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Cellular automata models for the simulation of real-world urban processes: A review and analysis

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ABSTRACT

In recent years, cellular automata (CA) models for urban growth simulation have proliferated because of their simplicity, flexibility and intuitiveness, and particularly because of their ability to incorporate the spatial and temporal dimensions of the processes. Though apparently simple, CA models are capable of modeling complex dynamic systems such as urban systems. Currently, one of the main problems in actually applying CA models to urban planning practice is the choice or design of the most suitable CA model. For this reason, a review of urban CA models applied to real-world cases is provided, along with an analysis of their capabilities and limitations. The review and classification of CA models based on the main characteristics of the models has allowed for the analysis of their strengths and weaknesses. Finally, a discussion of the needs for further research is presented.

1. Introduction

In recent decades, a number of modeling techniques have been developed to better understand and predict urban growth. Early studies of urban processes used transportation and land-use planning models based on gravity theory or optimizing mathematics, but soon evolved into more dynamic spatial models (Berling-Wolff and Wu, 2004a), such as cellular automata (CA).

CA were first developed in the late 1940s by S. Ulan and J. von Neumann like copies of the same Turing machine placed at each cell of a lattice and connected together. Wolfram (1984) demonstrated that complex natural phenomena can be modeled by CA and, later, laid the foundations for a Theory of Cellular Automata (Wolfram, 2002), defined as discrete dynamic systems in which local interactions among components generate global changes in space and time. CA simulation was soon applied to physical sciences, natural sciences and mathematics. Tobler (1979) first proposed the application of cellular space models to geographic modeling. In the 1980s, the first theoretical approaches to CA-based models for the simulation of urban expansion appeared (Batty and Xie, 1994; Couclelis, 1985; White and Engelen, 1994). Itami (1994) reviewed CA theory and its application to the simulation of spatial dynamics, and Batty (2005b) provided an analysis of diverse applications of urban CA.

Conceptual advances in CA research and the development of computing power led to the emergence of the first operational urban CA models applied to real-world urban systems in the 1990s. The ability of CA to simulate urban growth is based on the assumption that past urban development affects future patterns through local interactions among land uses. The interest of CA-based models for urban simulation can be explained in terms of the simplicity, flexibility, intuitiveness and transparency of CA. Additionally, CA can be easily integrated with Geographical Information Systems (Itami, 1994; Wagner, 1997) and, consequently, model at high spatial resolution with computational efficiency. Besides, many authors have shown that the nonlinearity of the iterative process of CA leads to regular fractal patterns, i.e. to regular and ordered spatial patterns that generate similar geometries at different scales. Such fractal structures, derived from complex phenomena, are characteristic of urban developments (Batty, 1991; Batty and Longley, 1994; Longley and Mesev, 2000).

When actually applying CA-based models to urban planning, choosing the most suitable model from among the many options available (Pinto and Antunes, 2007) is difficult (Li and Yeh, 2002a). In order to present a structured overview that facilitates the choice of a particular method for a given application problem, an analysis of 33 urban CA models has been performed. The differences among the different approaches are highlighted and a classification of the models is proposed. The objective of this paper is to provide a basis for a literature review of urban CA and for the future development

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of new advances in this area. To this end, the general characteristics of urban CA are described and the different techniques used in the design of such models are characterized and classified. Such techniques have been summarized in several tables. In addition, the strengths and weaknesses of the different models have been identified from the analysis and discussion of the characteristics of the models.

2. Relaxations of CA for urban simulation

A CA consists of a discrete cell space, in which states characterize every cell. In urban CA, states can be (i) binary values (urban, non-urban), (ii) qualitative values that represent different land uses, (iii) quantitative values that represent, for example, population density (Li et al., 2003), degree of development (Yeh and Li, 2002) or the value of buildings (Cecchini and Rizzi, 2001), or (iv) a vector of several attributes (Portugali and Benenson, 1995). The state of each cell depends on its previous state and on the state of its neighboring cells according to a set of transition rules. The 'background conventions' of CA limit their ability to realistically simulate complex geographical phenomena (Couclelis, 1985). For this reason, adapting CA to urban simulation requires considering the particularities of this phenomenon, which usually entails a relaxation of the original structure of CA in order to introduce more complexity in models (Couclelis, 1997). The most common modifications include:

(1) *Irregular cell space*. Formal CA assume a cell space represented by a regular grid usually composed of square cells, although some authors have proposed using hexagonal cells in order to obtain a more homogeneous neighborhood (Iovine et al., 2005). Additionally, the cell space can consist of a three-dimensional matrix that allows to represent growth in height of urban areas (Semboloni, 2000). The regular grid space can be modified by using irregular tessellations such as Voronoi polygons (Shi and Pang, 2000) or graphs (O'Sullivan, 2001a,b). Irregular spatial units may provide a more faithful representation of the objects being modeled. For example, using cadastral parcels instead of regular cells (Stevens and Dragicevic, 2007) provides a representation that comes closer to reality. Yet, using cadastral units complicates the definition of the neighborhood.

(2) *Non-uniform cell space*. In standard CA, the cell space is homogeneous, i.e., all cells are identical and are characterized exclusively by their state. However, land-use change depends largely on other land attributes such as slope, elevation or accessibility. Consequently, the cell space is not uniform, such that some cells are more suitable for certain land uses.

(3) *Extended neighborhood*. In strict CA, the neighborhood must be the same for every cell and must be composed of the geometrically closest set of cells (e.g. Moore and von Neumann neighborhood). In urban systems, this local neighborhood must be extended in order to consider the influence of neighboring cells located at a certain distance. When the neighborhood is extended, a distance-decay effect is usually introduced in the model, such that the effect of a neighboring cell decreases with the increase in distance between both cells. In spaces composed of irregular units, the neighborhood can be defined as the adjacent units, as the units within a specified distance or using the Voronoi spatial model (Shi and Pang, 2000).

(4) *Non-stationary neighborhood*. The neighborhood space may be defined differently for each cell. Such a relaxation is widely acknowledged (Couclelis, 1985), but seldom implemented. Models in which each cell receives a weight according to its state and location within the neighborhood (e.g. White and Engelen, 1993) allow for the application of neighborhoods of different sizes and shapes by introducing weights equivalent to zero.

(5) *More complex transition rules*. The transition rules of a formal CA consider solely the current state of the cell and its neighbors. However, a variety of factors influence urban processes, such as suitability for a land use, accessibility, socioeconomic conditions, or urban planning. Consequently, urban CA are not closed systems, as established by the CA formalism, since urban CA models can consider external factors. The transition rules of urban CA can be designed in many ways and reflect various urban theories, based on microeconomic theories of planning (Webster and Wu, 2001), centrality and potential models (Polidori and Krafta, 2005), etc.

(6) *Non-stationary transition rules*. The transition rules of strict CA are static, however the processes that govern land-use change may vary over time and space. Therefore, it may be necessary to adapt the transition rules to the specific characteristics of each area and period. Spatial and temporal variation can be achieved through calibration (Geertman et al., 2007; Li et al., 2008). The most evident example of transition rules that vary over time are the self-modification rules of SLEUTH (Clarke et al., 1997). Phipps and Langlois (1997) proposed a system that modified the transition rules at every time step according to changes in configuration and external parameters.

(7) *Growth constraints*. In conventional CA the number of cells that change state is endogenously defined by the application of transition rules. However, urban land demand is usually determined by exogenous social, economic or environmental constraints, such as demographic evolution or urban planning, which constrain overall urban growth.

(8) *Irregular time steps*. There are many urban CA in which different cells may be subject to time steps of different lengths (Stevens and Dragicevic, 2007). A less frequent relaxation is using variable time steps (Couclelis, 1997) to simulate specific events of different lengths of time. Cecchini and Rizzi (2001) suggested applying two types of rules: structure rules, applied in every iteration, and conjunctures rules, applied only when a specific event was implemented.

3. Analysis of urban CA models

Early applications of CA to urban dynamics modeling were theoretical models aimed at simulating simple urban structures. Takeyama and Couclelis (1997) defined the language of geo-algebra as the mathematical basis for the development of urban CA within GIS. Theoretical developments were followed by the design of abstract simulation models of urban evolution (Batty, 1998; Batty and Xie, 1994, 1997; Batty et al., 1999; Semboloni, 1997). Such theoretical approaches allowed modelers to test hypotheses of urban theories and simulate general urban forms (Batty, 2005a). Other theoretical applications of CA to urban modeling are described by Itami (1988), Portugali and Benenson (1995), Cecchini (1996), Phipps and Langlois (1997), Wu and Webster (1998a), Webster and Wu (1999a,b), Liu and Phinn (2003) and Kocabas and Dragicevic (2006a). These theoretical models laid the foundations for the development of operational urban CA, but were never tested in real cities.

