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A stochastically constrained cellular model of urban growth

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Abstract

Recent approaches to modeling urban growth use the notion that urban development can be conceived as a self-organizing system in which natural constraints and institutional controls (land-use policies) temper the way in which local decision-making processes produce macroscopic patterns of urban form. In this paper a cellular automata (CA) model that simulates local decision-making processes associated with fine-scale urban form is developed and used to explore the notion of urban systems as self-organizing phenomenon. The CA model is integrated with a stochastic constraint model that incorporates broad-scale factors that modify or constrain urban growth. Local neighborhood access rules are applied within a broader neighborhood in which friction-of-distance limitations and constraints associated with socio-economic and bio-physical variables are stochastically realized. The model provides a means for simulating the different land-use scenarios that may result from alternative land-use policies. Application results are presented for possible growth scenarios in a rapidly urbanizing region in south east Queensland, Australia. © 2000 Elsevier Science Ltd. All rights reserved.

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1. Introduction

The rapid development of computer graphics and spatial information technologies over the last few decades has enhanced the sophistication of landscape

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transformation modeling and analysis. The availability of high-resolution image and other data has also provided a spatial and temporal information dimension from which time series of landscape transformations can be represented (Aplin, Atkinson & Curran, 1997). Cellular models have proven useful space–time modeling environments in which raster-based information on spatial and temporal landscape change (derived from remotely sensed imagery) and information on factors that influence change (e.g. friction-of-distance and topographic factors) can be brought together. In particular, models based on, or associated with, cellular automata (CA) have recently become popular because of their dynamic behavior and conceptual link with notions of self-organization. These types of models provide effective ways of simulating the process of landscape transformation as well as offering a means of evaluating alternative planning scenarios.

Traditional applications of CA may be found in statistical and theoretical physics and stress linkages to chaos theory and fractal geometry. Simulations of one-dimensional CA based on simple rules can produce high degrees of complexity and order. More recently, CA applications have been structured for two-dimensional applications in urban growth modeling (Batty, 1991). The basic idea is very simple. In a gridded space (raster) a series of transition rules are enforced to govern the state of a randomly placed cell depending on the configuration of its neighborhood. If the process is allowed to run iteratively, the resulting spatial patterns can show surprising regularity and order. This can be viewed conceptually as analogous to the way in which apparently uncoordinated local decisions lead to coordinated regional patterns that may occur, for example, in urban morphologies.

The conceptual link with self-organization and associated dynamic behavior has lead to various applications of CA models to urban and regional growth analysis. Batty and Longley (1994) explore the use of cellular models of urban growth in Tauton, England, based on a process of diffusion-limited aggregation. More recently, Clarke, Hoppen and Gaydos (1997) have been successful in integrating remotely sensed information and CA to develop a model of the historical development of the San Francisco Bay and Washington, DC, areas. In this model the simple rules of CA are adapted to deal with probabilities of location by incorporating hard constraints, such as topography, road networks, and patterns of existing and historic settlement, that exclude or influence development.

In this paper, a cellular model of urban growth is developed. The initial conception and implementation of the model is orientated towards understanding the hypothesized relationship between CA models that show self-organization and the spatial characteristics of urban growth. In particular, the nature of the underlying rules that govern CA behavior in urban growth models are investigated. The model is also considered in the context of urban planning processes where growth scenarios can be developed and evaluated, and 'what if'-type questions asked. Using contemporary software development tools the model is developed with a graphical user interface (GUI) linked to a geographic information system (GIS). The first section of the paper gives a background and context for model development. The conceptual development of the model is then presented. This is followed by a brief discussion on model implementation. The spatial data requirements of the model are then discussed, and application results are presented for areas in south east Queensland, Australia.

2. Spatial modeling of urban development

Often born out of what has become known as social physics, numerous models of urban growth and development exist and have their origins in economic theory (e.g. Brotchie, Dickley & Sharpe, 1980), size relationship between cities (Zipf, 1949), or gravity models (Wilson, 1970). These types of models can be viewed as static and analytic, being able to explain urban expansion but are limited in their ability to simulate urban change. The spatial characteristics of these models are usually defined by aggregated units such as political or administrative boundaries, census districts, or transport planning zones. More recently there has been a trend towards cellular models that explain urban development in terms of principles of self-organization where large-scale urban structure evolves from local-scale decision-making processes (e.g. Batty & Xie, 1994). In particular, computer models based on CA are at the foundation of many of these models. A fundamental characteristic of these models is that they allow some aspects of the dynamic nature of urban systems to be realized.

Cellular models of urban development that are based directly on classical CA (Packard & Wolfram, 1985), or are closely related to CA have four main components. Firstly, the simulation process operates on lattice of cells in two-dimensional space. A fundamental characteristic of the lattice is that cells have some adjacency or proximity to one another in the same way as land parcels in urban systems. Usually the lattice is a uniform gridded space but cells could be of any shape. Secondly, each cell in the lattice can adopt only one state of a set of possible states defined by the system being modeled. For example, in the case of an urban system, states could be defined as residential, commercial and industrial. Thirdly, the configuration of the neighborhood of a cell defines the current state of the cell. In classical two-dimensional CAs the neighborhood is usually the four or eight nearest neighbors. Fourthly, there is a set of transition rules that govern the types of changes in cell states in relation to the neighborhood configuration. For example, in an urban system, development units are correlated in space such that vacant development units in the neighborhood of existing developed units are likely candidates for eventual development.

