Geospatial Modeling of Urban Landscape Changes through an Agent-based Approach

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ABSTRACT: Over the past years, the agent-based modeling approach has emerged as a promising geospatial technique for urban change simulation. In this paper, we review the status of agent-based models for urban land change research, with the emphasis on the issues of how far agent-based models have been implemented to model the real world complexity. For such a purpose, we have identified four features of agent-based land use models: agent heterogeneity, driving forces, system feedbacks, and spatial and temporal scales. We focus on how these issues have been addressed in existing models with respect to urban land changes. Along with these discussions, we have also identified some challenges for model implementation as well as some issues that need further research. Finally, we have implemented an agent-based model to explore the impacts of cross-scale feedbacks on land use patterns in an urban area. The results have demonstrated the influences of cross-scale feedbacks on land fragmentation, compactness and dispersion.

KEYWORDS: agent-based modeling, geospatial modeling, urban landscape change, complex systems, cross-scale feedbacks

Introduction

Rapid urban growth has been observed worldwide since the mid 20th century. The low density and leapfrog landscape patterns in suburban and exurban area have begun to undermine the overall urban sustainability. Recently, land use/cover modeling has become more popular in urban land change studies (Torrens, 2002; Parker et al, 2003). The use of geospatial modeling techniques supports a better understanding of how the world works. Urban models have been employed to study the driving forces of urban growth (e.g., Hu and Lo, 2007), to explore the impacts of specific factors on land use patterns (e.g., Parker and Meretsky, 2004; Ligmann-Zielinska, 2009), to simulate and predict the evolution of urban forms (e.g., Clarke et al., 1997; Xie et al., 2007), and to generate alternative scenarios to inform land use planning (e.g. Yang and Lo, 2003).

To a large degree, modeling is a way of thinking more than a technology. The development of geospatial modeling approaches reflects the changes in our ontological and epistemological traditions. A conventional modeling framework describes systems in equilibrium or as moving between equilibriums. However, the evolution of urban areas usually does not reach a stable equilibrium but exhibits features of complexity (e.g., edge of chaos, emergence, nonlinearity). The concept of complexity emphasizes on the interdependence among constituent parts. Therefore, complex adaptive system (CAS) is a system composed of interconnected parts that as a whole exhibit one or more properties not obvious from the individual parts. Both cellular automata (CA) and agent-based models (ABM) draw on complexity theory and build upon a bottom-up perspective, which model a system from its constituent parts (Batty, 2005; Miller and Page, 2007). While CA models focus on spatial transition of the cellular landscape (Clarke et al., 1997; Verburg et al., 2002), ABMs explicitly incorporate human actions in their modeling framework (Parker et al., 2003; Batty, 2005; Torrens and Benenson, 2005; Xie et al., 2007). Modeling human actions is particularly useful for understanding the complexity in urban systems, which belong to coupled human and natural systems (CHANS; Liu et al., 2007). By including the autonomous and interacting "agents", ABMs provide a natural narrative of how the real world works. Therefore, ABM emerges as a promising approach in understanding the complex urban processes, such as urban land use changes (Parker et al., 2003; Batty, 2005). Its flexible modeling framework allows the explanation of empirical regularities that conventional models cannot.

Several existing research on ABMs have suggested their strengths in modeling decision-making and human-nature interactions. In a comprehensive overview, Parker et al. (2003) discussed the potential and challenges of using ABMs to explore socioeconomic and biophysical complexity in land use/cover modeling. Matthews et al. (2007) reviewed the applications of agent-based land use models and emphasizes the role of ABMs for knowledge exploration in decision support. Zellner (2008) examined the potential contribution of ABMs for the understanding of human impacts on environmental functions in an integrated framework. However, there is a lack of detailed exploration on how far ABMs have been used to account for complexity in real world phenomena simulation. A recent contribution was made by An (2012), who focused on different methods used to model human decisions in CHANS research. Given recent developments, further research is needed to document the contributions of ABMs in modeling complexity.