The next step was the application of the above theoretical models to the simulation of real-world urban development processes. The emergence of GIS has contributed to the change from artificial applications to real simulations (Couclelis, 1997). This paper focuses on models that have been applied to real cities and, in most cases, have been subject to calibration and validation.

Some of the first applications of urban CA to the simulation of real-world cases were carried out by Batty and Xie (1994) and Xie (1996) in Amherst, New York. However, the first widespread empirical application of these models was developed by White et

Table 1
Main characteristics of urban CA models with strict transition rules.

Author	Objective[a]	Cell space	State	CA relaxations			Other methods	Calibration	Validation
				Neighborhood	Transition rule	Constraint[b]			
Besussi et al. (1998)	P-M	30 m cells	18 land uses	Moore	Land value transformation automata: modifies the value of residential cells as a function of the residential and commercial cells in the neighborhood according to 6 rules. Urban functions' transformation automata: modifies the density of residential cells as a function of the presence of commercial cells in the neighborhood and vice versa according to 4 rules. Urban functions' diffusion automata: simulates the change of residential, commercial, industrial, and park cells according to 9 rules	No	None	None	None
Jenerette and Wu (2001)	D, P	250 and 75 m cells	Urban, desert parks	Moore	The transition probability is based on the number of urban neighbors and on the state of the cell	No	Genetic algorithm (GA)	Empirical and GA	Landscape structure indices
Stevens and Dragicevic (2007)	P-M	Cadastral parcels	7 land uses	Adjacent parcels	Residential use: the attractiveness of the parcel for residential use is the sum of the scores given for proximity to parks, commercial areas, light industry and heavy industry, and the score given by adjacency to residential land. If the adjacency score is higher than the sum of the other four scores, all the parcels adjacent to currently developed parcels will begin to be developed until the demanded area is fully developed. Commercial use: if the parcel is adjacent to a road, the neighborhood has enough population and the neighborhood is not saturated with other developed commercial properties, the cell is developed. Park use: if the cell has a specified number of people living in its neighborhood	POP	None	Empirical	None
Ward et al. (2000)	D	50 m cells	Urban, non-urban	Moore and von Neumann	The state of a cell is urban if the cell is not affected by constraints, if at least one of the neighboring cells belongs to the transportation network, if the value of a random normal variable (u) is higher than an intrinsic growth rate, and if there is no directional bias in the location of the cell in the neighborhood	POP Ward et al. (2003) used linear programming to provide the urban area	None	Visual	None
Yüzer (2004)	P-M	100 m cells	5 land uses	Square with a radius of 6 cells	Transition potential is based on the land uses of the neighborhood. The mean of the potentials for transition is calculated. The cells with a potential higher than the product of the mean by a coefficient change from one state to another	AGR or POP	None	Surveys and spatial studies	None

[a] D – descriptive; P – predictive; M – multiple land uses; PC – prescriptive.
[b] AGR – annual growth rate for urban land; POP – population growth projection; PLA – urban regulation planning; MOD – model mentioned in the 'other methods' section; OTH – other studies.

Table 2
Main characteristics of urban CA models with transition rules based on transition potential or probability.

Author	Objective[a]	Cell space	States	CA relaxations			Other methods	Calibration	Validation
				Neighborhood	Transition rule (calculation of the transition potential)	Constraint[b]			
Almeida et al. (2003)/Almeida et al. (2005)	D-M	100 m cells	8 land uses	Moore	Complex function that includes the weights of evidence for different factors and the prior probability for each land-use transition	AGR	Weights of evidence to calculate transition probabilities	Test of independence/visual	Multiple resolution fitting procedure
Barredo et al. (2003)/Barredo et al. (2004)	D-M, P-M	100 m cells	22 land uses, 9 active uses/8 active land uses	Circular with a radius of 8 cells	Product of the accessibility, the suitability for that use, the zoning status for that use, a stochastic disturbance parameter, and the effect of the neighborhood	MOD/POP and AGR	Dynamic global model that calculates the area for every land use/none	Visual	Visual comparison. Fractal dimension. Coincidence matrix and kappa index./Other spatial metrics instead of the fractal dimension
Caruso et al. (2005)	D	250 and 500 m cells	Residential, agricultural	Moore, circular with radius of 3 and 5 cells	Complex function that includes the income of households (constant), the commuting cost, the social and environmental externalities, and the utility level to achieve (constant)	AGR	None	Sensitivity analysis	Fragmentation index: HF-edge-share. Fractal dimension and curve. Residential density vs. distance
Cheng and Masser (2004)	D, P	10 m cells	Urban, non-urban	Circular with a radius of 3–9 cells	Product of a stochastic disturbance term, the weighted sum of a set of factors, and a series of constraints	AGR	None	Empirical	Coincidence matrix. Consistency coefficients and Lee–Sallee index
Engelen et al. (1999)	D-M, P-M	100 m cells	14 land uses, 8 active uses	Circular with a radius of 8 cells	Product of a stochastic disturbance term, the suitability for the land use, the zoning for that use, and the effect of neighborhood	OTH	None	Sensitivity analysis	Kappa index
He et al. (2006)	D, P	180 m cells	Urban, non-urban	Not explicit	Weighted sum of a set of factors, the neighborhood effect, and an inertia constant. The result is multiplied by a stochastic disturbance term, and by environmental and planning constraints	MOD	System dynamics-based model that calculates the urban area	Monte-Carlo approach	Kappa index
He et al. (2008)	D, P	180 m cells	Urban, non-urban	Circular with a radius of 5 cells	The model of He et al. (2006), with the exception that the inertia constant is replaced by the urban expansion potential	AGR and POP	Linear regression to calculate urban area. Potential model to define the rules	Monte-Carlo approach	Kappa index
Lau and Kam (2005)	D-M	1 km cells	9 land uses, 6 active uses	Moore	Complex function of three indices: attribute, heterogeneity and gravity. The attribute effect comprises accessibility, residential density, property value and travel demand. The heterogeneity index is calculated from land-use data of the center cell. The gravity effect is the resistance to change. The result is multiplied by the suitability for the land use	PLA	Multivariate statistical tools to identify factors and weights	MANOVA and MDA	Overall accuracy

Table 2 (*Continued*)

Author	Objective[a]	Cell space	States	CA relaxations			Other methods	Calibration	Validation
				Neighborhood	Transition rule (calculation of the transition potential)	Constraint[b]			
Li and Yeh (2000)/Li and Yeh (2002b)/Yeh and Li (2002)/Yeh and Li (2001)	PC	50 m cells	Degree of development of a cell	Circular with a radius of 2 cells	The product of the neighborhood effect and the constraint score determines the additional 'grey' state, which is added to the previous 'grey' state to calculate the 'grey' state. The state of a cell will be: developed if the 'grey' state of the cell is 1, partially developed if the 'grey state' is between 0 and 1, and the previous state is the 'grey state' is 0./In Li and Yeh (2002b), the additional 'grey' state is the product of the stochastic disturbance term, the neighborhood effect, and a function of the distance from the cell to the 'ideal point', where this distance is based on the attributes in the principal component space./In Yeh and Li (2002), the additional 'grey' state is calculated by a more complex function which involves the neighborhood effect, a constraint function for the hierarchy of a major center and subcenters, and a nonlinear transformation of different weighted factors./Yeh and Li (2001) use the same function as Yeh and Li (2002) but multiplying the result by a stochastic variable	MOD/AGR/POP/AGR	'Equity model' to determine the optimal urban area/PCA to determine the factors/distance-decay functions to estimate population density/indices of sustainability for validation	Sensitivity analysis	Compactness index. Suitability loss./None./Population density, compactness and loss of agricultural land./Fractal dimension. Sustainability indices
Li et al. (2008)	D, PC	Not explicit	Urban, non-urban	Not explicit	The logistic form of the model built by Wu and Webster (1998b), and further developed in Wu (2002)	Not explicit	GA for calibration	GA	Shape index, fractal dimension, nearest neighbor, aggregation index
Sui and Zeng (2001)	D, P	180 m cells	Urban, non-urban	Von Neumann	Weighted sum of the elevation, the slope, the accessibility, the neighborhood index, the shape index and an error term	AGR-MOD	Logistic regressions to determine weights and urban area	Multiple regression	Locational errors. Spatial metrics
White and Engelen (2000)	D-M, P-M	500 m cells	16 land uses	Circular with a radius of 8 cells	Product of a stochastic disturbance term, the accessibility to the transportation network, the suitability for the land use, the zoning status for the land use and the neighborhood effect, and adding an inertia effect	MOD	Regional model that calculates the area for each land use	None	None
White et al. (1997)	D-M, P-M	250 m cells	6 land uses, 3 active uses	Circular with a radius of 6 cells	The model of White and Engelen (2000) but without using the zoning status for the land use	AGR	None	Empirical	Visual comparison. Coincidence matrix and kappa index. Fractal dimension
Wu (1998b, 2002); Wu and Martin (2002); Wu and Webster (1998b)	D and P	200 m cells, except in Wu (2002), with 30 m cells	Urban, non-urban	Moore	Complex function that includes a stochastic parameter and a suitability score. The suitability score is the weighted sum of the scores for different factors, one of which is the neighborhood effect	AGR, except for Wu and Martin (2002): POP	Wu (1998b), Wu and Webster (1998b): AHP to determine weights. Wu (2002): logistic regression to determine weights.	Wu (1998b), Wu and Webster (1998b): sensitivity analysis. Wu (2002): logistic regression	Wu (2002): overall accuracy, Moran's I index, development profile. Wu and Martin (2002): development profile. Wu and Webster (1998b): visual, development profile, coincidence matrix

[a] D – descriptive; P – predictive; M – multiple land uses; PC – prescriptive.