The ability to treat urban systems as a self-organizing phenomenon using CA has proved popular in the literature and the strict application of a number of classical CA components such as uniform transition rules and the size of the neighborhood have been relaxed. For urban systems it is unlikely that a local nearest neighbor neighborhood will be adequate to capture the spatial interactions necessary to produce a useful simulation. In the literature there are a variety of CA models that address this issue by defining neighborhood transition rules based on nested, local and extended neighborhoods (e.g. Batty & Xie, 1994; Semboloni, 1997; White, Engelen & Uljee, 1997). Simulations of urban development resulting from CA models produce spatial patterns that have visual and statistical characteristics very similar to real urban systems (Clarke et al., 1997). For example, the density decline with distance from the central city core described by exponential or power law functions in traditional models (Zielinski, 1979) can be replicated using CA simulations of urban systems. The fractal dimension of simulations generated, for example using diffusion-limited aggregation, have similar fractal dimensions to actual urban systems (Batty & Longley, 1994).

While the notion of cities as self-organizing systems is sound (Batty & Longley, 1994), in applying current CA models it is often difficult to understand how local CA transition rules relate to the way the actual geometry of urban form evolves. The structure of many CA-based urban growth models has departed so much from the fundamental characteristics of pure CA models that the results of the models are transparent and unlikely to produce emergent properties characteristic of self-organizing processes. Most CA models of urban systems produce simulations that are space filling with a density decline from some central core. However, urban systems do not necessarily fill space in this way but usually exist as parcels of land arranged in relation to hierarchical transport networks. Given this, CA models of urban systems generally do not produce realistic representations of urban geometry at a local level. Since the premise for using CA models of urban systems is that self-organization at a local level produces global patterns, questions exist as to how well CA models are actually operating at a local level and consequently the validity of the resulting global patterns. In the first part of this paper this issue is addressed by developing a CA model in which rules are developed that take into account some of the fundamental aspects of how the spatial configuration of urban systems evolve at a local level.

While there has been a shift in the approach of the development of urban models toward the simulation of processes operating at a local level, it is obvious from evidence presented by traditional models that the global patterns of urban form are unlikely to result from local decision-making processes alone (Martin & Wu, 1999). Global factors that are associated with the suitability of the land for urban development, such as proximity to services and transport networks, as well as factors such as the location of distant markets, play an integral role in the morphology of urban systems. Hence, there is a need to consider urban development as a process that is self-organizing at a local level but that is constrained and modified by broad-scale factors.

To incorporate global factors in CA models, transition rules must reflect significant factors that influence urban development and consequently can comprise a range of socio-economic and bio-physical factors. Wu (1996) treats transition rules related to land-use types as a fuzzy set and only the transition rule with the highest grade of membership of the set is implemented as a change in cell state. Multiple cell states (residential, industry, commercial) are modeled by White et al. (1997) using transition potentials on a neighborhood derived from calibration of the model using historic data on urban growth activities. Semboloni (1997) develops transition rules based on a land rent and demand model that considers white collar, blue collar, service and base activities. Clarke et al. (1997) developed a model of historic urbanization of the

San Francisco Bay area using transition rules based on topography and distance from road networks, capable of self-modification depending on growth rates.

Much of the work developing cellular urban models has been orientated towards either models that are designed for exploring the urban process as an artificial world (e.g. Cechini, 1996; Couclelis, 1985; Portugali, Benenson & Omer, 1997) or, more commonly, models that are calibrated with historic data and used to project future growth patterns (e.g. Clarke et al., 1997). Projecting future growth patterns based on historic trends is fraught with difficulties associated with the continuously evolving, often technologically driven dynamics of urban systems. As with many statistical models these models will be captive of their data sets. A limitation of models used for prediction, even if they are well calibrated is that they have a tendency to predict urban sprawl. If the projections are taken seriously they may become self-fulfilling prophecies. The reality of CA models is that they cannot predict future growth patterns but only provide realizations of the numerous potential forms an urban system may take, and therein lies their value.

It is questionable whether many cellular urban growth models can be referred to as CA models in a formal mathematical way. This is more than a point of semantics. The basis for rapid uptake of CA-type modeling approaches in the literature has been the hypothesized relationship between CA self-organization and the dynamic process of urban growth. Many cellular models of urban growth based on CA will not express emergent properties and are simply cellular models whose constraints and calibration dictate their outcomes. However, in an environment where a greater emphasis is placed on issues of sustainability in urban development, models that can simulate growth realistically but also be operated as an urban planning tool to build projected growth scenarios and answer 'what if'-type questions are desirable. Wu (1998) addresses this need in an integrated approach combining CA and multi-criteria evaluation with GIS.

This paper also contributes to the need for planning-based visualization and decision-making tools by developing a stochastically constrained urban growth model that incorporates economic, physical and institutional control factors that modify, constrain or prohibit growth. The stochastic approach recognizes the fundamental uncertainties associated with urban growth that may be a product of a chaotic system. As with many chaotic systems, their behavior can be described probabilistically (e.g. climate). The approach to model development is not to try to model the underlying dynamics but to simply provide a modeling tool whose dynamics are driven stochastically and that mimics the spatial patterns of actual urban systems.

3. Conceptual model

3.1. Local urban morphologies

In structuring the urban growth process as a CA, a starting point is determining what rules govern the growth process. Are there simple rules that when applied will produce morphologies similar the actual local urban morphologies? Common to many CA models of urban growth is the notion that development units are correlated in space and rule sets are developed that reflect this phenomenon (Batty & Xie, 1997; Clarke et al., 1997; Makse, Havlin & Stanley, 1995). These types of rules produce morphologies that are space filling with a density decline from some central core. The question is, are rules based on the spatial correlation of urban development units adequate for setting up a model of self-organization that can represent the urban growth process? To answer this question the starting point for model development is to look in detail at how urban development units are organized at a local level. There is no question that large-scale factors influence the urban growth process. However, since so much has been recently written about self-organization based on local CA transition rules, it is a logical place the begin exploring the notion of urban growth as a self-organizing process.