In this paper, we will review the research status of ABMs for urban land change modeling. Compared to other review papers, we specifically focus on how these models deal with complexity within urban systems. For such a purpose, we identify four features that are important to agent-based land use models: agent heterogeneity, driving forces, system feedbacks, and spatial and temporal scales. The four features cover the important components in land use systems. Agent heterogeneity is a unique feature of ABMs which is important to capture the human decision making process. Although the other three features share commonalities with conventional land use models, we are interested in how ABMs are implemented to represent these features in modeling complexity. The following four sections are organized by the discussions on each of the features. In these discussions, we present the findings from our literature review and identify the research challenges and future research directions along the way. Finally, we test and implement an ABM to explore the impacts of cross-scale feedbacks on land use patterns.

Agent Heterogeneity

Agent is the major component that distinguishes ABM from other modeling approaches. Previous studies have demonstrated some significant influences of agent heterogeneity on outcome patterns (Parker et al., 2003; Brown and Robinson, 2006). In an ABM, agent can differ in a number of ways. Agents have a set of internal properties, including domain knowledge, goals, and actions. Multiple groups of agents can therefore be differentiated by their internal structures. Another related concept is the interactions or communication (e.g., negotiation and competition for land) among agents. For land change modeling, communication among agents could be viewed as part of an agent's interaction with the environment.

Agent heterogeneity has been implemented in different manners. First, agent heterogeneity can be represented as different types of decision makers acting to influence the system outcomes. The ABMs framework provides a natural way to describe complex and interacting human actions. For example, Brown et al. (2008) discussed a residential development model that involves the decision-making and interactions among developers, township policy boards, farmers and residents. Second, a single type of agent can be further grouped into heterogeneous groups by their internal properties. For example, Ligmann-Zielinska (2009) simulated the impact of different risk-taking attitudes of developer agents on land use patterns. Developer agents were grouped into the risk-taking and risk-averse subgroups which were modeled by different attitude utility functions. A more complex and comprehensive empirical study to capture the heterogeneity of agent behavior can be found in An et al. (2005). They built an ABM to simulate the impact of population growth on panda habitat. The model considers the probability of households switching their energy source from fuel wood to electricity depending on a set of socioeconomic and demographic factors.

Interaction among agents is another interesting but challenging feature associated with heterogeneous agents within a system. It is represented in either simple or complicated form. Simple forms of agent communication are commonly represented by their competition for the same piece of land (Ligmann-Zielinska and Jankowski, 2010). The agreement is then reached through the comparison of their perception over the land utility or profitability in quantitative form. More complicated forms of agent communication are usually concerned with realistic processes of land use planning and real estate development. Examples include the equilibrium between demand and supply and the negotiation between public policy makers and individual developers (e.g. Saarloos et al., 2005). The communication among agents is usually realized indirectly through their interactions with the landscape. However, direct agent communication independent from the environment has been less explored in model implementation. Further research on direct agent communication should focus on their methodological and technological implications.

Driving Forces

Different taxonomies can be used to categorize the various factors driving urban landscape changes. Specific to the research in CHANS (Liu et al., 2007), the underlying drivers of urban sprawl include a set of socioeconomic and biophysical processes dominant at different scales. While conventional models usually treat drivers exogenously, ABMs provide a natural framework to endogenously introduce driving forces. The complexity arises from the potential interactions among different drivers across domains and scales, which links to the scale issues and system feedbacks that will be discussed later. In addition, drivers of land use/cover changes can be dynamic, adding to the complexity in model implementation.

In conventional models, biophysical factors are usually involved as static variables and therefore cannot address the feedbacks between human and environment. For example, Allen and Lu (2003) built a suitability model and considered topography, hydrology, and forestland in determining urban growth suitability. Each variable was then assigned with a fixed weight representing their relative importance to urban development. In contrast, ABMs allow the incorporation of biophysical factors endogenously in the model. They can be modeled as decision rules influencing human decision-making. For example, household usually prefer residential locations at lower altitude to higher (Evans and Kelley, 2004). More variation in topography and proximity to natural reserves are associated with the attractiveness of household location choices (Brown and Robinson, 2006). To better represent land use change processes, we need to integrate knowledge from physical science with social science to understand the interactions and feedbacks between the coupled systems.