[b] AGR – annual growth rate for urban land; POP – population growth projection; PLA – urban regulation planning; MOD – model mentioned in the 'other methods' section; OTH – other studies.

al. (1997), based on the previous models of White and Engelen (1993, 1997), which calculated for every cell the potential for transition to different land uses as a function of the neighborhood, the suitability for each land use, an inertia effect, and a stochastic disturbance term. A number of models based on this type of transition potential were applied to the Island of St. Lucia (Engelen et al., 1995), Cincinnati (White et al., 1997), the IJmond/Kennemerland region of Holland (Engelen et al., 1999), The Netherlands (White and Engelen, 2000), Dublin (Barredo et al., 2003), Lagos (Barredo et al., 2004) and San Diego (Kocabas and Dragicevic, 2006b). These studies confirmed the possibility of achieving highly realistic predictions of urban evolution using CA-based models. This type of models were improved by Arai and Akiyama (2004), who used discriminant analysis to facilitate their calibration, and Caruso et al. (2005), who incorporated an urban economic model to reinforce their theoretical basis.

Another widespread model is SLEUTH, developed by Clarke et al. (1997) to simulate urban dynamics in San Francisco and further applied to other regions in North America (e.g. Clarke and Gaydos, 1998; Yang and Lo, 2003; Herold et al., 2003), Europe (Silva and Clarke, 2002), South America (Leao et al., 2004) and Asia (Mahiny and Gholamalifard, 2007).

The models of Wu (1998b, 2002), Wu and Webster (1998b) and Wu and Martin (2002) focused on the calculation of the development probability for every cell according to a number of factors, such as the neighborhood. The first urban CA models developed by Li and Yeh (2000, 2002b) and Yeh and Li (2001, 2002) were based on grey cells, which represented the cumulative degree of development, and focused on finding feasible alternatives for the planning of sustainable development. More recently, these authors have focused on defining transition rules using artificial intelligence methods. DINAMICA (Soares-Filho et al., 2002) is a CA-based model originally designed for the simulation of deforestation processes that was later applied to urban processes (Almeida et al., 2003, 2005).

The analysis of the most relevant characteristics of these and other CA-based models has allowed us to group and characterize the models. The main characteristics of these urban CA are summarized as follows:

(1) *Transition rules*. The relaxations allowed in CA to more realistically simulate urban growth have led to the emergence of a large variety of rules. To facilitate analysis, transition rules have been classified into six types. Yet, some rules can be included in several groups.

Type-I rules are strictly orthodox transition rules, in the sense that the state of a cell is a function of the cell's current state and the state of its neighbors, which can be implemented by means of simple rules, based exclusively on the number of neighboring cells of each land use (Jenerette and Wu, 2001; Yüzer, 2004), or of more complex rules (Besussi et al., 1998; Stevens and Dragicevic, 2007; Ward et al., 2000) (Table 1).

Type-II rules. In type-II rules, the key driver of urban evolution is the transition potential, i.e. the probability that each cell changes to a specific land use, which is a function of the current land use of the cell and its neighbors (CA component), and of other factors that constrain land-use evolution.

White and Engelen were the first to propose the calculation of transition potentials (Engelen et al., 1999; White et al., 1997). The models designed by Wu (1998b, 2002), Wu and Martin (2002) and Wu and Webster (1998b) determined the probability of development as a function of a number of factors, such as neighborhood. These factors are not preset, which allows modelers to introduce the most suitable factors for each specific application. The same applies to the models developed by Almeida et al. (2003, 2005), Cheng and Masser (2004) and He et al. (2006, 2008). Conversely, the models proposed by Lau and Kam (2005), Sui and Zeng (2001) and White and Engelen (2000) used preset factors. Yet, the models by White and Engelen (2000) and Lau and Kam (2005) allowed for the incorporation of the desired factors in the calculation of the suitability or of the attribute effect respectively.

The transition potential is usually calculated as the weighted sum or product of a number of factors (Table 2), among which the effect of neighborhood stands out. In addition, a stochastic disturbance parameter is commonly used to model the uncertainty associated with urban processes. These models may include a series of constraints that take the value 0 if a cell cannot be developed or 1 otherwise. When the transition potential is calculated as a weighted sum, different techniques can be used to determine the weights, such as logistic regression (Sui and Zeng, 2001; Wu, 2002) or multicriteria evaluation (Wu, 1998b; Wu and Webster, 1998b).

In other models, the transition potential is calculated using more complex functions. For example, Wu (1998b) uses an exponential function justified because the sites with higher scores are more likely to be developed. Such complex functions are usually based on statistical or urban theories. The first group includes the models of Almeida et al. (2003), in which the transition probability is based on the weights of evidence for different factors; Li and Yeh (2002b), which uses Principal Components Analysis (PCA) to define the factors of the transition rule; and Lau and Kam (2005), which uses statistical tools to identify the factors to form the attribute and heterogeneity effects.

The second group includes the models of Caruso et al. (2005), based on urban economics, which allows, according to the authors, a further understanding of urban processes; He et al. (2008), which uses a potential model to calculate the urban expansion potential by taking into account the effect of the spatial distribution of capital and population; and Yeh and Li (2002), which incorporates density and constraint functions to simulate different types of urban forms.

Type-III rules. These transition rules are based on urban shape and form for the reproduction of the spatial patterns of urban growth (Table 3). An example of type-III rules is found in SLEUTH, a pattern-extrapolation model that considers four types of urban growth: spontaneous growth, new spreading center growth, edge growth and road-influenced growth. The model proposed by Li et al. (2003) is based on urban shape to the extent that it is based on the assimilation of the spatial appearance of urban expansion to a physical diffusion process. The DINAMICA model can be included in type-III rules because, from among the cells with the highest probabilities, some cells are chosen using two functions, which are aimed at spatially simulating urban growth: the Expander function, which expands or contracts the existing patches and the Patcher function, which generates new patches.

Type-IV rules. Type-IV rules use artificial intelligence methods (Table 4) such as neural networks, kernel-based learning methods, or Case-Based Reasoning (CBR), which are learning algorithms aimed at recognizing complex patterns based on data, or data mining methods, which automatically reconstruct explicit transition rules.

Type-V rules. Type-V rules are based on fuzzy logic, which allows the uncertainty of human behavior to be included in the simulation and the definition of transition rules through a natural language (Table 5).

Type-VI rules. Type-VI rules include transition rules that cannot be grouped into a general method (Table 6). These models are based on simple rules, defined through conditional logical operations. By contrast, the model developed by Xie (1996) is more complex insofar as it defines a general scheme on which multiple models can be built.

Table 3
Main characteristics of urban CA models with transition rules based on urban shape and form.

Author	Objective[a]	Cell space	States	CA relaxations			Other methods	Calibration	Validation
				Neighborhood	Transition rule	Constraint[b]			
Clarke et al. (1997)/Clarke and Gaydos (1998)	D, P	300 m cells/210 m cells	Urban, non-urban	Moore	4 types of growth rules: spontaneous, diffusive, organic, and road-influenced growth, controlled by 5 factors (a diffusion factor, a breed coefficient, a spread coefficient, a road-gravity factor and a slope resistance factor). Self-modification rules: at the end of each time period, these factors are adjusted if the growth rate is above or below a threshold	No	None	Simulation using combinations of parameter values in three phases (coarse, medium, and fine)	12 spatial metrics
Li et al. (2003)	PC	200 m cells	Urban, non-urban	Moore	The state of a cell will be urban if the population density for that cell is higher than a preset density value. The population density is calculated by adding to the previous density the density increase multiplied by a diffusion coefficient. The density increase is the weighted sum of the differences between the density of the neighboring cells and the density of the cell	POP	None	Sensitivity analysis	None

[a] D – descriptive; P – predictive; M – multiple land uses; PC – prescriptive.
[b] AGR – annual growth rate for urban land; POP – population growth projection; PLA – urban regulation planning; MOD – model mentioned in the 'other methods' section; OTH – other studies.