In most modern cities urban development units (e.g. residential block) are arranged on hierarchical transport networks. The geometry of the resulting urban matrix is generally orientated to the major transport networks (road and rail networks) that have evolved as the city grows (Hindley, 1971). The configuration of the major rail and road networks are in turn related to characteristics of the surrounding terrain and the location of other major urban centers. In the evolution of a modern city, rail lines followed by major roads often formed the initial focus for urban growth with the development of lower order transport networks reflecting the orientation of the major rail and road networks (Herbert & Thomas, 1997). Urban services such as drainage, water and sewerage provision are often aligned to these transport networks.

Common to many modern cities is the regular grid layout. Fig. 1a shows an air photo of a grid layout for a residential suburb in Brisbane, Australia. A fundamental feature of the layout of the urban matrix is that each urban development unit has access to the transport network. The requirement for transport access imposes constraints on the spatial geometry of the urban matrix. For a regular grid such as

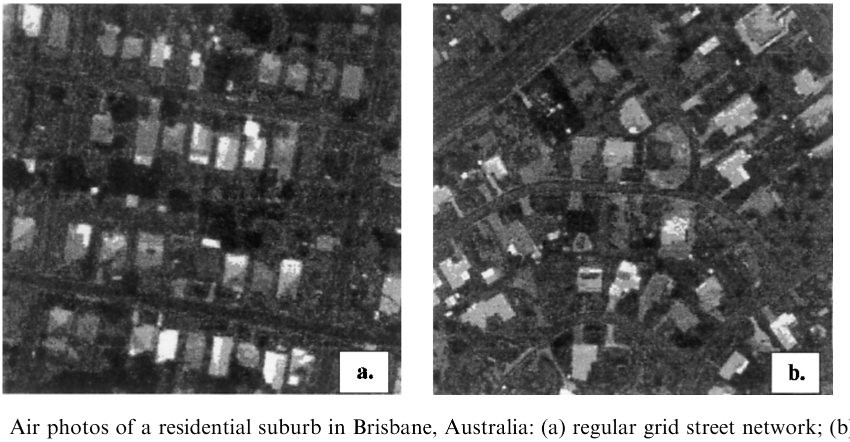

Fig. 1. Air photos of a residential suburb in Brisbane, Australia: (a) regular grid street network; (b) cul-desac street network.

shown in Fig. 1a urban development tends to evolve as rectangular units that are perpendicular to the transport network and that back on to each other. This type of urban morphology can exist for different types of transport networks such as in the culdesac design shown in Fig. 1b.

Model development in this research takes into account accessibility characteristics of local morphologies as depicted in Fig. 1a and b as well as the way in which friction-of-distance modifies and constrains infrastructure provision for urban development. In the model no account is taken of changes in internal urban structure in terms of change from developed to undeveloped, implying that the model is a birth-only type with no deaths. The prime focus in model development is on urban residential morphology. However, future multi-state models could be developed to include a number of urban states such as residential, commercial and industrial, with consideration of changes from one state to another over time.

Urban growth is considered to take place on a two-dimensional array of size L, in which a cell state, $S_t \in [1,0]$ at any time t, can adopt two states, developed or undeveloped. A birth $B = 1$ of a new development unit is generated at time $t+1$ if $S_{ti} = 1$ (i.e. some cell i is developed). The assumption is that if a cell i is developed then infrastructure for service provision exists and can be linked to the birth of a new development unit at some cell j. This is expressed as:

$$B_{jit} = \begin{cases} 1 & u > \beta \\ 0 & \text{otherwise} \end{cases}, \tag{1}$$

where β is an intrinsic growth rate (Batty, 1991) and u $(0 < u < 1)$ is a random normal variable.

When a birth is deemed to occur at some cell j, the morphology of the new urban growth is determined as follows. As can be seen in Fig. 1a and b, the relationship between the dimensions of the rectangular residential blocks is a ratio of approximately 1:3. From observations of street network data this ratio can vary from 1:2 to 1:4. Also, the relationship between the width of a development block and the width of the road (including verges) is approximately 1:1 and appears to remain constant irrespective of block width. These relationships are used in the model such that a developed residential unit ($S_{ti} = 1$) comprises two or more cells with one side in common.

The fundamental constraint that any development unit must have access to a transport network is then applied on a transport network array $\tilde{T}_k \in [1,0]$ for which $T_k = 1$ if cell k is on the transport network, 0 otherwise. To do this, an access constraint A_{jt} on cell j is determined such that:

$$A_{jt} = \begin{cases} 1 & \text{if} \quad 1 \leqslant \sum_{k \in \Omega} \tilde{T}_k \leqslant n \\ 0 & \text{otherwise} \end{cases}, \tag{2}$$

where Ω_j is the set of local nearest neighbors surrounding cell j. The Ω_j neighborhood can be either the Moore neighborhood (eight cell) or the Von Neumann neighborhood (four cell). The use of the Moore neighborhood allows diagonal and perpendicular access to the transport network whereas the Von Neumann neighborhood allows only perpendicular access. Consequently, the Moore neighborhood is most appropriate for culdesac networks and the Von Neumann neighborhood is best for regular grid networks.

A location for a birth at a cell j, $j \neq i$ is then chosen by conceptualizing the neighborhood space Ω_i of cell i to represent an infrastructure grid for service provision. The size of Ω_i is greater than or equal to Ω_j and depends on the significance of the effect of friction-of-distance on the location of new development units. Since services such as power and water are usually derived from a developed network, the probability p_{ijt} of a cell being developed decreases with distance from developed cell i. The spatial implication of this is that development units are correlated in space (Makse et al., 1995). This can be expressed as a power law where d_{ij} is distance from cell i to cell j, $d_{\max}$ is the maximum distance, and α is a distance parameter. This probability is determined as follows:

$$p_{ijt} = (1 - d_{ij}/d_{\max})^{\alpha}. \tag{3}$$

The location, L_{jt}, of a birth at some cell j in neighborhood space Ω_i is then determined such that there is no directional bias in the location of cell j in Ω_i (Batty & Xie, 1997) and is calculated as:

$$L_{jt} = \begin{cases} 1 & \text{if} \quad \sum_{z=1}^{j-1} p_{izt} \leqslant u \leqslant \sum_{z=1}^{j} p_{izt} \\ 0 & \text{otherwise} \end{cases}. \tag{4}$$