Socioeconomic factors driving land use changes can be summarized by their spatial scales (Irwin, 2006). The global variables tend to spread their influences over a longer period rather than having immediate effects on land use changes. For example, global economy restructuring may gradually alter the behaviors of households and firms in choosing locations. The declining transportation and communication costs may introduce foreign investments, which increase the future grow rate of a region. In current agent-based land use models, global level factors are mostly exogenously incorporated using statistical modeling (e.g., Xie et al., 2007). Incorporating global factors is complementary to the individual agents' behaviors from the bottom up. Such integrated structures also represent the cross-scale feedbacks in land use systems (Verburg, 2006). As opposed to global factors, regional and local factors are commonly represented as decision rules influencing human decisions in ABMs. The regional level is not usually incorporated due to the lack of explicit spatial representations in many cases. Also the regional influences can be disaggregated to finer scales, such as accessibility, land use policies. Models explicitly deal with regional factors incorporate administrative spatial units and consider regional interactions among them (e.g., Xie et al., 2007). At the very local scale such as the neighborhood and parcel level, surrounding land uses are of importance. In this case, neighborhood effects and interactions will influence human decision-making in choosing locations (Parker and Meretsky, 2004). However, as the factors are interacting cross multiple scales, it becomes very complex to capture such interacting factors. Also there are factors and processes that function across multiple scales. Therefore, it may be necessary to evaluate the factors according to their related scales and then find out the way that incorporating the cross-scale interactions among factors. In addition, the temporal dynamics of driving forces during the simulation need further exploration as well.

System Feedbacks

System feedback is one of the properties of CAS, which motivate the emergence of complex patterns. According to Verburg (2006), there are three types of feedbacks need to be considered in land use and land cover modeling: (1) feedbacks between the driving factors and the effects of land use change (e.g., impacts), which mainly deal with the mechanisms that land use changes will modify the original conditions of driving forces;

(2) feedbacks between local and regional processes of land use change, which address the cross-scale interactions underlying landscape dynamics; and (3) feedbacks between agents and the spatial units of the landscape, which concerns the corresponding relationships between agents and the spatial units used in the model.

For the feedbacks between driving forces and impacts, two types of feedbacks are defined by the internal mechanisms of a system: positive and negative feedbacks. The positive feedbacks are defined as that current urban growth may contribute to future development. For example, new development modifies the accessibility of remote areas which extends the potential of urban sprawl. Jayaprakash et al. (2009) simulated the feedbacks between social segregation (drivers/processes) and suburbanization (impacts). Social/racial segregation tends to accelerate the trend of suburbanization. In the case of negative feedbacks, the impacts of land use changes will attenuate the current trend of growth. For example, the interactions between landscape fragmentation and the spatial externality can be understood as a negative feedback (Parker and Meretsky, 2004). In this case, landowners consider the inefficiency brought by spatial externality and then modify their behaviors towards less fragmentation.

Land use change is essentially a multi-scale process, where the driving forces at multiple scales interacting with each other in driving the changes in patterns. The current land use models focus on two types of cross-scale dynamics: top-down and bottom-up simulation. The top-down control is represented by the government policies and global interactions affecting land demand and growth suitability. From the bottom-up perspective, human makes decisions on land allocation which generate the aggregate land use patterns. A number of researchers have identified the insufficiency of using a single modeling framework alone. Aggregated analysis of land use changes may overlook some important interactions at the local level. Human decision at the local scale alone may not be able to explain all the observed patterns. Researchers usually integrate ABMs with other models to capture the characteristics of land changes from multiple facets (e.g., Manson and Evans, 2007; Xie et al., 2007). In the case of top-down modeling, the driving forces are exogenous introduced to the system and function as constraint of land use changes. Approaches include statistical modeling which is interested in aggregated system behaviors. While ABM is developed to model the bottom-up process in which the local behaviors and interactions are the driving forces of the system change. The two perspectives are complementary and it is necessary to examine the hierarchies of processes influencing the emergent land use dynamics. Moreover, there are factors that function across multiple scales. Towards the goal of modeling cross-scale feedbacks in urban area, there is a clear need to examine multiple-scale dynamics in land use systems.