Alternatively, transition rules can be classified into rules that include a stochastic component and deterministic rules. The stochastic component can be introduced by using: (i) a Monte-Carlo method that compares the transition probability with a random number, such that the cell will change state if its probability is higher than the random number, and (ii) a stochastic disturbance term ν defined as: $\nu = 1 + [-\ln(\text{rand})^{\alpha}]$, where $0 < \text{rand} < 1$ is a random variable and α is a parameter that allows to adjust the size of the disturbance. A consequence of stochastic implementation is that the model can produce different results every time the model is run. This problem can be overcome by using a Monte-Carlo simulation to obtain spatial probability distributions (Ward et al., 2003; Yeh and Li, 2006).

Despite the large variety of transition rules, the factors that influence such rules are usually repeated. Most of the models shown in Table 7 include road accessibility (81%) and distance to urban centers (50%). Next in frequency are slope and accessibility to railway, followed by planning and environmental factors, suitability for development and population density.

(2) *Objective*. According to their objective, CA-based models can be classified into three categories: descriptive models, which analyze the factors and dynamics that govern the evolution of urban land; predictive models, which simulate land-use change in a near future; and prescriptive models, aimed at obtaining the optimal configuration of land uses. Most of the analyzed models are calibrated to simulate the dynamics observed, and some models are further applied to predict future developments.
(3) *Cell space*. All the models use a cell-space composed of square cells of different resolutions (of 10 m to 1 km), except for the model developed by Stevens and Dragicevic (2007), with an irregular cell-space composed of cadastral parcels. Ménard and Marceau (2005) and Samat (2006) demonstrated the sensitivity of geographic CA to cell size and highlighted the importance of adjusting cell size to the objects that compose the landscape.
(4) *Cell states*. Most models simulate transitions from non-urban to urban land uses, but some models extend these transitions to multiple land uses. White et al. (1997) make a distinction between fixed land uses, which affect transitions but remain stable, and functions, which can change to another state. Barredo et al. (2004) identifies two types of functions: active functions (urban uses) and passive functions.
(5) *Neighborhood.* Less than half of the analyzed models use the local neighborhood of strict CA. The Moore neighborhood is the most frequent neighborhood. The rest of the models extend the neighborhood space to a radius of 2–9 cells in order to consider distance effects. Kocabas and Dragicevic (2006b) have demonstrated that neighborhood size and type significantly affect the model outcomes.
(6) *Growth constraint*. The total land area that changes from its current land use to another land use is endogenously generated by the CA only in seven models. In the rest of the models, this area is determined by an external constraint that can be obtained in a variety of ways: (i) by extrapolating the urban growth rate of previous historical periods or predicting population evolution, (ii) by integrating the CA with other models, (iii) by calculating a dynamic growth rate that varies at each time step as a function of the characteristics of urban growth, and (iv) according to urban planning guidelines.
(7) *Integration with other models.* Many authors have suggested the integration of CA with other modeling techniques to improve the application of CA to real-world processes. Such techniques are commonly used to calculate growth constraints, to define transition rules or to calibrate the model.
(8) *Calibration*. The aim of calibration is to obtain the values of the transition rule parameters that allow for the most accu-

Table 4
Main characteristics of urban CA models with transition rules based on artificial intelligence.

Author	Objective[a]	Cell space	States	CA relaxations			Other methods	Calibration	Validation
				Neighborhood	Transition rule	Constraint[b]			
Li and Liu (2006)	D	Not explicit	Urban, non-urban	Not explicit	The development probability of a cell is the product of the number of developed cells in the neighborhood, the constraint factor and the k-NN algorithm of Case-based Reasoning (CBR)	AGR	CBR for the definition of the transition rules	Sensitivity analysis. CBR	Visual comparison. Coincidence matrix Moran's I index. Comparisons with other models
Li and Yeh (2001)/Li and Yeh (2002a)/Yeh and Li (2003)	D, P/D-M, P-M/PC	50 m cells	Urban, non-urban/6 land uses/Urban, non-urban	Square of 7 × 7 cells	A neural network provides the probability of development for each cell based on the number of developed cells in the neighborhood and other cell attributes./The network provides the probability of conversion from each land use to another land use./The same as in Li and Yeh (2001)	AGR	Neural network for calibration and prediction	Neural network training	Error matrix and overall accuracy
Li and Yeh (2004)	D, P	30 m cells	Urban, non-urban	Square of 7 × 7 cells	Explicit transition rules (expert system) are defined using a data mining technique based on the information gain ratio. A heuristic rule is added, such that the area that changes state in each time step adjusts to the growth observed during that period	AGR	Data mining for definition of rules and calibration	Data mining	Overall accuracy. Visual comparison. Moran's I index
Liu et al. (2008a)	D, P	Not explicit	Urban, non-urban	Moore	Definition of explicit transition rules using a data mining technique based on an ant colony optimization algorithm. A heuristic rule is added, such that the area that changes state in each time step adjusts to the growth observed during that period	AGR	Ant colony optimization algorithm for definition and calibration of rules	Ant colony optimization algorithm	Visual. Coincidence matrix. Moran's I index. Other spatial indices. Comparison with null model
Liu et al. (2008b)	D	50 m cells	Urban, non-urban	Moore	The development probability is the product of the total score of the constraints, the percentage of urbanized cells in the neighborhood and a logistic model in which the kernel Fisher discriminant (KFD) function (kernel-based learning technique) is introduced	AGR	KFD and logistic regression to define the transition rules	Empirical	Visual. Confusion matrix. Overall accuracy and k index. Spatial indices. Comparison with neural network and logistic regression
Yang et al. (2008)	D, P	30 m cells	Urban, non-urban	Moore	The development probability is the product of the stochastic variable, the constraint factors, the number of urban cells in the neighborhood, and the Support Vector Machines (SVM) optimization function (kernel-based learning technique)	AGR	SVM for the definition of the transition rules	Empirical	Visual comparison. Coincidence matrices. Overall accuracy. Kappa index. Comparison with other model

[a] D – descriptive; P – predictive; M – multiple land uses; PC – prescriptive.
[b] AGR – annual growth rate for urban land; POP – population growth projection; PLA – urban regulation planning; MOD – model mentioned in the 'other methods' section; OTH – other studies.

Table 5
Main characteristics of urban CA models with transition rules based on fuzzy logic.

Author	Objective[a]	Cell space	States	CA relaxations			Other methods	Calibration	Validation
				Neighborhood	Transition rule	Constraint[b]			
Al-Ahmadi et al. (2009)	D	20 m cells	Urban, non-urban	Is calibrated	The development probability is the product of the stochastic disturbance variable and the development suitability. The development suitability is a fuzzy function of a set of factors	AGR	Fuzzy logic for rule definition. GA and simulated annealing for calibration	GA and simulated annealing	Visual comparison. Coincidence matrix. Overall accuracy. Lee–Sallee index. Spatial Pattern Measure
Al-kheder et al. (2008)	D-M, P-M	60 m cells	3 land uses	Moore	Development potential is calculated by combining a set of fuzzy variables. The fuzzy value of the development potential is defuzzified and related to the number of developed cells (y^*) required in the neighborhood. The transition rules are defined in each case using y^* as input value	No	Fuzzy logic for the definition of rules	Sensitivity analysis	Ratio of number of urban cells in the simulated and the real maps. Type-I and Type-II errors
Wu (1996, 1998a)	PC-M	28.5 m cells	5 land uses	Square of 5 × 5 cells	The initial state of a cell decides which instructions to invoke. Such instructions depend on a number of indicators, calculated from the number of cells of each land use in the neighborhood. These indicators are fuzzified by applying a membership function and then defuzzified using the maximum method, such that each cell is assigned the land use that corresponds to the instruction for which the cell shows the highest grade of membership	No	Fuzzy logic for the definition of rules	Modification of membership functions to simulate different scenarios	Assessment of scenarios

[a] D – descriptive; P – predictive; M – multiple land uses; PC – prescriptive.
[b] AGR – annual growth rate for urban land; POP – population growth projection; PLA – urban regulation planning; MOD – model mentioned in the ‘other methods’ section; OTH – other studies.

rate reproduction of the past evolution of land uses. There are two traditional methods to calibrate CA-based models: methods based on trial and error and methods based on statistical techniques. The first ones do not require strict mathematical formulation and include the assessment of the results obtained from alternative combinations of parameter values (Ward et al., 2000), the sequential multistage optimization by automated exploration of combinations of parameters (Silva and Clarke, 2002), the manual tuning of the parameters through interactive graphs (Barredo et al., 2004) or the adaptive Monte-Carlo approach (He et al., 2008). This type of calibration requires that the model is run many times, so it is computationally intensive insofar as calculation time increases exponentially with the number of parameters. The most frequent statistical method is logistic regression, which intuitively provides the weights of the variables involved. However, logistic regression is based on mathematical equations that are sometimes unable to capture the complexity of the relationships.