Having established a location for cell j in neighborhood space Ω_i, the state of cell S_j at time $t+1$ is:

$$S_{jt+1} = A_{jt} L_{jt} B_{it} S_{it}. \tag{5}$$

3.2. *Morphological experiments*

Eq. (5) is best understood using simulated growth examples to produce morphologies shown in Fig. 2a–e. Fig. 2a and b show simulations for which no knowledge of a transport network exists and the access constraint term, A_{jt} is set equal to one in Eq. (5). In Fig. 2a the initial conditions for the model are set by 10 randomly placed cells. In Fig. 2b initial conditions are set from a network developed using a process of diffusion-limited aggregation (Batty, 1991). For Fig. 2a and b the Ω_i neighborhood is a square neighborhood with a width of 11 cells. The spatial configuration of the simulations in Fig. 2a and b show the decline in density and spatial correlation of development units that is characteristic of urban fringe growth.

Fig. 2c and d show simulated residential growth on an actual regular grid network and a culdesac network, respectively. Both the transport networks shown in Fig. 2c and d were obtained from digital maps of transport networks for Brisbane, Australia. Since knowledge of the transport network is required for full implementation of the model given by Eq. (5), some experiments are presented using

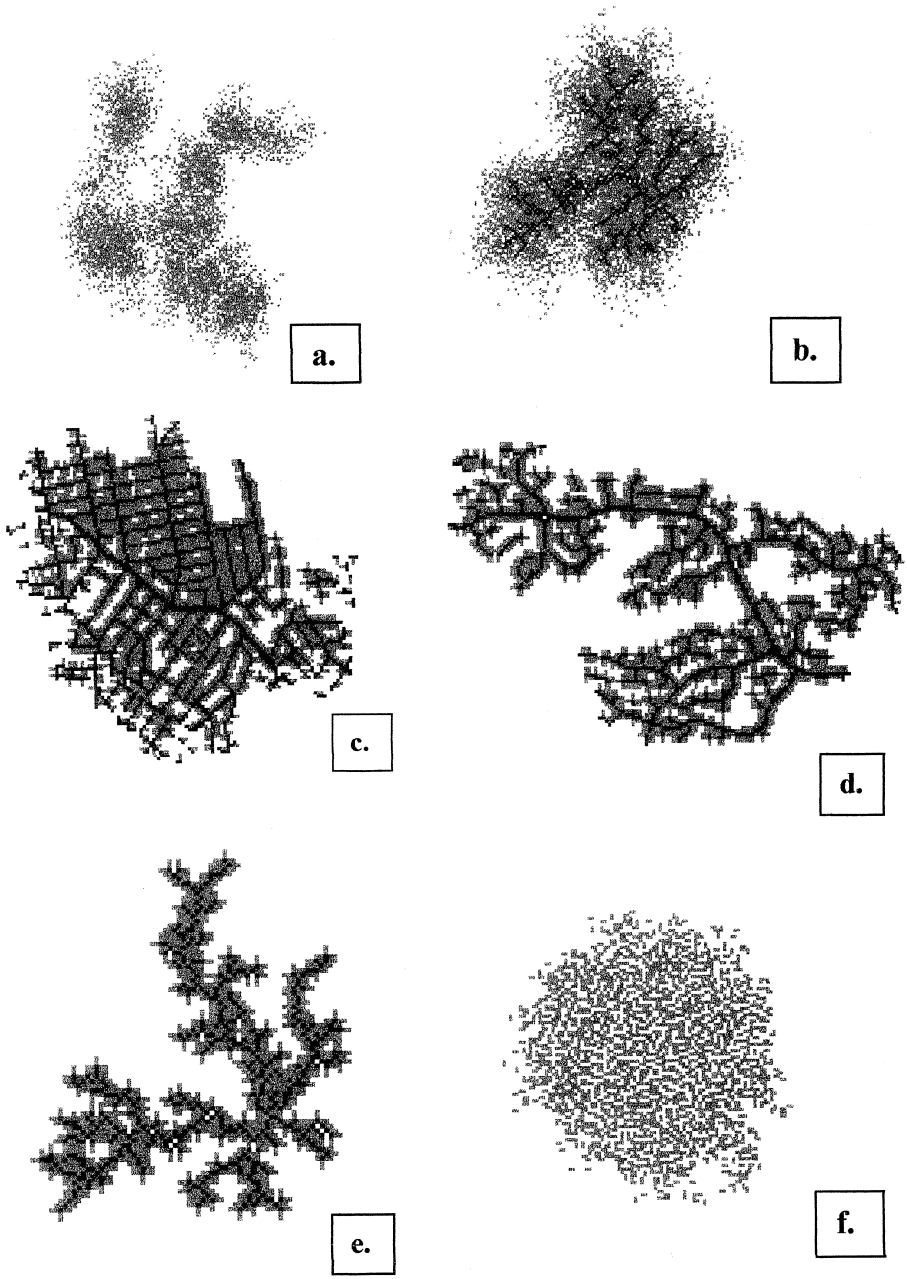

Fig. 2. Simulated urban growth patterns constrained by different transport networks: (a) no network; (b) no network with growth seeded with a diffusion-limited aggregation (DLA) network; (c) actual regular grid network; (d) actual culdesac network; (e) DLA-derived network; (f) access-constrained growth with no network.

artificially developed transport networks. Fig. 2e shows simulated growth on a network developed using a process of diffusion-limited aggregation. In Fig. 2c–e the initial conditions and neighborhood size are the same as for Fig. 2a, with block size set at two cells.

