical yearbook. These were used to create the required spatial factors (for example, proximity and density variables) for the CA modelling using simple GIS operations such as overlay, buffering, and neighbourhood statistics. The image processing for land-cover mapping was implemented through the ERDAS IMAGINE 8.4 package, and onscreen digitising and spatial data analysis were carried out in the ArcView environment (for details, see Cheng and Masser, 2003).

The land-cover transition from 1993 to 2000 shown in table 2 was calculated based on the use of a 10 m × 10 m cell size. It can be seen from this table that major land-use and land-cover changes affected waters, towns and villages, and agricultural land, which were physically or functionally transferred to urban builtup area. Towns and villages with the highest annual transition rate were only functionally transferred to urban administration

Table 2. Wuhan City: the land-cover transition from 1993 to 2000.

Major types	Water	Towns and villages	Agricultural land	Other	Total
Area in 1993 (ha)	30 258	8 669	51 585		
Area undergoing transition:					
hectares	1 131	1 530	3 527	72	6 260
percentage[a]	18.1	24.4	56.3	1.2	100
Annual rate of transition (%)	0.5	2.3	0.9	na	na

na, Not applicable.
[a] Area of land undergoing transition in the given category as a percentage of the total amount of land undergoing transition (6 260 ha).

because of the rapid expansion of Wuhan municipality. Agricultural land has experienced the highest transition percentage. Water bodies include ponds and lakes. A higher percentage area occurred for the transition from ponds than from lakes (see figure 6 below). The category 'other' includes green areas, sands, and misclassified areas (misclassified during image processing, and so on) which are omitted for modelling.

3.2 Project planning and site selection

With assistance from historical documents, local planners, and fieldwork, four large-scale projects that were planned before or around 1993 were identified (WBUPLA, 1995). All small scale projects were merged into one class, resulting in five projects [see table 3 (over); see also figure 6 below] as follows:
Project 1, Zhuankou: car manufacturing plant, planned from 1988;
Project 2, Wujiashan: Taiwanese investment zone, planned from 1992;
Project 3, Guanshan: high-technology development zone, planned from 1988;
Project 4, Changqing: large-scale residential zone, planned from 1994;
Project 5, 'the rest': small-scale development (commercial, institutional, and residential).

In a GIS environment (ArcView 3.2a), we created the required spatial layers (figure 5, over), including land cover for 1993, distance to road networks and to city centres and subcentres, and population density. These layers were exported into a computer program for testing different site-selection rules for each project according to equation (2). As a result of a sensitivity analysis conducted in a visual programming environment, we tested the constraints at three levels for each project—global, regional, and local—as listed in table 3. The total amount of development L_d (from the actual urban growth shown in figure 6 below) and the temporal control mode (from documents and interviews) are also displayed in this table.

After 1992, Wuhan entered a new wave of development characterised by more actors, diverse functions, and a new industrial structure (Cheng and Masser, 2003). We are able to explain the spatial behaviour of the actors involved in each project in this table. For instance, the dominant actor in the Zhuankou, Wujiashan, and Guanshan projects is Wuhan municipality, which obtained financial resources from the central government, foreign investors, and local enterprises (WSB, 2000). Being the owner of the land, the actor did not need to consider the costs of land utilisation. Hence, for large-scale projects, the first rule is the availability of a certain amount of developable land. Being orientated to manufacturing and tertiary industry, the second rule concerns accessibility to major road networks. Strictly speaking, the second rule is true not only for large-scale developments but also for small-scale land development such as for commercial use. Moreover, accessibility to developed areas is crucial for the economic development zone (Wujiashan) and the high-technology zone (Guanshan).

Table 3. Site-selection of the five projects studied.

	Project				
	Zhuankou	Wujiashan	Guanshan	Changqing	'the rest'
Number of cells, L_d	1390	314	514	160	3710
Land use	Manufacturing	Economic zone	High-technology zone	Residential	Mixture
Constraints					
Global					
must be	< 300 m to a major road	< 300 m to a major road	< 300 m to a major road	< 300 m to a major road	Close to city centres and subcentres
must be	–	–	< 4.2 km to university street	< 3.5 km to subcentres	Close to road network
must have	–	–	–	> 560 persons per hectare net population density	–
Regional					
density of developable land (%) in a square of					
4.5 km × 4.5 km	> 62	–	–	–	–
3 km × 3 km	–	–	> 68	–	–
2 km × 2 km	> 90	–	–	–	–
1 km × 1 km	–	> 69	–	> 60	–
density of developed area (%) in a					
2 km × 2 km	–	>18.7	–	> 10	–[a]
Local					
can transit if the land is:	agricultural or village	agricultural or village	agricultural, village, or hill	agricultural or pond	agricultural village, pond or lake
Temporal control	Quick	Slow	Quick	Quick	Normal

– This constraint is not relevant to the specified project.
[a] Density should be higher than starting density.