To overcome these drawbacks, more elaborate empirical calibration methods were developed (Straatman et al., 2004). However, these methods are inapplicable to models of considerable size. For this reason, in recent years, a number of authors have studied the application of more efficient heuristic methods such as genetic algorithms (e.g., Jenerette and Wu, 2001; Li et al., 2008; Shan et al., 2008) or simulated annealing (Al-Ahmadi et al., 2009). Almeida et al. (2008) used a neural network to calibrate DINAMICA. In models that use artificial intelligence techniques to define the transition rules, the design and calibration of the rules occur simultaneously.

(9) *Validation*. The most simple validation method consists in the visual assessment of modeled and real maps, and is usually complemented by quantitative methods that evaluate overall accuracy. For this purpose, the most frequent metrics in increasing order of complexity are (i) ratio of simulated to real number of cells (or clusters) for a given land use, (ii) overall accuracy, i.e. the percentage of correctly classified pixels, (iii) regression analysis between simulation results and real data, and (iv) confusion matrix and kappa index.

However, the likelihood that a simulation algorithm matches the exact spatial location of land-use change is very low and even not necessary (Jantz and Goetz, 2005). Given that the aim of these models is to generate urban morphologies similar to real morphologies and to analyze the factors that generate the various urban patterns, the results must be analyzed in terms of spatial structure. Pattern based map comparison techniques include: (i) profiles of development as a function of physical distance or travel time to city center, (ii) a great variety of spatial metrics, among which the most frequent are Moran's I and shape indices, the number or density of edges, the patch number, the mean patch area, the mean nearest neighbor, and the contagion and Lee–Sallee indices, (iii) different fractal measures, and (iv) the multiple resolution fitting procedure (Costanza, 1989).

Moreover, a CA-based model can be validated by comparing the output of the model with the output of another model or with a null model. Generally, the validation method used is dependent upon the aims of the simulation. In fact, in prescriptive models that search optimal solutions, validation consists in assessing the quality of the scenarios obtained.

4. Strengths and weaknesses of urban CA models

Because all the models have advantages and disadvantages, some of the most relevant aspects of urban CA models have been

Table 6
Main characteristics of other urban CA models.

Author	Objective[a]	Cell space	States	CA relaxations			Other methods	Calibration	Validation
				Neighborhood	Transition rule	Constraint[b]			
Deadman et al. (1993)	D	100 m cells	Urban, non-urban	Not explicit	4 rules: (1) houses are built adjacent to roadways, (2) houses are not to be built in hazard lands or on lands with high extracting or agricultural capabilities, (3) 80% of new houses are to be located between existing houses and (4) 85% of new houses are to be located on major roadways	AGR	None	None	Visual. Annual comparison of modeled and real clusters, corresponding to 3 classes of densities
Shan et al. (2008)	D, P	60 m cells	Urban, non-urban	Moore	If a pixel is water, road or urban, it does not change. If a pixel is non-urban, it changes to urban if its population density is higher than a threshold and the number of neighboring residential pixels or the number of neighboring commercial pixels are higher than a threshold	No	GA for calibration	GA and exhaustive search	Total error and degree of adjustment (ratio of number of modeled urban pixels to number of real urban pixels)
Xie (1996)	D-M	Not explicit	Residential, commercial	3 types of neighborhood	DUEM is a generic paradigm for model design, based on 3 types of spaces (neighborhood, field and region) and operationalized through a growth generator and a growth locator, which implement respectively the temporal and spatial dimensions of urban growth	No	None	None	Regression analysis (r-square values of the simulation results regressed against the observed values)

[a] D – descriptive; P – predictive; M – multiple land uses; PC – prescriptive.
[b] AGR – annual growth rate for urban land; POP – population growth projection; PLA – urban regulation planning; MOD – model mentioned in the 'other methods' section; OTH – other studies.

Table 7
Factors used together with neighborhood effect to model the evolution of urban land. * - the factor indicated by the column is used by the authors indicated by the row to model urban growth.

	Distance to roads/ accessibility/ no. of travels/travel time	Distance to railway	Distance to airport	Distance to urban centers	Social services	Slope	Elevation	Environmental factors	Hazard lands	Agricultural value/soil type	Urban suitability	Zoning	Population density	Land value	Construction year	Water supply	Social housing
Al-Ahmadi et al. (2009)	*			*	*	*	*										
Al-kheder et al. (2008)	*					*	*						*				
Almeida et al. (2003, 2005)	*			*									*			*	*
Barredo et al. (2003, 2004)	*										*	*					
Caruso et al. (2005)	*				*			*									
Cheng and Masser (2004)	*			*								*	*				
Clarke et al. (1997)	*					*		*				*					
Deadman et al. (1993)	*								*	*							
Engelen et al. (1999)											*	*					
He et al. (2006)	*	*	*			*		*				*					
He et al. (2008)	*	*	*	*		*		*				*					
Lau and Kam (2005)	*				*						*		*	*			
Li and Yeh (2000)											*						
Li and Yeh (2001) and Yeh and Li (2003)	*	*		*						*							
Li and Yeh (2002a)	*			*		*				*							
Li and Yeh (2002b)	*	*		*				*									
Li and Yeh (2004)	*	*		*		*				*							
Li et al. (2003)													*				
Li et al. (2008)	*	*		*													
Liu et al. (2008a)	*	*		*		*											
Liu et al. (2008b)	*	*		*			*	*		*							
Shan et al. (2008)													*				
Sui and Zeng (2001)	*			*		*	*										
White and Engelen (2000)	*										*	*					
White et al. (1997)	*										*						
Wu (1998b, 2002)				*		*	*										
Wu and Martin (2002)	*	*		*													
Wu and Webster (1998b)	*	*		*		*						*					
Xie (1996)	*							*							*		
Yang et al. (2008)	*	*		*													
Yeh and Li (2001, 2002)				*				*									

analyzed separately, such that the choice of a particular model will depend on the characteristics that are most interesting for each specific situation.

4.1. Balance between realism and preservation of CA features

The relaxations of the original scheme of CA may lead to the loss of the fundamental characteristics of simplicity and locality, or even to models in which the CA component is no longer the core of the model. Except for the models developed by Besussi et al. (1998) and Jenerette and Wu (2001), most models show some relaxation. Yet, some models present more important modifications. For example, in the neural network proposed by Li and Yeh (2001), the CA component is present exclusively in the network input variables pertaining to the distance from a cell to each land use. In this model, even the application of the only concept that is essential to the definition of a model as a CA-based model, namely, the neighborhood concept, is quite vague. Almeida et al. (2003) defined their model as a cell-space model rather than a CA model because the CA component was quite hidden. In Li and Yeh (2004) and Liu et al. (2008a), the neighborhood function was only one of the nine spatial variables used to define the transition rules, whereas in Li and Liu (2006) and Deadman et al. (1993), neighborhood was not explicitly addressed.

A possible solution to the problem of achieving a balance between realism and simplicity is the multi-cellular automaton proposed by Cecchini and Rinaldi (1999), which consists in an ordered sequence of CA sub-models, such that every single CA conforms to the orthodox formulation (Besussi et al., 1998).

4.2. Flexibility

Flexibility is the ability of the model to adapt to different real-world urban situations and depends on the flexibility of the transition rules, on the factors considered in such rules, on the land uses modeled and on neighborhood adaptability.

With regard to transition rules, the most flexible models are the models that propose a general scheme within which multiple specific models can be defined (e.g. Xie, 1996; Besussi et al., 1998). The least flexible models are the models that use neural networks, CBR or data mining, in which rule definition and calibration are simultaneous, such that the resulting transition rules are closely adapted to local conditions. Consequently, these models are not suited to define general urban CA, but rather a methodology to define specific models for each situation. Most of the rest of the models show intermediate flexibility because they are based on more or less general rules that are adjusted to every situation through calibration. The adaptability of the model largely depends on calibration.

With regard to the factors included in the transition rules, using strict rules limits the ability of the model to represent different real-world urban situations. For type-II rules, a distinction has been made between rules that include specific factors and more flexible rules that allow for the use of any factor. Models that use artificial intelligence techniques are flexible in terms of the factors considered, as opposed to models based on urban shape and form. In principle, CA-based models based on fuzzy logic allow modelers to consider an indefinite number of factors. However, in practice, problems arise when a large number of factors are included in such models.

With regard to land uses, simulating the evolution of multiple land uses is far more complex than simulating urban growth. However, Dietzel and Clarke (2006) demonstrated that models that include only urban/non-urban data oversimplify the dynamics of the system because of the strong link between the likelihood of urbanization and the type of land use that will be converted to urban. Yet, only 13 out of the 33 models reviewed in this paper consider multiple land uses.

With respect to neighborhood, only a few models provide the possibility of applying different types of neighborhood. Only the model developed by Stevens and Dragicevic (2007) considered adjacent parcels or parcels located at a specified distance depending on each land use. Xie (1996) considered three types of neighborhood, whereas Ward et al. (2000) used a local neighborhood and a wider one. In the models proposed by White and Engelen, the size and shape of the neighborhood can be adjusted, and different neighborhoods can be applied to different uses by setting weights equal to zero from a certain distance, in some cells or for certain uses. In Al-Ahmadi et al. (2009), neighborhood size is one of the parameters defined during calibration. Other models were tested using several neighborhoods, but in different simulations.