The experiments depicted in Fig. 2a–d show firstly that urban morphologies with characteristics very similar to actual urban growth can be simulated using a CA model with transition rules derived from notions of spatial correlation and access. However, it is unlikely that these rules will produce emergent properties associated with self-organization. The experiments in Fig. 2a and b are what would be expected of growth based on a friction-of-distance neighborhood. Similarly, in Fig. 2c and d the resulting morphologies are what is to be expected due to the access constraint being applied to a predefined transport network. The cellular model given by Eq. (5) can produce realistic urban morphologies but simulations show none of the emergent properties that can be associated with CA.

The experiment shown in Fig. 2f is the only simulation that shows anything that might resemble emergent properties. The experiment in Fig. 2f was developed using Eq. (5) with no knowledge of a transport network and the access constraint rule set such that each development unit must have access to a vacant cell (analogous to space required for transport access). Given that the access constraint is met, the orientation of any new development unit is chosen randomly in the four principle compass directions provided a development unit does not already exist in the randomly chosen direction. The result is a chaotic assemblage of development units each of which has access to at least one vacant cell. However, no rule for connectedness of the vacant cells to represent a transport network is implemented and consequently the simulation shown in Fig. 2f does not represent a realistic urban pattern.

The orientation of model development in this paper is toward the application of cellular models as planning tools for exploring possible regional-scale growth scenarios. For example, given a population projection and land-use constraints what is a possible pattern of future growth? To this end, models that produce regional-scale urban morphologies are adequate without the need to the pursue detailed urban morphologies at a local level. For this reason the focus of model development is now turned to regional-scale factors that modify and prohibit growth and that can be influenced by policy decisions. From here on the model is referred to simply as a cellular model and not a CA in the sense that no emergent properties are expected.

3.3. Global constraints

The growth of cities is influenced strongly by economic constraints, physical constraints, and institutional controls. Physical factors such as water bodies and steep terrain constrain growth, as do institutional controls such as zoning that prohibit or determine the type of growth. Economic factors such as distance from transport networks, distance from commercial outlets and land values also play a significant role (Batty & Longley, 1994).

It is unlikely that the process of urban growth can be modeled deterministically with limited information. Human behavior introduces considerable uncertainty into the sequence and form of growth. If CA can be used to model urban growth and growth is a self-organizing process, as is the fundamental idea behind the use of CA, then links to chaos theory can be made. Chaotic processes, such as the climate, may show high degrees of uncertainty and this uncertainty can be described probabilistically. Recognizing the intrinsic uncertainty in the urban growth process, the approach to model development is now to treat constraints, associated with economic and other factors, stochastically.

The approach is to develop a simple model for which actual information on socio-economic and bio-physical factors that play a significant role in the location of growth areas can be easily developed using contemporary GIS software. To incorporate these ideas, a constraint vector $\tilde{C}_n$ of M constraints is introduced into the model. Potentially, $\tilde{C}_n$ could have any number of elements representing a wide variety of factors that are important either as fundamental constraints to growth or that are of interest in a particular planning process. However, for the purposes of demonstrating the introduction of constraints into the model, $\tilde{C}_n$ is assigned three elements ($n=3$) associated with, institutional controls, growth-prohibiting constraints, and growth-modifying constraints. The classification of constraint types is arbitrary but a distinction is made between constraints that prohibit and those that act to modify growth.

Institutional controls, I_j, resulting from land tenure and planning policies can be represented in binary form. That is, $I_j \in [1,0]$ such that for any cell j, $I_j = 1$ if development can occur, or $I_j = 0$ if development is prohibited. Similarly, growth-prohibiting constraints, $E_j \in [1,0]$ result from physical barriers to development such as water bodies. Growth-modifying constraints $G_j \in [1,0]$ are associated with economic and physical factors that do not necessarily prohibit growth but act to modify growth patterns. The constraint vector is then given by:

$$\tilde{C}_n = \begin{bmatrix} I_j \\ E_j \\ G_j \end{bmatrix}. \tag{6}$$

We consider three growth-modifying constraints in the model, land slope, distance from roads, and distance from population centers. The assumption here is that these growth-modifying constraints modify growth patterns according to some function of their magnitude. For example, as growth occurs on the urban fringe, the likelihood of development taking place decreases as slope and distance from the transport network increase. The geographic constraint variables are represented such that any cell j is calculated to have an geographic constraint probability g_j given by:

$$g_j = W_m \prod_{m=1}^{N} P_{jm}, \tag{7}$$

where P_{jm} represents the probability of the mth geographic constraint at cell j and W_m is a weight that specifies the relative importance of the mth geographic constraint. The probability P_{jm} is calculated using a negative exponential function of the form:

$$P_{jm} = \exp[-\phi(q_{jm}/q_{\max})], \tag{8}$$

where q is a variable representing the mth geographic constraint and ϕ is a tunable parameter. At this stage of model development the choice of the negative exponential function in Eq. (8) is based on the common use of the negative exponential function in describing urban population density (e.g. Anas, 1982; Braken & Tuckwell, 1992; Muth, 1969). G_j is then determined stochastically as:

$$G_j = \begin{cases} 1 & \text{if} \quad u \leqslant P_{jm} \\ 0 & \text{otherwise} \end{cases}. \tag{9}$$

Using the model given by Eq. (5) in which a birth is generated and located, the constraint model is completed with the inclusion of the constraint vector $\tilde{C}_n$ to give:

$$S_{jt+1} = A_{jt} L_{jt} B_{it} S_{it} \prod_{n=1}^{N} C_{jn}. \tag{10}$$

4. Implementation

The model outlined in the previous section provides a method for exploring urban development across the landscape. Parameters and weights in the model offer a means of exploring different development scenarios. By modifying constraint information, 'what if'-type questions can be asked of the model, and stochastic realizations developed.

Model implementation represents an urban planning tool for use by planners and local governments to explore growth scenarios associated with population projections. So as to make the model as user friendly as possible commercial software development tools and GIS are utilized. In this research, DELPHI (object-orientated Pascal) is used to implement the CA model and develop a GUI.