Access to research resources including nearly twenty universities is a prerequisite for the location of a high-technology zone such as Guanshan (WBUPLA, 1995). In contrast, the major actors in the Changqing housing project are local real estate companies and the relevant work units (WSB, 2000). Land value is becoming an important criterion, weakening the role of accessibility to city centres. Low-quality land cover such as ponds is much cheaper than agricultural land. However, higher population density can guarantee greater market demand and is an influential factor in residential development. For small-scale projects, particularly within urban districts, more actors are involved in the decisionmaking including local residents, investors, work units, planners, and lower levels of local government. This results in a more stochastic process of site selection, as a result of which the constraints become more uncertain and fuzzy. However, generally speaking, accessibility to the city centre or subcentre and to road networks are the key factors.

3.3 Local growth

The cell size used in this research is 100 m × 100 m, which results in a 640 × 410 grid. A smaller cell size (such as 10 m × 10 m) would cause an overload in terms of model computation. The state of the cells is binary (1 = change, 0 = no change). The initial layer is the 1993 land cover. This includes developed land, agricultural land (A), village or

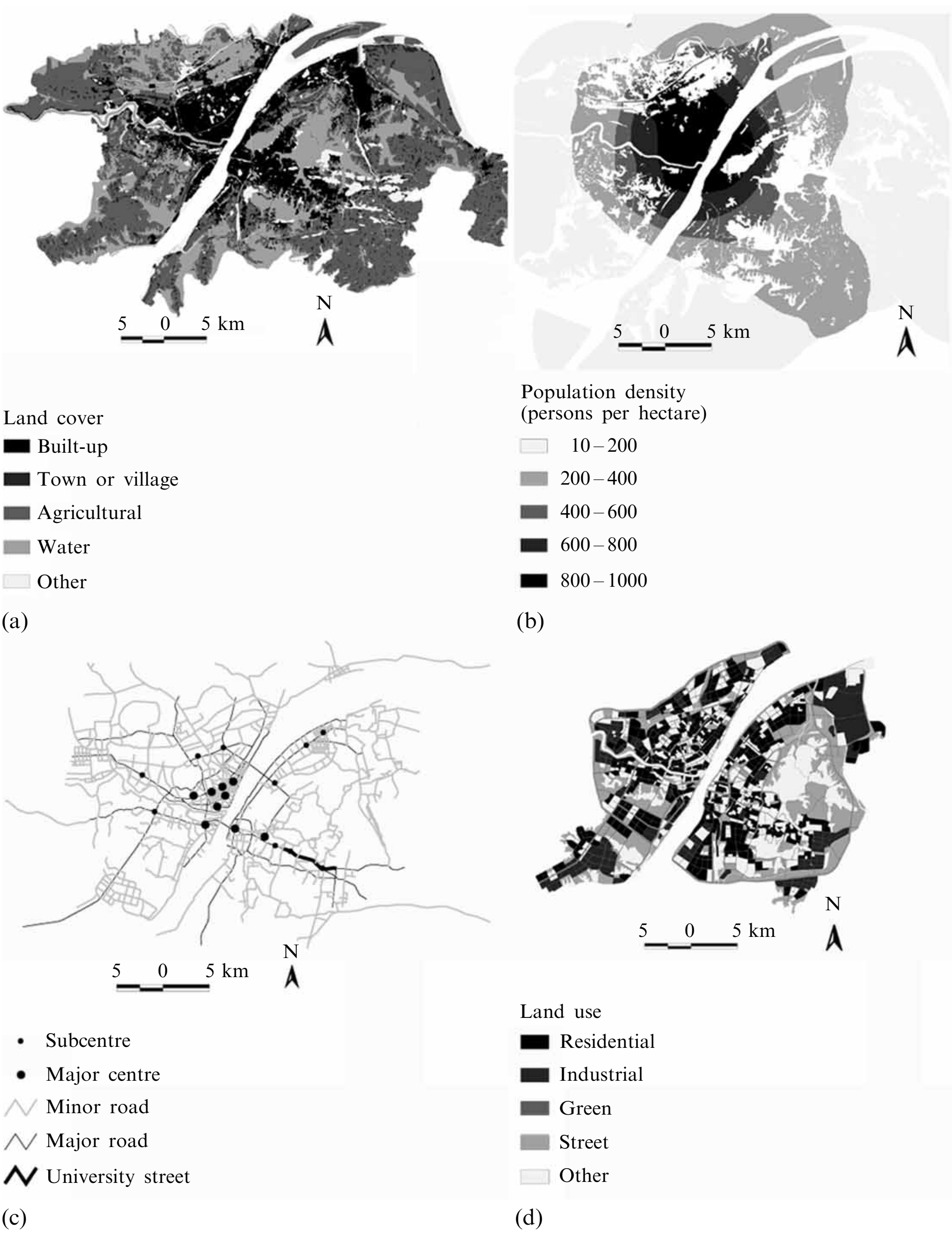


Figure 5. Spatial factors and constraints for site selection and cellular automata modelling: (a) land cover per 1993; (b) population density (persons per hectare); (c) road networks and centres and subcentres; (d) master plan for 1996 – 2020.

town land (V), ponds (P), lakes (L), and protected land (public green, parks, and sands). In figure 5(a), the categories ponds and lakes are merged into the category 'water'; and 'other' includes protected land. As described in section 3.1, only four types of land—agricultural, villages and towns, ponds, and lakes—underwent much change. The pattern model from another part of this research (Cheng and Masser, 2003) shows that the major spatial determinants of urban growth in the period 1993 – 2000 included major road networks, minor road networks, centres and subcentres, and master planning, as displayed in figure 5. They are selected here as nonconstrictive factors for evaluating the potential for land conversion.

