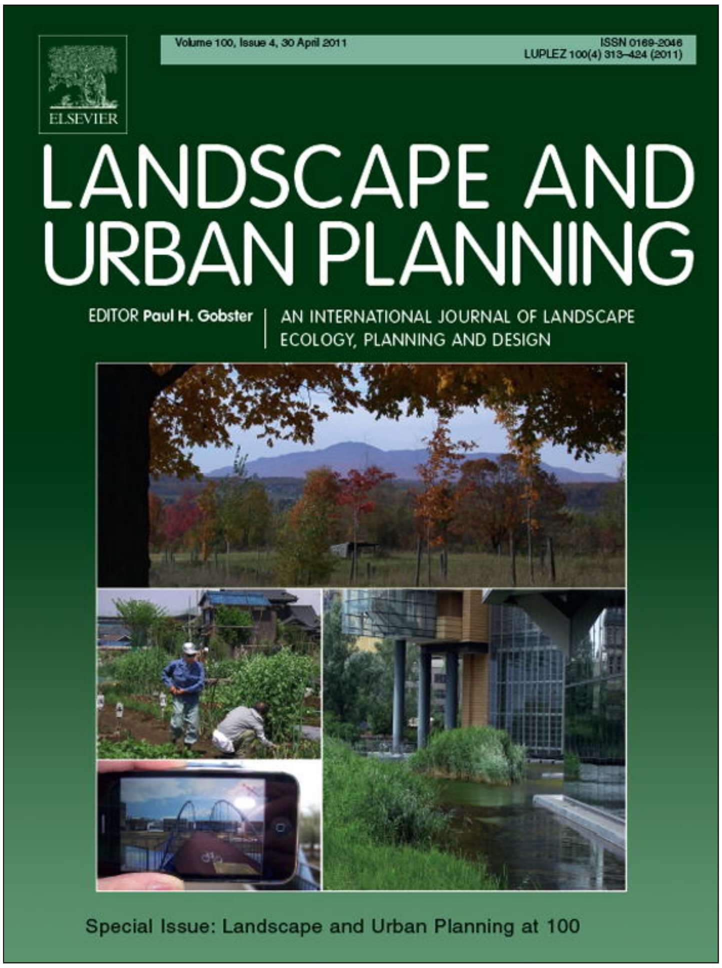
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Emergence of bottom-up models as a tool for landscape simulation and planning

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ABSTRACT

Geographical Information Systems (GIS) adopt a top-town approach which may have limitations for solving many landscape simulation and planning problems. Recently, a number of bottom-up models, such as cellular automaton models (CAs), agent-based models (ABMs), and swarm intelligence models (SIMs), have emerged as an important tool for assisting complex decision-making processes associated with landscape changes. These bottom-up models can be combined together and integrated with GIS to produce better modeling effects. This paper discuses the potentials and challenges for using these models.

Urban growth and landscape changes have been considered among the biggest challenges for humankind in the twenty-first century. A better understanding of these changes is prerequisite for fulfilling various landscape simulation and design tasks. Geographical Information Systems (GIS) can be used to store, manipulate, and visualize spatial information for landscape analyses. However, GIS usually adopt a top-down approach which is to break down a phenomenon (system) into its compositional elements for tackling complex geographical problems by using a series of deterministic models. This approach is less suitable for handling a series of behavioral, self-organization, and micro-simulation issues about complex systems. Geographical processes, such as diffusion of disease, wildfire spread, ecological evolution, transport and residential development, urban dynamics, and land use changes are usually very complex and often include non-linear and emergent behaviors, stochastic components, and feedback loops over spatial and temporal scales. For example, studies have indicated that urban and land use systems are complex systems that mainly grow from the bottom up (Batty and Xie, 1994; White and Engelen, 1993). It is difficult or even impossible to develop deterministic, equation-based models to capture and represent these processes by using top-down GIS functionality.