The last type of feedback is the one between agents and the spatial units. The spatial units employed in ABMs can be either grid cells or vector-based spatial units (e.g., land parcels). In the case of land parcel, the linkage is straightforward. Landowners are the agents who make decisions on land use transition for a particular parcel. If the landscape is represented in raster cells, the challenges arise. Different cell sizes may have substantial influences on the modeling results for land allocation (Evans and Kelley, 2004). Multi-scale analysis is one way to deal with this issue to determine a reasonable cell size. Further, some researchers use both cell and land parcel in their models as a hierarchy to control different levels of land allocation (Kelley and Evans, 2011).

Spatial and Temporal Scales

Scale, both spatial and temporal, matters in urban land use change modeling. There are a number of terms relating to the concept of scale, such as level, extent, resolution, grain, hierarchy, absolute and relative scale. Even within the discipline of geography, human and physical geographers see “scale” from different perspectives. The study of urban systems as CHANS (Liu et al., 2007) requires the integration of both social and ecological science which put the challenges of integrating the scale concepts from different perspectives. Therefore, a single definition and perspective on scale is insufficient to understand the complexity of urban systems. Manson (2008) has proposed an epistemological scale continuum ranging from realist to constructionist view of scale to understand the complex human-environment systems. The concept of scale in modeling urban dynamics is therefore challenged by the intrinsic conflicts among the realist, hierarchical, and constructionist perspectives of scale and the potential of bridging these views in complexity theory.

The realist perspectives provide the foundation for urban modeling research. One of the fundamental issues in model implementation is to determine the spatial resolution and extent, as well as the time step and duration. Challenges relate to the identification of “optimal” modeling scale. Evans and Kelley (2004) conducted a research on the scale dependency of ABMs by varying the resolution of input land cover data for model calibration. However, such analysis is also challenged by the level of data collection and computational capacity. Current agent-based land use models tend to converge in both spatial and temporal scales. Spatially, these models are usually applied to the extent of local or regional level, with computationally efficient cell size in raster format or available spatial units in vector format. Temporally, existing models usually deal with simulation in tens of years with finer time steps (e.g., 1 year) according to the empirical evidence. While the realist scale sets the starting point for model implementation, the challenges arise in defining scale dependence, variance, and invariance (Manson, 2008). Further exploration needs to rely on more complex views of scale.

A number of researchers have applied a hierarchical framework to explore the local-global linkages and their impacts on land use changes using agent-based approaches (Xie et al., 2007). The hierarchy of neighborhood-city-county-state-nation has been commonly employed to define the cross-scale interactions in urban systems. This hierarchical scale is complementary to the “bottom-up” perspective of ABMs by imbuing the “top-down” control from institutional agency to individual actions. Nonetheless, it is still not clear if such a hierarchical structure can fully capture the cross-scale interactions within urban systems. As most researchers have built their models from the perspectives of realist and hierarchical scales, the importance of the constructionist scale has been less concerned. The constructionist scale emphasizes the material impacts of socially constructed space and scale. Within the urban contexts, there are ample evidences supporting the need to incorporate constructionist perspectives of scale to study the complex human and natural interactions. For example, a land developer may position within a network of relationships extended beyond a certain spatial extent, which may affect their decisions. The constructionist scale offers us a more complex framework to deal with the human dimension within the systems. Further exploration on how to deal with scales in agent-based land use models may foster our understanding of complexity.