Most models have been tested only for the regions for which they have been designed. Examples of the adaptability of urban CA models to the local characteristics of very different regions can be found only for the most widespread models, among which SLEUTH and the family of models designed by White and Engelen.

4.3. Explanatory power

There are descriptive and explanatory models. Descriptive models tell us what is happening, but not why. For example, the transition rules of SLEUTH do not allow for the analysis of the causes of the spatial patterns generated. In the neural network of Li and Yeh (2001), knowing the weight of each variable in the final output and, consequently, explaining the origin of the simulated phenomenon are not possible. Something similar happens in the model of Li and Liu (2006). However, this limitation does not affect the ability of the model to predict urban growth or to solve 'what if'-type questions.

At the opposite end of a black-box approach are explicit transition rules obtained using data mining techniques or fuzzy inference, which are transparent and easily understood by decision-makers. However, explicit rules have difficulties in representing very complex relationships and the choice of fuzzy functions is subjective and largely influences the results.

An intermediate approach uses models based on mathematical equations that provide information about the causes of the process but are less intuitive than explicit rules, and can manage more complex relationships than explicit rules but show more limitations than artificial intelligence techniques to simulate nonlinear complex systems.

Generally, the main advantage of descriptive models, particularly of models based on informing theories (e.g. Wu and Webster, 1998a), is their ability to explore and validate hypothetical ideas related to urban dynamics (Torrens and O'Sullivan, 2001). Yet, only a few urban CA models applied to real-world processes are based on well-developed theoretical models (e.g. Caruso et al., 2005; He et al., 2008).

4.4. Data requirements

Data requirements depend upon the factors considered in the model, so are usually in opposition to flexibility: the only input required for strict rules are land-use maps, whereas in rules of types II, IV and V, input data vary greatly.

4.5. Software availability

Most of the models reviewed use the geographic information management capabilities of standard GIS, and program the models using general programming languages or macro-languages. In both cases, modelers need programming knowledge to implement the models, which makes their diffusion dif-

Table 8
Overall accuracy and kappa index of the results of various models.

	Overall accuracy (%)	Kappa index
Al-Ahmadi et al. (2009)	92–94	
Barredo et al. (2003)		0.62–0.93
Barredo et al. (2004)		0.63–0.88
Cheng and Masser (2004)	55	
Engelen et al. (1999)		0.88–1
He et al. (2006)		0.73–0.80
He et al. (2008)		0.75–0.86
Lau and Kam (2005)	82.9–99.5	0.71–0.99
Li and Liu (2006)	82–86	0.51–0.53
Li and Yeh (2001)	79	
Li and Yeh (2002a)	83	
Li and Yeh (2004)	72.4–82	
Liu et al. (2008a)	76.8–83.3	0.53–0.64
Liu et al. (2008b)	74.1–79.0	0.48–0.57
Sui and Zeng (2001)	71–83	
White et al. (1997)		0.51–0.69
Wu (2002)	72.6–79.5	
Wu and Webster (1998b)	68.9–81	
Yang et al. (2008)	84.9–87.25	0.68–0.7

ficult and impedes non-expert users to apply such models. Some authors have developed independent software applications, such as AUGH (Besussi et al., 1998), or iCity (Stevens and Dragicevic, 2007). Among the few applications available are SLEUTH (http://www.ncgia.ucsb.edu/projects/gig/) and DINAMICA (http://www.csr.ufmg.br/dinamica/).

4.6. Accuracy of the results

Overall, the accuracy of these models is good (Table 8). Nevertheless, the results are not directly comparable because they are largely dependent on the land-use pattern of each area. However, all the models considered the total surface area of the study area and, therefore, the percentage of cells that changed land use with respect to the total number of cells was usually low. By excluding the area that was already developed at the beginning of the simulation, Jantz et al. (2003) obtained an accuracy of 19% and a k value of 0.19. However, when the entire surface area was considered, the accuracy amounted to 93.1% for an area in which the developed area accounted for 22% of total area. Overall accuracy will be less significant for areas in which the developed area is smaller. Consequently, when the evaluation is performed without excluding the area in which land uses remain constant, such an evaluation should include at least the proportion of converted area. Almeida et al. (2008) have solved this problem by using a fuzzy similarity metric to compare patterns.

5. Conclusions

Urban CA models provide a tool with great potential for the development of operational models that generate realistic urban patterns, and contribute to a better understanding of urban dynamics and theories. The main strength of CA-based models is their ability to integrate the modeling of the spatial and temporal dimensions of urban processes. Yet, the main reason for the widespread acceptance of these models is their simplicity. Anyway, the relative simplicity of CA-based models is also their main weakness insofar as flexibility limits the ability of the model to represent real-world phenomena, thus leading to the relaxations mentioned earlier in this paper. As stated in Section 4.1, when modifications are too extensive, it remains in doubt as to whether urban CA actually constitute CA at all. Another shortcoming of urban CA is the lack of a standard method for the definition of transition rules, although this allows modelers to design the most suitable model for each case. The main difficulty is the definition of simple rules that represent the complexity of the processes. The tradeoff between simplicity and flexibility in the design of the transition rules has been discussed in Section 4.2. Other difficulties for the implementation of urban CA models, described in Sections 4.4 and 4.5, include data requirement and the lack of easily configurable and usable software. Because of the above shortchomings, the use of urban CA models is most often limited to academic exercises.

In recent years, many researchers have focused on calibration because calibration is a key aspect to achieve reliable simulations and, therefore, to apply CA-based models to practical cases of urban planning. Recently, some authors have used artificial intelligence techniques to calibrate urban CA models or to define the transition rules of the models. Other authors have focused on the analysis of the effects of the different parameters included in the model, such as neighborhood type and size (Kocabas and Dragicevic, 2006b), cell size (Dietzel and Clarke, 2004; Jantz and Goetz, 2005; Samat, 2006), both (Ménard and Marceau, 2005), land-use classes (Dietzel and Clarke, 2006) or temporal resolution (Liu and Andersson, 2004). However, the impact of other factors such as cell type or the stochastic component remains unstudied.

Further research in this area would involve the development of new validation methods, based on urban pattern recognition, and the exploration of the CA potential for integration with other conventional geographical and urban theories, which would provide urban CA with a better developed theoretical background. Similarly, by integrating CA-based models with other techniques such as multi-agent systems or transportation models, hybrid models that overcome some deficiencies of CA could be obtained (e.g. Torrens and Benenson, 2005). Finally, further demonstrations of how such models can help solve practical planning issues are required (e.g. Berling-Wolff and Wu, 2004b; Jantz et al., 2003; Syphard et al., 2005). Mainly, such models will be not be used to exactly predict a phenomenon, but to interactively simulate different scenarios by modifying the parameters of the model.

References

Al-Ahmadi, K., See, L., Heppenstall, A., Hogg, J., 2009. Calibration of a fuzzy cellular automata model of urban dynamics in Saudi Arabia. Ecol. Complex 6 (2), 80–101.
Al-kheder, S., Wang, J., Shan, J., 2008. Fuzzy inference guided cellular automata urban-growth modelling using multi-temporal satellite images. Int. J. Geogr. Inform. Sci. 22 (11–12), 1271–1293.
Almeida, C.M., Batty, M., Monteiro, A.M.V., Camara, G., Soares-Filho, B.S., Cerqueira, G.C., Pennachin, C.L., 2003. Stochastic cellular automata modeling of urban land use dynamics: empirical development and estimation. Comput. Environ. Urban Syst. 27, 481–509.
Almeida, C.M., Gleriani, J.M., Castejon, E.F., Soares-Filho, B.S., 2008. Using neural networks and cellular automata for modelling intra-urban land-use dynamics. Int. J. Geogr. Inform. Sci. 22 (9), 943–963.
Almeida, C.M., Monteiro, A.M.V., Camara, G., Soares-Filho, B.S., Cerqueira, G.C., Pennachin, C.L., Batty, M., 2005. GIS and remote sensing as tools for the simulation of urban land-use change. Int. J. Remote Sens. 26 (4), 759–774.
Arai, T., Akiyama, T., 2004. Empirical analysis for estimating land use transition potential functions—case in the Tokyo metropolitan region. Comput. Environ. Urban Syst. 28, 65–84.
Barredo, J.I., Demicheli, L., Lavalle, C., Kasanko, M., McCormick, N., 2004. Modelling future urban scenarios in developing countries: an application case study in Lagos, Nigeria. Environ. Plann. B: Plann. Design 31, 65–84.
Barredo, J.I., Kasanko, M., McCormick, N., Lavalle, C., 2003. Modelling dynamic spatial processes: simulation of urban future scenarios through cellular automata. Landsc. Urban Plann. 64, 145–160.
Batty, M., 1991. Generating urban forms from diffusive growth. Environ. Plann. A 23 (4), 511–544.
Batty, M., 1998. Urban evolution on the desktop: simulation with the use of extended cellular automata. Environ. Plann. A 30, 1943–1967.
Batty, M., 2005a. Agents, cells, and cities: new representational models for simulating multiscale urban dynamics. Environ. Plann. A 37, 1373–1394.
Batty, M., 2005b. Cities and Complexity: Understanding Cities with Cellular Automata, Agent-based Models, and Fractals. The MIT Press, Cambridge, MA.
Batty, M., Longley, P.A., 1994. Fractal Cities. Academic Press, London.
Batty, M., Xie, Y., 1994. From cells to cities. Environ. Plann. B: Plann. Design 21, s31–s48.
Batty, M., Xie, Y., 1997. Possible urban automata. Environ. Plann. B: Plann. Design 24, 175–192.