Instead of using traditional top-down models, recent studies have shown that these complex natural systems can be effectively simulated by using a number of bottom-up models, such as cellular automaton models (CAs) (Batty and Xie, 1994; White and Engelen, 1993), agent-based models (ABMs) (Torrens and Benenson, 2005), and swarm intelligence models (SIMs) (Li et al., 2009) or other artificial intelligence models (Wu and Silva, 2010). These bottom-up models are based on the interaction between individuals and their environment for modeling the behavior of complex systems. Although these models are highly simplified abstractions of reality, they are able to provide useful insights into generic features of urban and land use dynamics. Studies have demonstrated that very complex behaviors and global patterns of geographical phenomena can be generated from these bottom-up models (Batty and Xie, 1994; Li et al., 2010). Their simulation results can coincide with the fluctuations of a series of landscape indices of real cities (Li et al., 2008).

In the past, bottom-up models were mainly used to simulate realistic patterns according to the trajectories of landscape changes (Batty and Xie, 1994). However, there are an increasing number of studies that use these models to generate alternative scenarios or even optimized scenarios subject to a series of constraints (Li and Yeh, 2000; Li et al., 2008). Therefore, these models can have two different types of important tasks; simulation and optimization. Simulation aims to explore realistic scenarios under given conditions, whereas optimization is to generate optimal solution(s) to a given planning problem. By combining simulation with optimization, these models can help planners to predict and explore the likely consequences of changes occurring with planning or without planning (Li et al., 2010).

Over the past three decades, CAs for landscape dynamic simulation and urban and architectural design have proliferated because of their simplicity, flexibility, and intuitiveness (Castilla and Blas, 2008; Santé et al., 2010; Wu and Silva, 2010). CAs have become an experimental tool for urban and regional planning. An example of using CAs is to simulate population dynamics in modeling complex natural systems. Couclelis (1988) suggested that the whole range of

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complex and seemly bizarre population dynamics could be easily reproduced by using some simple CAs. White and Engelen (1993) developed a CA model to investigate general features of urban structure - the fractal or bifractal properties of cities and their evolution. Fractal structures which have been considered as the most important features of urban geometry can be used to evaluate the validity of urban simulation models. Actually, fractal patterns can be generated by incorporating stochastic disturbance variables into CAs (White and Engelen, 1993). So far CAs seem to be quite successful for simulating the evolution of urban geometry and morphology in many cities around the world.

Agent-based models (ABMs) are increasingly considered to be superior to CAs because they are effective for capturing human and social behaviors in urban and landscape modeling (Torrens and Benenson, 2005). Besides modeling land use dynamics, ABMs can be applied to fields of resource management such as fisheries management, agricultural land management, and forest management. This means that ABMs have quite diversified model structures which are strongly dependent on applications. The implementation of ABMs requires the understanding of human behavior and environmental responses so that the real world can be translated into formal model specifications. For example, economic theories and urban growth theories can be incorporated in the definitions of agents' behaviors. Therefore, the implementation of ABMs requires sophisticated techniques, such as such as sample surveys, participant observation, and model configuration and calibration.

As another type of bottom-up model, swarm intelligence models (SIMs) or other artificial intelligence models (Wu and Silva, 2010) have recently emerged as a tool to solve complex spatial optimization and design problems. Unlike ABMs, SIMs solicit simple intelligence from animals (e.g. birds, fish, and ants) instead of from human beings. For example, ant intelligence can be used to solve a variety of spatial optimization problems, such as traveling salesman problems (TSP), data mining, network routing optimization, location and allocation, siting of service facilities (Li et al., 2009), path finding, and zoning of natural protection areas by using a huge volume of spatial data (Li et al., 2010).