The basic model inputs are information on institutional controls, growth-prohibiting constraints, and growth-modifying constraints. Since the model operates on a lattice, raster data are required to produce spatial output. Data are managed and manipulated using ArcView Spatial Analyst, a commercial GIS.

The model interface presents a main menu and a series of pull-down sub-menus that initiate data input and output, setting initial and boundary conditions, parameter setting, data viewing, and model choices. Data transfer between the modeling software and the GIS is via binary data files. Before running the model, data are loaded from the GIS and parameters are set according to the scenario being explored. Model simulations can be viewed in real time and the results of simulation runs read as binary files by the GIS and displayed with overlay of contextual data stored in the GIS.

5. Application

To demonstrate the simulation model, it was applied to an area in the Gold Coast, a rapidly urbanizing region of coastal eastern Australia. This area has experienced rapid growth over the past decade with a 32% increase in urban area from 1988 to 1995 (Ward, Murray & Phinn, 2000). The Gold Coast is a satellite city associated with the major metropolitan center of Brisbane, Queensland, and has developed on the low-lying coastal plain that is dissected by numerous man-made canals. Population growth is now pushing urban development towards the north, and east into the coastal hinterland. The objective of presenting results for this area is to demonstrate how the model can be used to develop different residential growth scenarios and how the model produces different urban morphologies.

5.1. Spatial information

The model requires three types of spatial information, an initial urban configuration (initial conditions) to seed the simulation run, population projections (boundary conditions for the model) and, constraint data in the form of institutional controls, growth-prohibiting constraints, and growth-modifying constraints. Very little historic data on urban extent exists for the area in contrast to other similar studies such as Clarke et al. (1997). Landsat Thematic Mapper (TM) imagery captured from the mid 1980s to the present is available for the Gold Coast and has been used by Ward et al. (2000) to map urban extent for 1988 and 1995 for the Gold Coast area. An adjusted overall classification accuracy of 83% for classification of broad land cover types was achieved. However, due to the coarse spatial resolution of Landsat TM data the classification accuracy of the lower density urban fringe and rural residential areas was reduced. For the simulations presented here, the 1988 classification maps provide initial urban configurations with which to seed a simulation run. The area of change from 1988 to 1995 is used as boundary conditions to explore the characteristics of change in urban extent over time. Both the Landsat TM imagery and the classification maps are stored, manipulated and viewed using ArcView.

Data on institutional controls, I_j, were derived from local government land-use zoning for the Gold Coast and were used to identify areas for which development can proceed or be excluded. The assumption is that all land zoned for a use (e.g. residential) is available for development, while state-owned land such as reserves and state forests are unavailable. Data on growth-prohibiting constraints, E_j, such as water bodies is derived from the 1988 and 1995 image classification maps. Three geographic constraint variables, land slope, distance from major and minor road networks, and distance from major commercial centers are used in the simulation runs presented here. Land slope was derived from a digital elevation model of the area (50 m resolution), using the slope derivation procedure available in ArcView Spatial Analyst. A Euclidean distance function in ArcView Spatial Analyst computed the distance from major and minor road networks and from major commercial centers.

The GIS was used in the simulation process to provide data storage, manipulation and display functionality for both the model and ancillary data. It is likely in application that many simulation runs would be performed and the results of simulation runs explored and evaluated. The results of the simulation runs can be imported as spatial layers into the database and contextual information (e.g. census data) and analytical GIS tools applied to evaluate different growth scenarios.

5.2. Simulated growth

The preliminary results presented here demonstrate the application of the model to an actual residential growth situation associated with local government land-use zoning. Two types of simulations were developed. In the first, transport network-based growth was used to develop residential growth scenarios from 1988 to 1995 based on detailed knowledge of the 1995 transport network. The second type of simulation is developed with only knowledge of the major transport network and shows growth based on a friction-of-distance neighborhood for which constraints associated with distance from major roads, distance from population centers and land slope are stochastically realized. For all simulations, residential growth can occur only in areas prescribed for residential growth by the 1997 land-use zoning for the Gold Coast. 1997 land-use zoning was used because no digital information on the 1995 land-use zoning for the Goal Coast was available.

5.2.1. Transport network-based growth

Two sub-areas of the Gold Coast were used to demonstrate transport network-based residential growth. Fig. 3a and b show actual and simulated residential growth, respectively, for the Helensvale area, a new residential development on the fringe of the main urban extent of the Gold Coast. The transport network for the residential development is a culdesac design. Fig. 3c and d show actual and simulated residential growth for the Labrador area, an older established part of the Gold Coast and demonstrates the phenomenon of in-filling. The transport network for the Labrador area is a mix of older established regular grid network and more recent culdesac networks.

For both areas, the 1995 transport network is taken from cadastre information and rasterised at a 20-m cell size which is the approximate road width (including verges) in residential areas. Residential block sizes are set at 1:3 ratio in cells. In both simulations shown in Fig. 3 the boundary conditions for the model are set to the area of residential growth from 1988 to 1995. Initial conditions for the simulations are set using a combination of the 1988 urban extent and random seeding. Random seeding is performed by randomly allocating seed cells across the area zoned as residential. The value of the ϕ parameter in Eq. (10) for each of the constraints was determined by adjusting the parameter to give the best fit based on visual assessment.