It should be noted that the classification of each layer is of great importance, as the model is sensitive to classification, particularly when the study area is large and the period is long. For instance, the construction of roads may occur during different phases of the period to be modelled. Their construction time should be taken into account. In this research, a major road connection (providing a link to the third bridge over the Yangtze River) was completed in early 2000. This is clearly visible in the 2000 SPOT images. However, this major road is not included in the major road network layer because it had no practical impact on urban development in the period 1993–2000. This judgment is confirmed by very sparse and limited land-cover change surrounding the road. Other layers were spatially defined by following similar rules.

Wuhan city can be treated as a flat landscape, its elevation ranging between 22–27 m above sea level, apart from a few hills. Hence, slope is not an influential factor. Physical constraints comprise principally water bodies [see figure 5(a)]. Theoretically, water bodies should be completely excluded. However, in this case study, 18% of the land-cover change comes from water bodies, which include ponds and lakes (see table 2). As this change affects mostly small-scale ponds or the fringes of large lakes, a general procedure can be designed for defining a specific layer (exclusion layer):
Step 1: select a water body cell from the land-cover layer of 1993.
Step 2: look at neighbourhood statistics (based on a circular neighbourhood with a 200 m radius).
Step 3: exclude the cell if the neighbouring 4 ha are also under water.

The layer will be utilised as a physical constraint on the water body, defining zones excluded from transition. In the five CA models corresponding to the five projects, a circular neighbourhood is chosen because it does not display significant directional distortion. Its radius varies with different projects, ranging from 3 to 9 cells. The selection of neighbourhood size for each project relies on empirical study and sensitivity analysis (see section 4.1). The heterogeneity of spatial processes is indicated by using various combinations of influential factors, weight values, and parameters, to imply differences in local spatial behaviour.

Given that local growth is impacted by the master plan to be implemented in the period concerned, we must incorporate the master plan for 1996–2020 as an influential factor (this scheme was initiated in 1990 and approved by the central government in 1996). Owing to the rapid urban expansion at the fringe, some projects such as Changqing and Wujiashan were not planned until their construction. These will be excluded from the master planning analysis. Only the projects covered by master planning are considered (that is, Guanshan, Zhuankou, and 'the rest'). Each cell j is assigned a value X_j, representing the degree of influence of the planned land use on its land-cover transition in a given project. If M_i denotes the total area of land-use i in a specific project, C_i denotes the part of M_i undergoing a transition, then, C_i/M_i generally indicates the degree of influence of land use i. If a cell j was planned for land use i,

$$X_j = \frac{C_i}{M_i} . \tag{20}$$

X_j needs to be standardised according to equation (5) before it can be incorporated into the evaluation formula [equation (4)]. The M_i and C_i/M_i values of the major land uses are listed in table 4. The code refers to the National Urban Land-use Classification Standard (NULCS). From table 4 we can see that, in general, the master plan was more successful in guiding large-scale projects in the fringe than it was in guiding small-scale projects in urban districts. In figure 5(d), 'residential' includes codes R_1

Table 4. Influential degree of master planning on land cover transition in the Zhuankou and Guanshan projects, and 'the rest'.

Code[a]	Classification	Zhuankou		Guanshan		'The rest'	
		C_i/M_i	M_i	C_i/M_i	M_i	C_i/M_i	M_i
R_1	Low-rise residential	0.237	265	0.23	57	0.087	1082
R_3	Poorer environment	–	–	–	–	0.1333	149
M	Industry	0.318	508	0.24	172	0.049	419
G_1	Public green	0.27	137	–	–	0.0916	416
G_2	Protected land	0.147	58	0.33	112	0.041	222
G_3	Ecological agriculture	–	–	–	–	0.0216	82
C_1	Administration or offices	0.26	52	–	–	0.0787	17
C_3	Cultural or recreational	0.528	16	–	–	–	–
C_4	Sports facility	–	–	0.3	44	0.035	89
C_5	Hospital or health	0.742	33	–	–	–	–
S_1	Street	–	–	–	–	0.069	354

– Value omitted as $M_i < 15$.
[a] The code utilised in the National Urban Land-use Classification Standard.
Note: M_i, total area in land-use i; C_i, area of land in land use i undergoing transition; for more details of the projects Zhuankou, Guanshan, and 'the rest', see section 3.2 and table 3.

and R_3, 'green' includes $G_1 - G_3$, and 'street' includes S_1; the remaining coded areas (C_1, C_3, C_4, C_5) are merged into 'other'.

The calibration of parameters has proven a difficult task in urban CA modelling (Clarke and Gaydos, 1998; Li and Yeh, 2001), particularly when there are many factors and parameters to be considered. The difficulty lies in the fact that most urban CA modelling takes the whole municipality into account in the calibration procedure, resulting in intensive computational overload. In this research, project-based CA modelling has largely reduced the computational time of calibration as the spatial extent of each project is much smaller than the whole study area, as shown in table 5 and figure 6 (see over).