These three types of bottom-up models can be combined together and even integrated with GIS for enhancing their capabilities in landscape simulation and optimization (Li et al., 2010). CAs and ABMs can be merged together for representing physical, social, and economic factors in shaping landscape dynamics (Torrens and Benenson, 2005). Moreover, the integration of these bottom-up models with GIS allows them to benefit from each other. CAs can serve as an analytical engine to provide a flexible framework for the programming and running of dynamic spatial models which are missing in traditional GIS (Li and Yeh, 2000). On the other hand, GIS are also important for providing spatial data as the inputs to these models. GIS itself is also evolving and some commercial GIS software is now including some modeling capabilities of these bottom-up models. For example, IDRISI software has embedded a CA-Markov model for modeling land use dynamics.

Although these bottom-up models are attractive, there are some challenges that still need to be addressed. A common feature of these bottom-up models is that individuals (entities) are used to represent organizations, residents, developers, and animals that can affect the environment. The interaction between individuals and the environment is governed by transition rules. The solicitation of transition rules requires users to have rich domain knowledge and good modeling skills. It is essential to calibrate these models for solving a specific problem. However, modeling natural systems are beset by problems of inherent unpredictability because of path dependence and stochastic uncertainty in these systems. There are also a series of questions on model configuration, verification, and validation: Should these models be calibrated by spatial validation (e.g. using overall accuracies and kappa coefficient) or by aggregate validation (e.g. using landscape pattern metrics)? Are these models fitted to the observed patterns, functions, or processes? What kinds of measures can be adopted to avoid the dangers of over-fitting? How can we ensure that the agents perform their functions in the same manner as human experts? Are there automatic methods for soliciting spatio-temporal heterogeneity in defining agents' behavior?

At present, a number of techniques have been proposed for calibrating CAs, including logistic regression, neural networks, decision trees, and genetic algorithms (Li et al., 2008, 2010). However, there are very few such studies for developing some standard agent-based models or toolboxes. Considerable effort is required to understand even the simplest of ABMs because their model structures are much more complex than those of CAs. Moreover, existing calibration procedures emphasize the fitting to spatial patterns instead of functions and processes.

The development of software and toolboxes can alleviate the problems of using these models. For example, SLEUTH is a CA package for urban growth simulation and prediction with wide applications (Clarke et al., 1997). This software can be downloaded at http://www.ncgia.ucsb.edu/projects/gig/. CLUE-S is a spatially explicit CA package for the analysis of Land Use Change and its Effects (downloaded at http://www.cluemodel.nl/). This software is developed by a combination of dynamic modeling and empirical quantification of the relations between land use and its driving factors. OBEUS (Object-Based Environment for Urban Simulation) is operationally implemented according to the paradigm of Geographic Automata System (GAS) (Torrens and Benenson, 2005). Another attempt is to develop the integrated Geographical Simulation and Optimization System (GeoSOS) (downloaded at http://www.geosimulation.cn/) by using the bottom-up techniques of CAs, ABMs, and SIMs (Li et al., 2010). The integration of CAs, ABMs, and SIMs may lead to more powerful frameworks for assisting complex decision-making processes associated with landscape changes.

The coupling between these bottom-up models and other environmental and ecological models should be given a higher priority in future studies. So far various forms of CAs or ABMs have been proposed based on experts' preferences and domain knowledge. There is a question if two or more of these models can be simultaneously used because different models have their advantages and limitations. Future research may include the development of methodologies for assimilating or blending different types of these models in effective ways. Some initial studies have demonstrated that coupling spatial optimization with landscape simulation can produce much better modeling effects. For example, the coupling of path optimization with land use simulation has shown an improvement of total utility by 4.1% (Li et al., 2010).

Moreover, the development of high performance models will become important when these models are applied to large study areas or fine-resolution data. Most of the existing ABMs and SIMs can only be run in coarser resolutions and smaller study areas because these models are computationally intensive. The computation burden becomes much more severe when a larger volume of GIS data and higher resolution remote sensing images are available. Parallel computation and graphics processing unit (GPU) techniques may be adopted so that these models can solve real-world application problems.

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