Case Study: Impacts of Cross-scale Feedbacks

We constructed a developer model to explore the impacts of cross-scale feedbacks on land use patterns, which is one of the three types of feedbacks in land use systems discussed by Verburg (2006). Specifically, our model considers three types of cross-scale feedbacks: (1) land developers evaluate the land utility subject to the regional zoning regulation (e.g., maximum development density) in land allocation to fulfill their global land demand; (2) the developers' estimation of local utility of a specific site may break the zoning restrictions by rezoning application (i.e., negotiation); and (3) the global land demand may not be achieved if there is a scarcity of optimal lands in the process of local land allocation.

We implemented the model within an artificial cellular landscape using Repast 3 (North et al., 2006). The artificial landscape consists of 10,000 raster cells with 100 rows and 100 columns. To demonstrate the impacts of cross-scale feedbacks, we simplified the model input to a single layer of land utility values, which represents a combination of accessibility, amenity, and price for each cell. The utility is a spatially autocorrelated layer with higher values indicating more desirable land (Figure 1). At the beginning of simulation, the entire area was set to undeveloped. We then implemented the model to represent the three types of cross-scale feedbacks:

(1) Developer agents first sample 10% of candidate cells (i.e. bounded rationality) and choose the ones with the highest utility to develop. The land allocation is constrained by a maximum density restriction (e.g., developed cells in immediate neighbors). We ran the model in 10 time steps. At each time step, 400 cells (i.e., land demand) were being developed. Therefore, an overall of 40% of the landscape will be developed after the simulation;

(2) If the optimal land within the candidate sets has very high utility (e.g. utility threshold), developer agents may break the maximum density restriction and make the development; and

(3) If the optimal land within the candidate sets has very low utility (i.e., scarcity), developer agents may give up the development and thus cannot fulfill the global land demand (40%).

We tested the model in four experiments by using different combinations of the three types of cross-scale feedbacks (Figure 2). The specific parameters (e.g., land demand, maximum density, utility thresholds) in the experiments were determined iteratively based on our preliminary experimentation for better visual results. The simulation results are shown in Figure 2. The results show the impacts of cross-scale feedbacks on land fragmentation, compactness and dispersion. However, further exploration is needed for the understanding of the complex interactions among various factors driving land use

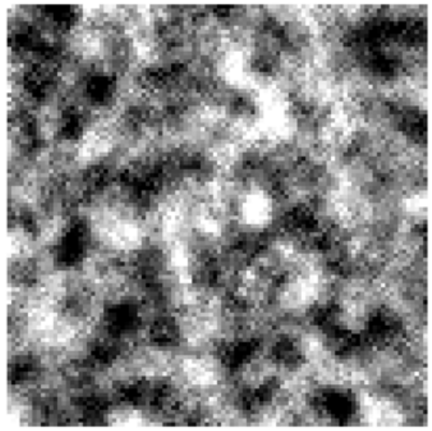

Figure 1: Model input: land utility layer. The darker color on the image represents higher utility value.