Batty, M., Xie, Y., Sun, Z., 1999. Modeling urban dynamics through GIS-based cellular automata. Comput. Environ. Urban Syst. 23, 205–233.
Berling-Wolff, S., Wu, J., 2004a. Modeling urban landscape dynamics: a review. Ecol. Res. 19 (1), 119–129.
Berling-Wolff, S., Wu, J., 2004b. Modeling urban landscape dynamics: a case study in Phoenix, USA. Urban Ecosyst. 7, 215–240.
Besussi, E., Cecchini, A., Rinaldi, E., 1998. The diffused city of the Italian north-east: identification of urban dynamics using cellular automata urban models. Comput. Environ. Urban Syst. 22 (5), 497–523.
Caruso, G., Rounsevell, M., Cojocaru, G., 2005. Exploring a spatio-dynamic neighbourhood-based model of residential behaviour in the Brussels periurban area. Int. J. Geogr. Inform. Sci. 19 (2), 103–123.
Cecchini, A., 1996. Urban modelling by means of cellular automata: generalised urban automata with the help on-line (AUGH) model. Environ. Plann. B: Plann. Design 23, 721–732.
Cecchini, A., Rinaldi, E., 1999. The multi-cellular automaton: a tool to build more sophisticated models. A theoretical foundation and a practical implementation. In: European Symposium on Intelligent Techniques, Orthodox Academy of Crete, Greece.
Cecchini, A., Rizzi, P., 2001. The reasons why cellular automata are a useful tool in the working-kit for the new millennium urban planner in governing the territory. In: CUPUM 2001 Proceedings, Honolulu.
Cheng, J., Masser, I., 2004. Understanding spatial and temporal processes of urban growth: cellular automata modelling. Environ. Plann. B: Plann. Design 31, 167–194.
Clarke, K.C., Gaydos, L.J., 1998. Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. Int. J. Geogr. Inform. Sci. 12 (7), 699–714.
Clarke, K.C., Hoppen, S., Gaydos, L., 1997. A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. Environ. Plann. B: Plann. Design 24, 247–261.
Costanza, R., 1989. Model goodness of fit: a multiple resolution procedure. Ecol. Model. 47, 199–215.
Couclelis, H., 1985. Cellular worlds: a framework for modeling micro–macro dynamics. Environ. Plann. A 17, 585–596.
Couclelis, H., 1997. From cellular automata to urban models: new principles for model development and implementation. Environ. Plann. B: Plann. Design 24, 165–174.
Deadman, P., Brown, R.D., Gimblett, H.R., 1993. Modelling rural residential settlement patterns with cellular automata. J. Environ. Manage. 37, 147–160.
Dietzel, C., Clarke, K.C., 2004. Spatial differences in multi-resolution urban automata modeling. Trans. GIS 8 (4), 479–492.
Dietzel, C., Clarke, K.C., 2006. The effect of disaggregating land use categories in cellular automata during model calibration and forecasting. Comput. Environ. Urban Syst. 30, 78–101.
Engelen, G., White, R., Uljee, I., Drazan, P., 1995. Using cellular automata for integrated modelling of socio-environmental systems. Environ. Monitoring Assess. 34, 203–214.
Engelen, G., Geertman, S., Smits, P., Wessels, C., 1999. Dynamic GIS and strategic physical planning support: a practical application to the IJmond/Zuid-Kennemerland region. In: Stillwell, S., Geertman, S., Openshaw, S. (Eds.), Geographical Information and Planning. Springer-Verlag, Berlin.
Geertman, S., Hagoort, M., Ottens, H., 2007. Spatial–temporal specific neighbourhood rules for cellular automata land-use modelling. Int. J. Geogr. Inform. Sci. 21 (5), 547–568.
He, C., Okada, N., Zhang, Q., Shi, P., Li, J., 2008. Modelling dynamic urban expansion processes incorporating a potential model with cellular automata. Landsc. Urban Plann. 86, 79–91.
He, C., Okada, N., Zhang, Q., Shi, P., Zhang, J., 2006. Modeling urban expansion scenarios by coupling cellular automata model and system dynamic model in Beijing, China. Appl. Geogr. 26, 323–345.
Herold, M., Goldstein, N.C., Clarke, K.C., 2003. The spatiotemporal form of urban growth: measurement, analysis and modeling. Remote Sens. Environ. 86, 286–302.
Iovine, G., D'Ambrosio, D., Di Gregorio, S., 2005. Applying genetic algorithms for calibrating a hexagonal cellular automata model for the simulation of debris flows characterised by strong inertial effects. Geomorphology 66, 287–303.
Itami, R.M., 1988. Cellular worlds: models for dynamic conceptions of landscape. Landsc. Archit. 78 (5), 52–57.
Itami, R.M., 1994. Simulating spatial dynamics: cellular automata theory. Landsc. Urban Plann. 30, 24–47.
Jantz, C.A., Goetz, S.J., 2005. Analysis of scale dependencies in an urban land-use-change model. Int. J. Geogr. Inform. Sci. 19 (2), 217–241.
Jantz, C.A., Goetz, S.J., Shelley, M.K., 2003. Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore–Washington metropolitan area. Environ. Plann. B: Plann. Design 30, 251–271.
Jenerette, G.D., Wu, J., 2001. Analysis and simulation of land-use change in the central Arizona-Phoenix region, USA. Landsc. Ecol. 16, 611–626.
Kocabas, V., Dragicevic, S., 2006a. Coupling Bayesian networks with GIS-based cellular automata for modeling land use change. Lect. Notes Comput. Sci. 4197, 217–233.
Kocabas, V., Dragicevic, S., 2006b. Assessing a cellular automata model behaviour using a sensitivity analysis approach. Comput. Environ. Urban Syst. 30, 921–953.
Lau, K.H., Kam, B.H., 2005. A cellular automata model for urban land-use simulation. Environ. Plann. B: Plann. Design 32, 247–263.
Leao, S., Bishop, I., Evans, D., 2004. Simulating urban growth in a developing nation's region using a cellular automata-based model. J. Urban Plann. Dev. 130 (3), 145–158.
Li, L., Sato, Y., Zhu, H., 2003. Simulating spatial urban expansion based on a physical process. Landsc. Urban Plan. 64, 67–76.
Li, X., Liu, X., 2006. An extended cellular automaton using case-based reasoning for simulating urban development in a large complex region. Int. J. Geogr. Inform. Sci. 20 (10), 1109–1136.
Li, X., Yeh, A.G.-O., 2000. Modelling sustainable urban development by the integration of constrained cellular automata and GIS. Int. J. Geogr. Inform. Sci. 14 (2), 131–152.
Li, X., Yeh, A.G.-O., 2001. Calibration of cellular automata by using neural networks for the simulation of complex urban systems. Environ. Plann. A 33, 1445–1462.
Li, X., Yeh, A.G.-O., 2002a. Neural-network-based cellular automata for simulating multiple land use changes using GIS. Int. J. Geogr. Inform. Sci. 16 (4), 323–343.
Li, X., Yeh, A.G.-O., 2002b. Urban simulation using principal components analysis and cellular automata for land-use planning. Photogram. Eng. Remote Sens. 68 (4), 341–351.
Li, X., Yeh, A.G.-O., 2004. Data mining of cellular automata's transition rules. Int. J. Geogr. Inform. Sci. 18 (8), 723–744.
Li, X., Yang, Q., Liu, X., 2008. Discovering and evaluating urban signatures for simulating compact development using cellular automata. Landsc. Urban Plann. 86, 177–186.
Liu, X.H., Andersson, C., 2004. Assessing the impact of temporal dynamics on land-use change modeling. Comput. Environ. Urban Syst. 28, 107–124.
Liu, Y., Phinn, S.R., 2003. Modelling urban development with cellular automata incorporating fuzzy-set approaches. Comput. Environ. Urban Syst. 27, 637–658.
Liu, X., Li, X., Liu, L., He, J., Ai, B., 2008a. A bottom-up approach to discover transition rules of cellular automata using ant intelligence. Int. J. Geogr. Inform. Sci. 22 (11–12), 1247–1269.
Liu, X., Li, X., Shi, X., Wu, S., Liu, T., 2008b. Simulating complex urban development using kernel-based non-linear cellular automata. Ecol. Model. 211, 169–181.
Longley, P.A., Mesev, V., 2000. On the measurement and generalisation of urban form. Environ. Plann. A 32 (3), 473–488.
Mahiny, A.S., Gholamalifard, M., 2007. Dynamic spatial modeling of urban growth through cellular automata in a GIS environment. Int. J. Environ. Res. 1 (3), 272–279.
Ménard, A., Marceau, D.J., 2005. Exploration of spatial scale sensitivity in geographic cellular automata. Environ. Plann. B: Plann. Design 32, 693–714.
O'Sullivan, D., 2001a. Exploring spatial process dynamics using irregular cellular automaton models. Geogr. Anal. 33 (1), 1–18.
O'Sullivan, D., 2001b. Graph-cellular automata: a generalized discrete urban and regional model. Environ. Plann. B: Plann. Design 28, 687–705.
Phipps, M., Langlois, A., 1997. Spatial dynamics, cellular automata, and parallel processing. Environ. Plann. B: Plann. Design 24, 193–204.
Pinto, N.N., Antunes, A.P., 2007. Cellular automata and urban studies: a literature survey. Archit. City Environ. 1 (3), 367–398.
Polidori, M.C., Krafta, R., 2005. Simulando crescimento urbano com integração de fatores naturais, urbanos e institucionais. Geofocus 5, 156–179.
Portugali, J., Benenson, I., 1995. Artificial planning experience by means of a heuristic cell-space model: simulating international migration in the urban process. Environ. Plann. A 27, 1647–1665.
Samat, N., 2006. Characterizing the scale sensitivity of the cellular automata simulated urban growth: a case study of the Seberang Perai Region, Penang State, Malaysia. Comput. Environ. Urban Syst. 30, 906–920.
Semboloni, F., 1997. An urban and regional model based on cellular automata. Environ. Plann. B: Plann. Design 24, 589–612.
Semboloni, F., 2000. The dynamic of an urban cellular automata in a 3-D spatial pattern. In: Proceedings of the XXI National Conference, Aisre: Regional and Urban Growth in a Global Market, Palermo.
Shan, J., Al-kheder, S., Wang, J., 2008. Genetic algorithms for the calibration of cellular automata urban growth modeling. Photogram. Eng. Remote Sens. 74 (10), 1267–1277.
Shi, W., Pang, M.Y.C., 2000. Development of Voronoi-based cellular automata—an integrated dynamic model for Geographical Information Systems. Int. J. Geogr. Inform. Sci. 14 (5), 455–474.
Silva, E.A., Clarke, K.C., 2002. Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. Comput. Environ. Urban Syst. 26, 525–552.
Soares-Filho, B.S., Cerqueira, G.C., Pennachin, C.L., 2002. DINAMICA—a stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier. Ecol. Model. 154, 217–235.
Stevens, D., Dragicevic, S., 2007. A GIS-based irregular cellular automata model of land-use change. Environ. Plann. B: Plann. Design 34, 708–724.
Straatman, B., White, R., Engelen, G., 2004. Towards an automatic calibration procedure for constrained cellular automata. Comput. Environ. Urban Syst. 28, 149–170.
Sui, D.Z., Zeng, H., 2001. Modeling the dynamics of landscape structure in Asia's emerging Desakota regions: a case study in Shenzhen. Landsc. Urban Plann. 53, 37–52.
Syphard, A., Clarke, K.C., Franklin, J., 2005. Using a cellular automaton model to forecast the effects of urban growth on habitat pattern in southern California. Ecol. Complex. 2, 185–203.
Takeyama, M., Couclelis, H., 1997. Map dynamics: integrating cellular automata and GIS through Geo-Algebra. Int. J. Geogr. Inform. Sci. 11 (1), 73–91.
Tobler, W.R., 1979. Cellular geography. In: Gale, S., Olsson, G. (Eds.), Philosophy in Geography. Reidel, Dordrecht.