The factors and parameters for model calibration include six spatial factors, neighbourhood size (radius), and stochastic disturbance α. Other parameters (for example, the temporal pattern mode parameter, λ, and iteration time t) are utilised for sensitivity analysis (see section 4.1). The six spatial factors are 'distance to minor road', 'distance to major road', 'distance to centre or subcentres', 'density of neighbouring developed areas', 'density of neighbouring new development', and 'master planning'. Their ϕ parameters [see equation (6)] are taken from the global pattern model from a logistic regression carried out in another part of this research (Cheng and Masser, 2003). Automatic search for the best-fit parameters was carried out by using a hierarchical method—that is, by reducing the step size in two stages over five loops, for each of the six factors. For example, the step size of loops for calculating the weight values was set first as 0.05—that is, it was increased from 0.05 to 1.00 in steps of 0.05. Once the scope of the parameter for the ideal accuracy was determined, such as from 0.20 to 0.25, we set a second step size (0.005) for finer calibration, so that the value was increased from 0.20 to 0.25 in steps of 0.005.

The validation accuracy depends on the approach used to compare simulated with actual patterns. The comparison is traditionally made by means of a coincidence matrix generated by a cell–cell comparison of the two pattern maps. Some researchers argue that CA simulations should not be assessed only on the goodness of fit (that is, on a cell-by-cell basis) but should also be assessed on their feasibility and plausibility, as urban systems are rather complicated and their exact evolution is unpredictable

Table 5. Cellular automata simulation of five projects.

Projects	Zhuankou-1	Zhuankou-2			Wujiashan	Guanshan	Changqing	Rest
Land demand, L_d (cells or ha)	1 390	1 390			314	514	160	3 710
Accuracy, CC	54	54			51.6	53.2	85	55
Lee – Sallee index, LI	0.37	0.37			0.35	0.36	0.74	0.38
Neighbourhood size (radius in no. of cells)	6	6			5	8	3	7
Temporal pattern mode parameter, λ	4/3	4/3			4	4/3	4/3	2
Dynamic weighting (%)	–	<15	15 – 55	>55	–	–	–	–
Major road[a]	0.2	–	0.5	0.05	0.325	–	0.1	0.3
Minor road[b]	0.3	–	0.1	0.15	0.1	0.35	0.55	0.15
Centres[c]	–	0.7	–	0.5	–	–	–	0.2
Neighbourhood								
new	0.3	0.3	0.1	0.15	0.3	0.35	0.35	0.1
old	–	–	–	–	0.275	0.25	–	0.2
Master planning	0.2	–	0.3	0.15	–	0.05	–	0.05
Total (%)	100	100	100	100	100	100	100	100

– Not applicable.
[a] Distance-decay parameter: $\phi = 0.000765$.
[b] Distance-decay parameter: $\phi = 0.0012$.
[c] Distance-decay parameter: $\phi = 0.000272$.
Note: $\alpha = 1\%$ (parameter controlling strength of stochastic pertubation), $n = 50$ (number of iterations); for details of Zhuankou-1 and Zhuankou-2, see section 3.5.

(White and Engelen, 2000; Wu and Webster, 1998; Yeh and Li, 2001). Some global measures that have been used for testing the validity of CA simulation include the fractal index and Moran I index (Wu, 1998b), fractal analysis (Yeh and Li, 2001), and the landscape metric (Soares-Filho et al, 2002). Wu (2002) emphasises the need to validate the model through structural and cross-tabulation measures. Structural measures can be used to compare pattern (the outcome of the process) but not the spatial location (or process). We consider spatial location match also to be of great importance in support of planning decisionmaking, despite the difficulties imposed by CA modelling. Another reason lies in the fact that local processes at the project level require more accurate cell-based measures, as their morphology is less definite compared with those at the global level.

Clarke and Gaydos (1998) outline four ways to test the degree of historical fit statistically (through three R^2 fits and one modified Lee – Sallee shape index). For the Lee – Sallee shape index (combining the actual and the simulated distributions as binary urban or nonurban and by computing the ratio of the intersection over the union), they reported that the practical accuracy is only 0.3. In this paper, we use consistency coefficients, CC (the percentage of the matched over the actual) and the Lee – Sallee index, LI for the evaluation of goodness of fit. As the total number of pixels is the same in the simulation as in the actual pattern (that is, $L_d = L_n$) we can write