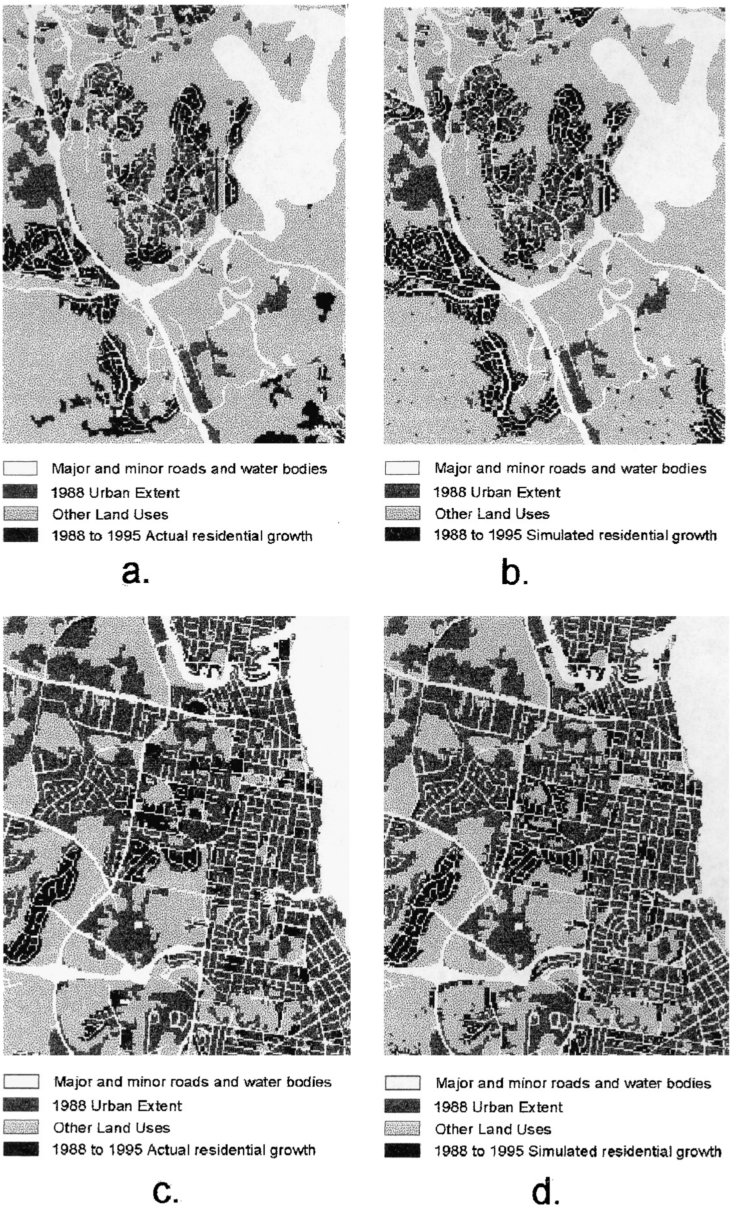

Fig. 3. (a, b) 1988–95 actual and simulated residential growth, respectively, for the Helensvale region, a new residential development of the Gold Coast. (c, d) 1988–95 actual and simulated residential growth, respectively, for the Labrador region, an older established area of the Gold Coast.

Visual tests are non-quantitative and subjective but offer a useful and quick way of calibrating and verifying that the model is replicating the historic spatial growth pattern (Clarke et al., 1997).

To assess the performance of the model, omissions (erroneously excluded elements), commissions (erroneously included elements) and the level agreement is calculated and presented in Table 1. The transport network-based model performs reasonably well with agreement between the simulated and actual growth of 74 and 65% for the Labrador and Helensvale regions, respectively. Many of the omission errors occur because some areas determined as actual growth from 1988 to 1995 and zoned as residential do not have a transport network associated with them. This is due to the definition of urban used by Ward et al. (2000) to include areas of exposed land that are in the process of being transformed to urban but do not as yet have a transport network. Consequently, the model cannot produce growth in these areas. Since the model is run with a boundary condition of the area of change from 1988 to 1995, the model will compensate for the area associated with omissions by over-predicting growth on the transport network.

5.2.2. Constrained growth

An objective in developing the CA simulation tool is to explore possible urban growth patterns associated with planning scenarios. In this type of situation detailed knowledge of the local transport network is unlikely to exist. However, information on factors such as the major transport network, distance from population centers, and land slope are likely to be available for a particular planning scenario (e.g. land-use zoning). To apply the model in this context the A_{jt} term is dropped from Eq. (10) and growth is based on friction-of-distance allocation on the Ω_i neighborhood.

Fig. 4a and b show actual and simulated residential growth from 1988 to 1995, respectively, for the Gold Coast area. As in the examples shown in Fig. 3 the boundary conditions are set by the area of growth on the Gold Coast from 1988 to 1995, and initial conditions are set by the 1988 urban extent and random seeding. Growth is based on single cells of size 50 m. Visual calibration (e.g. Clarke et al., 1997) was used to determine the value of the ϕ parameter in Eq. (10) for each of the constraints to give the best fit to actual growth patterns.

As in the examples in Fig. 3, omission and commission errors, and agreement levels are used to assess the performance of the model and the results are presented in Table 1. The model performs reasonably well with agreement between the simulated and actual growth of 63%. A large amount of the area associated with commission errors results for over-estimating the degree of in-filling in the older established urban matrix. This is associated with the way initial conditions for the model are set using 1988 urban extent. Since the density of urban extent is greatest

Table 1
Agreement level, omission and commission errors associated with simulations of residential growth for the Helensvale, Labrador and Gold Coast regions

Location	Agreement (%)	Omission (%)	Commision (%)	Area of change (ha)
Helensvale	65	34	39	285
Labrador	74	26	37	166
Gold Coast	63	36	38	1886