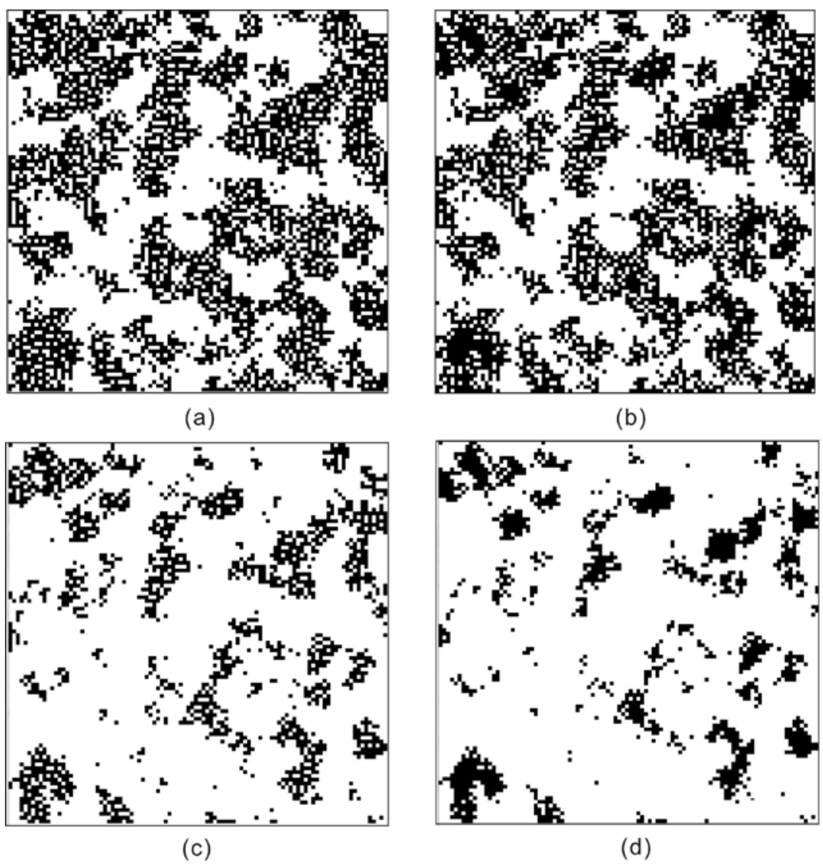

Figure 2: Simulation results of: (a) incorporating feedback (1); (b) incorporating feedback (1) and (2); (c) incorporating feedback (1) and (3); (d) incorporating feedback (1), (2) and (3).

changes. In our future research, we will improve the model by considering heterogeneous agents and experiment with real world data.

Discussion and Conclusions

Agent-based approach has emerged as a promising technique for urban land use change simulation. Although it can be computationally intensive and may need substantial programming efforts, the fundamental challenges of implementing an agent-based model (ABM) are with the lack of theoretical and conceptual foundations. In this paper, we have discussed several critical issues concerning concepts, theories, implementation of ABM in simulating complex urban land changes. We have specifically considered four important features: agent heterogeneity, driving forces, system feedbacks, and spatial and temporal scale. First, agent heterogeneity describes the process of urban development in a natural way by incorporating the interactions among stakeholders, which may have significant impacts on land use patterns. Second, a variety of socioeconomic and biophysical factors across multiple scales need to be considered in modeling land use changes in urban areas. Challenges arise from the potential interactions among various factors across dimensions and scales. Third, three types of system feedbacks characterize land use systems, which can be summarized as driver-impacts feedbacks, cross-scale feedbacks and agent-cell feedbacks. Further exploration is needed to explicitly simulate feedbacks of different types in land use change research. Fourth, current agent-based land use models tend to converge in spatial and temporal scales. The complexity of urban systems calls for a more complex view on the concept of scale. Finally, we have conducted a case study to explore the impacts of cross-scale feedbacks on land use patterns using the agent-based approach. Results from our experiments suggest the importance of simulating cross-scale feedbacks in urban landscape changes.

Based on the above discussions and findings from the literature review and our case study, we have further identified several areas for future research. First, it is necessary to consider both human and natural processes in urban areas which affect landscape changes. Human decision making is a major component of ABMs. However, biophysical factors have only been incorporated as either driving forces (e.g., natural amenity) or spatial constraints (e.g., land suitability) in the models. There is a need to examine other potential ways to incorporate the biophysical domain in urban land use models. Second, ABMs help foster our understanding of complexity. The flexible framework of ABM supports the easiness of adding components and interactions. More comparative analysis between competing theories for modeling decision making is needed to help maximize the potential of ABMs. Last, the complexity of land use modeling arises from the interactions among different components as discussed in this paper. For example, driving forces of land use/cover change are conditional to the spatial and temporal scale of modeling. And they are also interacting across scales and thus can be dynamic. The development of a comprehensive framework may support the design and implementation of ABMs in future urban land modeling research.

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