$$\mathrm{LI} = \frac{\mathrm{CC}}{2 - \mathrm{CC}}. \tag{21}$$

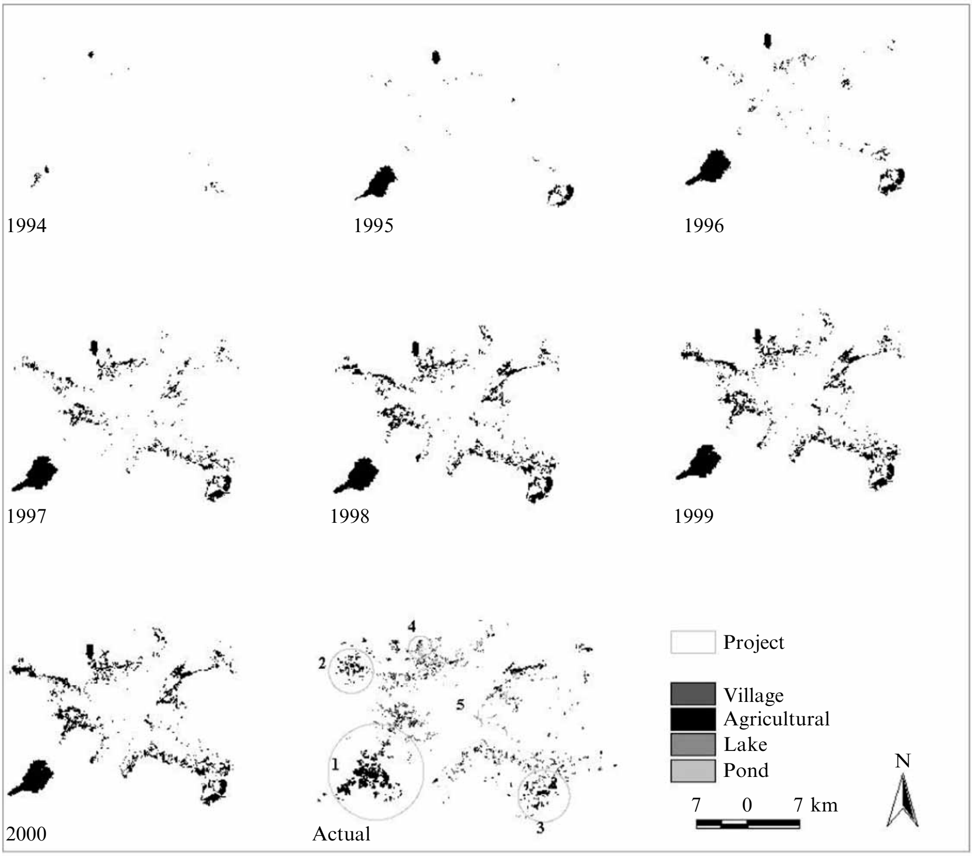


Figure 6. Simulated (1994 – 2000) patterns and actual pattern.

For example when CC = 0.57, LI = 0.4. Following this formula, the Lee – Sallee indices for five projects were computed and are listed in table 5. The overall accuracy based on the weighted combination (L_d) of the five projects, is 0.554 in CC and 0.383 in LI, greater than the measures of Clarke and Gaydos.

3.4 Temporal control

With local knowledge, we were able to identify the patterns of temporal development of each project (see table 3). In 1993 Zhuankou was still completely rural. By 1995 nearly half was developed. There was not much change from 1997 and 2000. Therefore, its temporal growth pattern is defined as 'quick' ($\lambda = 4/3$). The small-scale projects, 'the rest', are a mixture of all three patterns. Some may be quick, others slow ($\lambda = 4$). On average, it is reasonable to classify them as 'normal' ($\lambda = 2$). The number of iterations is defined as $n = 50$ because the greater the number the finer the discriminative capacity of the models.

In figure 7 (over) we show the trajectories of temporal development for the five projects according to the results of the validated CA simulations. As described by equation (17), the output of CA simulation is $L_i(t)$ ($t = 1, 2, ..., n$), which is different from the yearly actual amount $L_i(\tau)$ ($\tau = 1, 2, ..., m$) for each project i. We need a transition from $L_i(t)$ to $L_i(\tau)$. The transition function h in equation (17) should be based on an understanding of the actual temporal development process, which is determined by its socioeconomic development. For the sake of simplicity, we use an equal time

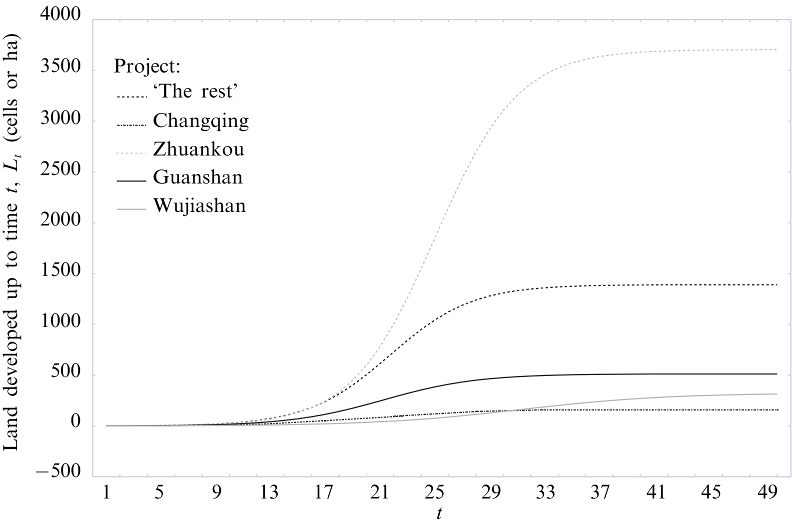


Figure 7. Temporal control patterns of the five projects.

interval—that is, a linear function: $\tau = t/7$. As t ranges from 1 to 50 ($n = 50$) and τ from 1 to 7 ($m = 7$),

$$\mathrm{L}_i(\tau) = \sum \mathrm{L}_i(t), \qquad \text{for } t = 7(\tau - 1) + 1, ..., 7\tau . \tag{22}$$

A series of new created layers for the whole study area corresponding to the seven-year urban growth (from 1993 to 2000; see figure 6) were imported into animation software (Animagic32, Right to Left Software, New York) for dynamic visualisation. This animation is helpful for exploring and comparing the temporal dynamics of spatial processes.