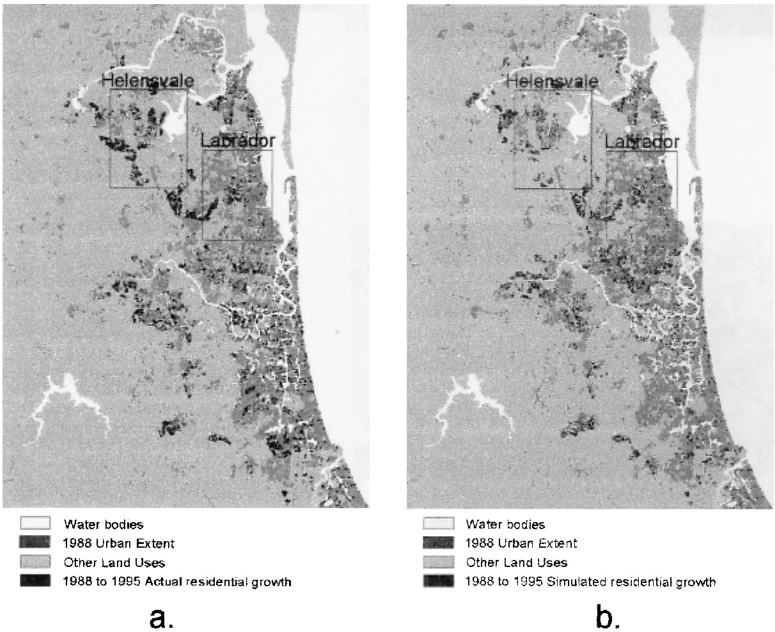

Fig. 4. (a, b) 1988–95 actual and simulated residential growth, respectively, for the Gold Coast.

in the older established areas the model will tend to have growth occur rapidly in these areas leading to an over-estimation of new development in these areas.

6. Discussion and conclusions

The work presented in this paper follows on from recent developments in cellular modeling approaches to urban growth (e.g. Batty & Xie, 1994; Clarke et al., 1997; White et al., 1997). The notion of urban growth as a self-organizing process is explored using CA and questions are raised as to the nature of transition rules that produce emergent properties characteristic of CA. However, it is argued that whether models are capable of emergent properties or not they still offer a useful method for exploring urban growth. Due to the increasing availability of spatial information and the need for new approaches in planning and managing growth, cellular models of urban growth may offer useful adjuncts to planning information and decision-support systems.

The question of whether there are simple rules that when applied will produce morphologies similar the actual local urban morphologies are difficult to answer. CA transition rules associated with spatial correlation of urban development units (Fig. 2a and b) produce morphologies with characteristics similar to actual growth patterns. These growth patterns are meaningful at a broad scale but show none of the true intricate detail of the spatial distribution of development units in real urban systems. Access constraints can produce exact local urban morphologies (Fig. 2c and d) but require predefined transport networks.

The question of scale becomes important and the significance of the level of resolution of the model will depend on the application of the model. However, it is argued that access-based transition rules must be included in any CA models of local urban growth if any interesting emergent properties are to be expected. A way forward in exploring the notion of urban growth as a self-organizing process using CA may be to apply access transition rules as in Eq. (2) in association with a rule for connectedness of the vacant cell network. The idea being that each new development unit must have access to a transport network and that network must be connected. This type of model would be a true CA in the sense that the model may show unexpected emergent properties.

Stochastic implementation was undertaken to reflect the uncertainty in the influence of economic and physical constraints on growth. A consequence of this is that the model can produce different realizations for the same parameter settings. Hence, any realization of a growth scenario can be seen only as one possible form that growth may take. This uncertainty is paralleled in the real growth situation in that for a particular planning scenario (e.g. land-use zoning) growth can take many different forms depending on factors that influence human decision making such as economic trends or land values. However, the result of driving the model stochastically over time is that the density of development units reflects the suitability of the landscape for development. A useful approach would be to use a Monte-Carlo simulation to develop a probability space of development potential similar to the work of Clarke et al. (1997).

The model can potentially simulate a wide variety of urban forms depending on parameter values associated with the constraint variables. Consequently, the method of parameter estimation or model calibration is an important one. Currently parameter estimates are developed using visual calibration (Clarke et al., 1997). Parameter estimates could be derived by developing statistical relationships between the information on urban extent and the constraint variables used in the model. For example, using information on urban extent and change over time derived from remotely sensed data, logistic regression techniques could be applied to develop relationships with the constraint variables (e.g. slope, distance from commercial centers) that allow parameter estimates to be made. The problem with visual and statistical calibration is that parameter values are specific to the data used for calibration and will vary from region to region and city to city. Parameter values are not likely to be stationary and will show changes with time that reflect new planning and engineering approaches and technologies. However, flexibility in parameter input facilitates the application of the model to explore different policy and land-use scenarios. For example, density and spatial distribution characteristics can be controlled by parameter settings. Hence, flexibility in the choice of parameter settings can be useful in exploring different growth scenarios.

In the applications presented in this paper constraints on growth are based on friction-of-distance associated with transport networks and population centers as well as land slope. These types of constraints are used only as examples and have been applied based on their use by other authors (e.g. Clarke et al., 1997; White et al., 1997). No account is taken of factors that influence growth from a distance such as the location of distant markets or population centers. Despite this, the model produces patterns of urban growth that are highly correlated with actual growth patterns over relatively short time periods. This demonstrates the significance of local planning constraints, and the influence of physical and economic constraints on the spatial configuration of urban form. Potentially, any number of constraints could be introduced into the model depending on the objectives of the planning process. Other constraints could be related to, for example, service provision or environmental factors such as the preservation of natural areas in the urban matrix.

At this stage of development the model only deals with residential growth. However, the model can potentially be extended to a multi-state model that includes a number of different urban land uses such as commercial and industrial land uses. For example, given a particular growth scenario the relative proportions of commercial and industrial areas required to support an increase in the residential population could be estimated based on factors such as employment and service provision.

The urban growth model developed in this paper is orientated towards application as a planning tool. To be able to use the model as a planning tool, boundary conditions for the model are required. These can be defined as target and constraint values associated with a particular planning scenario. A common target used in local government planning is a population projection for a particular sub-area. By building into the simulation tool the ability to allocate development units based on population projections to local sub-areas, the model can be used to explore growth scenarios. By modifying constraints associated with institutional controls that come from policy associated with sustainable urban development and other economic and growth-modifying constraints the model can be used to develop different growth scenarios.

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