Torrens, P.M., Benenson, I., 2005. Geographic automata systems. Int. J. Geogr. Inform. Sci. 19 (4), 385–412.
Torrens, P.M., O'Sullivan, D., 2001. Cellular automata and urban simulation: where do we go from here? Environ. Plann. B: Plann. Design 28, 163–168.
Wagner, D.F., 1997. Cellular automata and geographic information systems. Environ. Plann. B: Plann. Design 24, 219–234.
Ward, D.P., Murray, A.T., Phinn, S.R., 2000. A stochastically constrained cellular model of urban growth. Comput. Environ. Urban Syst. 24, 539–558.
Ward, D.P., Murray, A.T., Phinn, S.R., 2003. Integrating spatial optimization and cellular automata for evaluating urban change. Ann. Regional Sci. 37, 131–148.
Webster, C.J., Wu, F., 1999a. Regulation, land-use mix, and urban performance. Part 1: theory. Environ. Plann. A 31, 1433–1442.
Webster, C.J., Wu, F., 1999b. Regulation, land-use mix, and urban performance. Part 1: simulation. Environ. Plann. A 31, 1529–1545.
Webster, C., Wu, F., 2001. Coase, spatial pricing and self-organising cities. Urban Stud. 38 (11), 2037–2054.
White, R., Engelen, G., 1993. Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land use patterns. Environ. Plann. A 25, 1175–1199.
White, R., Engelen, G., 1994. Cellular dynamics and GIS: modelling spatial complexity. Geogr. Syst. 1, 237–253.
White, R., Engelen, G., 1997. Cellular automata as the basis of integrated dynamic regional modelling. Environ. Plann. B: Plann. Design 24, 235–246.
White, R., Engelen, G., 2000. High resolution modelling of the spatial dynamics of urban and regional systems. Comput. Environ. Urban Syst. 24, 383–400.
White, R., Engelen, G., Uljee, I., 1997. The use of constrained cellular automata for high-resolution modelling of urban land-use dynamics. Environ. Plann. B: Plann. Design 24, 323–343.
Wolfram, S., 1984. Cellular automata: a model of complexity. Nature 31, 419–424.
Wolfram, S., 2002. A New Kind of Science. Wolfram Media, Canada.
Wu, F., 1996. A linguistic cellular automata simulation approach for sustainable land development in a fast growing region. Comput. Environ. Urban Syst. 20 (6), 367–387.
Wu, F., 1998a. Simulating urban encroachment on rural land with fuzzy-logic-controlled cellular automata in a geographical information system. J. Environ. Manage. 53, 293–308.
Wu, F., 1998b. SimLand: a prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rules. Int. J. Geogr. Inform. Sci. 12 (1), 63–82.
Wu, F., 2002. Calibration of stochastic cellular automata: the application to rural–urban land conversions. Int. J. Geogr. Inform. Sci. 16 (8), 795–818.
Wu, F., Martin, D., 2002. Urban expansion simulation of Southeast England using population surface modelling and cellular automata. Environ. Plann. A 34, 1855–1876.
Wu, F., Webster, C.J., 1998a. Simulation of natural land use zoning under free-market and incremental development control regimes. Comput. Environ. Urban Syst. 22 (3), 241–256.
Wu, F., Webster, C.J., 1998b. Simulation of land development through the integration of cellular automata and multicriteria evaluation. Environ. Plann. B: Plann. Design 25, 103–126.
Xie, Y., 1996. A generalized model for cellular urban dynamics. Geogr. Anal. 28, 350–373.
Yang, Q., Li, X., Shi, X., 2008. Cellular automata for simulating land use changes based on support vector machines. Comput. Geosci. 34, 592–602.
Yang, X., Lo, C.P., 2003. Modelling urban growth and landscape changes in the Atlanta metropolitan area. Int. J. Geogr. Inform. Sci. 17 (5), 463–488.
Yeh, A.G.-O., Li, X., 2001. A constrained CA model for the simulation and planning of sustainable urban forms by using GIS. Environ. Plann. B: Plann. Design 28, 733–753.
Yeh, A.G.-O., Li, X., 2002. A cellular automata model to simulate development density for urban planning. Environ. Plann. B: Plann. Design 29, 431–450.
Yeh, A.G.-O., Li, X., 2003. Simulation of development alternatives using neural networks, cellular automata, and GIS for urban planning. Photogram. Eng. Remote Sens. 69 (9), 1043–1052.
Yeh, A.G.-O., Li, X., 2006. Errors and uncertainties in urban cellular automata. Comput. Environ. Urban Syst. 30, 10–28.
Yüzer, M.A., 2004. Growth estimations in settlement planning using a Land Use Cellular Automata Model (LUCAM). Eur. Plann. Stud. 12 (4), 551–561.