In table 5 we list the spatial heterogeneity of the causal factors, which vary spatially in terms of their weight values. The neighbourhood effect is represented by neighbourhood size and by the weight values of new and old developed areas. Table 5 suggests that there are some similarities and some dissimilarities between the five projects. The weight values of the major roads, minor roads, city centres and subcentres, and master planning also show some differences. Major roads played a greater role in 'the rest' and Wujiashan projects, and less important roles in the Changqing and Guanshan projects. Conversely, minor roads played a greater role in the Changqing and Guanshan projects than in 'the rest' and Wujiashan projects. By linking the site-selection rules shown in table 3, it can be seen that the road network system actually plays various roles during different phases of urban growth. The major road network is the key at the site-selection stage and remains important for some areas at the local growth stage. However, the minor road network is active only at the local growth stage. This is because of the fact that minor road networks are created after the site-selection stage together with the new growth. Relatively, city centres and subcentres are influential only for 'the rest' as the other projects are located at the urban fringe. Master planning is less influential for 'the rest' than it is for the other projects. The spatial heterogeneity described above suggests that the causal effects of urban growth vary from place to place. Local process modelling may offer deeper insights into urban growth processes.

3.5 Local temporal dynamics

For each project we focus on local temporal dynamics. The following examples may be highlighted.

(a) Compared with the major road network, minor roads, especially in new zones that are also new development units, may occur at different phases of the period studied: that is, between T_0 and T_n, but not immediately from T_0.
(b) The spatial impacts of various factors such as roads and centres do not affect local growth simultaneously.
(c) Neighbourhood effects may show temporal variation; for example, they may be stronger at T_0 than at T_n, or vice versa.

These examples show qualitatively the complex pattern and process interaction as discussed in section 2.4. The two models for the Zhuankou project (table 5) have similar model accuracy and similar patterns. However, their spatiotemporal processes are quite different, as shown quantitatively in figure 8 (over). Model 1 exhibits a more random process. Model 2 shows a more self-organised process. Model 2 is based on the assumption that new development in Zhuankou first occurred at the centre, then along the major road, and then finally spread from the centre. The assumption corresponds to a temporal dynamics that is spatially controlled by three sets of weight values (table 5). To calibrate this process-oriented CA model, manual tests based on the moeller's understanding of local growth processes and the visual exploration of model outputs (temporal patterns) are very important for reducing parameter ranges and making rough estimates of dynamic weight values. Limited automatic search can be followed for the best (or ideal) combination of parameters.

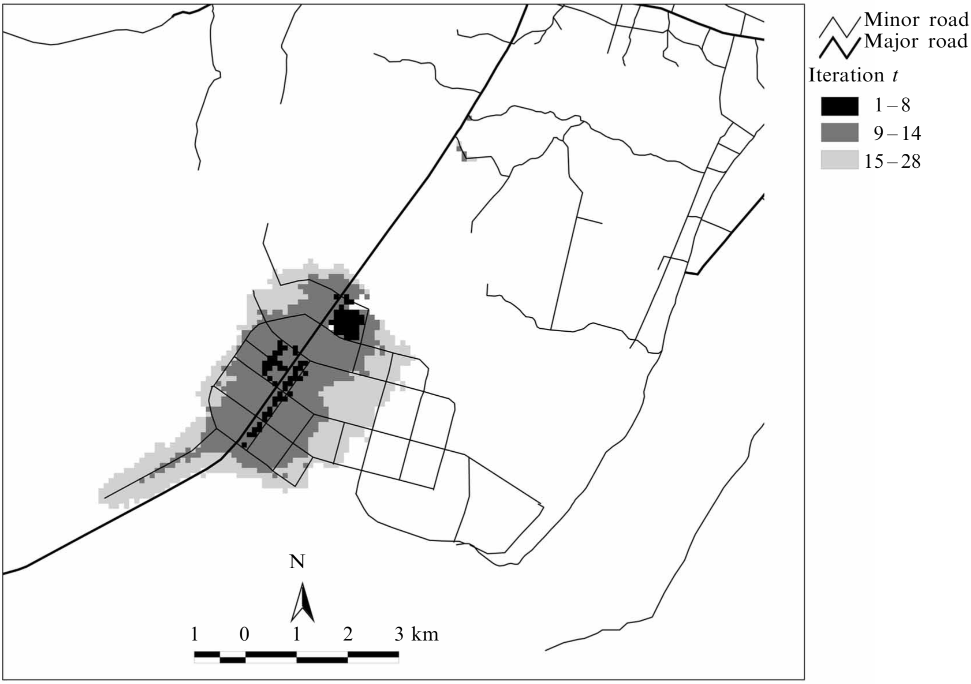
To some extent, the dynamic weighting implies the temporal lag of the spatial influences of locational factors on urban growth. This example suggests that local temporal dynamics can enable us to understand better organised local growth. If we explore the changes in weight values, it can be found that major changes are seen in major roads and centres. As described by equation (19), the weight values should be nonlinear functions of temporal land-development demand. In table 5 it can also be seen that the functions are highly complex in reality. They are frequently phased. Model 2 is based on local knowledge. The other projects can be calibrated temporally by the same procedures as those followed in the Zhuankou project.

4 Discussion and conclusions

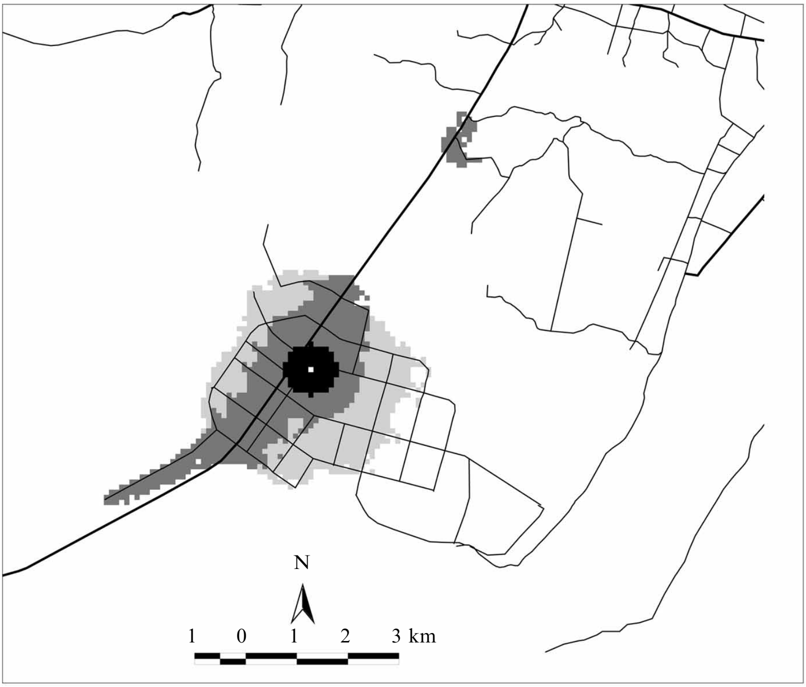
4.1 Model calibration and validation

Li and Yeh (2001) report a calibration procedure for CA modelling involving use of an artificial neural network. In their method, the neural network is utilised to obtain the optimal parameter values automatically, based on the training of empirical data; the parameter values thus calibrated are then used to carry out CA simulations on new data. In CA models of this kind, the transition rules represented by the neural network structure are not transparent to users. Consequently, this method can be used for prediction by using the same set of rules but is not ideal for interpreting the logic of land conversion or spatiotemporal processes; it is a 'black box' (Wu, 2002).

It has been found in this research that visual tests offer a useful and quick way of calibrating and verifying CA models (Clarke et al, 1997; Ward et al, 2000), particularly with respect to sensitivity analysis. In this project-based CA modelling exercise, calibration did not prove to be a severe problem in terms of computation time. However, the optimal combination of parameters from automatic searches may not give the best results, as socioeconomic systems essentially produce no 'best' solution. Consequently, the calibrated results need further confirmation with respect to their interpretation and the plausibility of their spatial and temporal processes. In table 6 (over), we take the Wujiashan project as an example to illustrate this issue. When neighbourhood size (radius) is set as 5 cells, the optimal parameters for accuracy (ι^{CC}) 52.8% are calculated from an automatic search (the step size for the weight value is 0.005), together with the



(a)



(b)

Figure 8. Local temporal dynamics of (a) Zhuankou-1 and (b) Zhuankou-2 (see table 5).

Table 6. Calibration of cellular automata modelling and sensitivity analysis: the Wujiashan project.

Accuracy, ι^{CC} (%)	52.8	51.6	51.3	50.8	29.5	46	49	50	50
Neighbourhood size (radius in cells or ha)	5	5	5	5	5	8	6	4	5[a]
Major road[b]	0.2	0.325	0.325	0.225	0.375	0.1	0.325	0.325	0.325
Minor road[c]	0.1	0.1	0.05	0.25	0.3	0.3	0.1	0.1	0.1
Neighbourhood									
new	0.45	0.3	0.35	0.15	0.3	0.4	0.3	0.3	0.3
old	0.25	0.275	0.375	0.025	0.2	0.275	0.275	0.275	
Total (%)	100	100	100	100	100	100	100	100	100

Note: $\alpha = 1\%$, $n = 50$, $\lambda = 4$.
[a] Temporal pattern mode paraemter: $\lambda = 4.5$.
[b] Distance-decay parameter: $\phi = 0.000765$.
[c] Distance-decay parameter: $\phi = 0.0012$.

other parameter combinations. However, the spatial processes produced by the set of weight values (0.2, 0.1, 0.45, 0.25) are not the same as the real temporal pattern based on visual comparison. Conversely, another combination of weight values (0.325, 0.1, 0.3, 0.275) is able to create more satisfactory temporal patterns, although its model accuracy (51.6% in ι^{CC}) is lower. Consequently, visual tests are still a necessary means for process modelling in contrast to pattern modelling.

Another aspect of calibration is sensitivity analysis as the results of CA simulation are very sensitive to the parameter values (for example, neighbourhood size, weight values, λ, and n). This is an issue of uncertainty in CA simulation that is not given enough attention in most applications. For the Wujiashan project, before accepting the weight values (0.325, 0.1, 0.275), we need to test the stability of this set by slightly, or greatly, adjusting the weight values and other parameters, such as neighbourhood size, as shown in table 6. The changes (slight or great) in validation accuracy that are identical to those observed in the parameters assure the reliability of this set.

4.2 Visualisation of processes

To implement site-selection and CA modelling, a loose coupling strategy is frequently adopted for various applications (Bell et al, 2000; Clarke and Gaydos, 1998). In general, loose coupling means that a data-transfer procedure is implemented between a CA model, GIS, and an animation module. This loose-coupling strategy sacrifices the 'friendly' interface but improves the computational efficiency of CA simulation. Here, the site-selection rules and the CA model are programmed in object-oriented programming language. Spatial data analysis and visual exploration tasks are implemented under a GIS environment (the ArcView platform). Each layer produced is exported as an ASCI raster file. A subprocedure is programmed to read and write the ASCII raster files between the CA and ArcView. The major parameters include the weight values, the temporal pattern control parameter λ, the neighbourhood size, and the stochastic perturbation α. The validation results are stored into a text file and an ASCII raster file. A validated urban growth layer (for the period 1993–2000) from the simulation is separated into a series of maps, each corresponding to one year. The layers created are exported as a JPG file or any other type of image file. These are inserted as an individual frame into the animation file for visual checking of the spatial process. However, a major deficiency of this strategy is that it is not a very 'friendly' environment for the immediate visualisation of spatial temporal processes, although it is effective for model calibration. In the future, CA modelling tightly coupled with GIS and animation should be further studied to enhance its visualisation function with regard to spatial temporal processes.

4.3 Process modelling

To some extent, the accuracy of a simulation model depends on the complexity and stochasticity of the real city and on the availability of detailed information. Although the overall accuracy of the five CA models run here is only 55%, on a cell-by-cell municipal and project basis, the methodology proposed in this paper illustrates the potential for gaining an understanding of spatial processes and their temporal dynamics at the level. The spatial clustering of land-development projects indicates a self-organising process. The timing schedule of various projects exhibits global temporal dynamics. Dynamic weighting is an important concept in the simulation of process, in contrast to the situation for the simulation of pattern. Spatial classification based on the project concept is subjective but transparent to urban planners. The spatio-temporal processes explored by project-based modelling can easily be interpreted with reference to socioeconomic and decisionmaking processes. To be a true process model, CA modelling, as suggested in this research, should incorporate dynamic weighting methods, although there is still much difficulty in systematically defining these functions in practice.

From a local spatial modelling point of view, a possible future direction lies in applying a moving window or kernel in defining a project for each cell, so that generalised local process modelling can be repeatedly applied to each cell. This is a similar principle to that applied in GWR modelling. This idea can result in universally localised process modelling. The parameters for understanding local processes vary by cell. Users can redefine interesting projects for further interpretation by focusing on a 'hot spot'.

From the perspective of spatial data analysis, the methodology can be utilised to discover hidden processes in an integrated spatial database regarding temporal urban growth. This has been one of the major concerns in the field of spatial data mining or knowledge discovery. When socioeconomic data become available at detailed levels, project-based CA modelling can be further linked to microscale multiagent and economic modelling. Such integration may allow an exploration of the spatial and economic behaviour of various actors at the microscale.

The major purpose of CA simulation is to generate alternative scenarios for decision support for smart-growth management. The methodology developed here can be extended in this direction. In this case, stages 1 and 4 need to incorporate top-down socioeconomic models for predicting the demand for new land development in the future [that is, for predicting L_d in equation (1)]. Stages 2 and 3 are subject to some modification in quantification. The construction of plan scenarios is based on soft-system thinking, which stresses the role of user subjectivity. In this way, the intentions of local planners can be transformed into spatially and temporally explicit weight values and into certain parameters (for example, see Wu, 1998b). With a user-friendly visualisation environment, the framework tested in this research can be used to facilitate decisionmaking regarding urban spatial development.

We cannot ignore the fact that any advanced modelling technique, including CA must be based on a proper understanding and abstraction of the systems studied. The better the understanding the more accurate the modelling is likely to be. Planning will never be a hard science, for it is built on humanistic assumptions, values, and goals (Shmueli, 1998). Our understanding of the new urban reality will ultimately be based upon a combination of the use of computers and human judgment (Sui, 1998).

CA form a simulation tool only for testing a decisionmaker's understanding. Limited by existing GIS theory and methods, the identification of various spatial and temporal heterogeneity cannot be completed without the assistance of local knowledge. This implies that local knowledge is an important ancillary data source for CA modelling, especially under the framework presented in this paper. During the modelling process, project planning, site selection and temporal control needs more input from local experts. For dynamic weighting, because of the limited temporal resolution, local knowledge is an essential source of qualitative information. It has been stressed in this research that a soft-system methodology, stressing the roles of decisionmakers, and feedback between modellers and users and between various stages of the decisionmaking process is helpful, especially when complete information resources are not guaranteed.

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