Chapter 4
Planning in Complex Spatial and Temporal Systems: A Simulation Framework

Shih-Kung Lai and Haoying Han

Introduction

Planners are confident that their planning affects not only behaviors in organizations, but also outcomes. There is, however, little backing for this confidence. Surprisingly little is known about planning processes and how they affect organizations. One approach to gaining understanding of planning behaviors in organizations is to develop and analyze simulation models. The framework presented here builds on two streams of previous work: the garbage can models of organizational behavior presented by Cohen et al. (1972) and the spatial evolution models of Nowak and May (1993). Our objective is to develop a framework sufficient to investigate the implications of introducing planning behaviors into complex organizational systems evolving in space and time. Our primary focus for this *chapter* is on devising simulations from which we might discover general principles about the effects of planning the behavior of organizations. Additional work will be necessary to determine the external validity of these simulations, that is, to interpret concrete situations in terms of such principles.

We focus on the planning activities of considering related choices (Hopkins 2001), setting aside for this *chapter* planning with respect to uncertainty about planning objectives, environments, and available alternatives. Information that reduces uncertainty arises from some regularity about observed phenomena that permits prediction across actors, space, or time. The level of planning investment can be measured by the number of comparisons and judgments made in gathering

S.-K. Lai
College of Public Administration, Zhejiang University, Hangzhou, China

Department of Real Estate and Built Environment, National Taipei University, Taipei, Taiwan
e-mail: lai@mail.ntpu.edu.tw

H. Han (✉)
Department of Land Resource Management, Zhejiang University, Hangzhou, China
e-mail: hanhaoying@zju.edu.cn

Z. Shen, *Geospatial Techniques in Urban Planning*, Advances in Geographic Information Science, DOI 10.1007/978-3-642-13559-0_4,

information about related choices while making a plan, as manifested by the manipulation of these choices. Plans are sets of decisions, which are contingent on outcomes resulting from prior decisions and system behavior based on exogenous parameters. Plans persist in time and space. As decisions become actions yielding outcomes, further contingent decisions can be enacted. These contingent decisions are, however, part of the persistent plan. Revising a plan thus implies changing the contingencies on which ensuing decisions are based.

We construct the elements of this simulation framework in sequence. Planning is understood here as gathering information to reduce uncertainty (e.g., Friend and Hickling 2005; Schaeffer and Hopkins 1987). Section “Planning Behaviors in the Planning Process” explains the garbage can model and develops one definition of planning as manipulation of decision situations within that framework. Section “Incorporation of Spatial Relationships” explains the spatial process of urban modeling and the spatial framework in terms of evolutionary planning behavior in a prisoner’s dilemma game. Section “Idea for Integrating the Garbage Can Model with a Spatial Evolution Game for Planning Simulation” introduces an idea of how these two types of models can be integrated and the questions that might be addressed by analysis of such simulations. Section “Conclusions” concludes.

Planning Behaviors in the Planning Process

As everyone knows, scientific technology is developing day and night. Since computer models have emerged, there are various models developed for scientific research. While one of them, namely agent-based modeling (ABM) has been proven to be an effective way to simulate activities in which entities participate (Torrens 2007). This kind of simulation is expected to provide a valuable tool for exploring the effectiveness of policy measures in complex environments (Jager and Mosler, 2007; Jager 2007). Before discussing planning the behavior of organizations and its effects on a complex urban society, we should take a retrospective glance reviewing the current research on ABM with respect to urban social systems.

Agent-Based Modeling

ABM for Planning Support Systems

In the last decades, influenced by rapid urbanization, the relationships between policies, the location and intensity of urban activities, and related urban environmental problems have become a hot topic for planners and researchers (Chin 2002; Ewing 1994, 1997; Neuman 2005). This research is always carried out using statistical analysis or investigated in ways such that the variability of entities’ activities and the influences between different entities cannot been represented particularly well. When computer models were first constructed for urban systems, they were built for testing the impacts of urban plans and policies rather than for scientific understanding purposes (Batty 2008). The basic argument was that given a good theory, a model would be constructed based on it, which would then be validated and, if acceptable, used in policy making (Batty 1976). Topical examples can be gleaned from urban growth simulations, in which the spatial process of urban growth can be visualized and represented in a very realistic way using cellular automata (CA) models. These can be used to support decision-making (Batty et al. 1997, 1999; Clarke and Gaydos 1998; Wu 2002; Li and Yeh 2000; Fang et al. 2005).

Now ABM is becoming the dominant paradigm in social simulations due primarily to its priority on reflecting agents' choices in complex systems. Researchers employ ABM for planning support and decision-making on urban policies. One example is a role-playing approach introduced by Ligtenberg, in which a complex spatial system including a multi-actor spatial planning process can be simulated for spatial planning support (Ligtenberg et al. 2010). Furthermore, in regard to the highly complex process of making urban policy decisions, a multi-agent paradigm has been built to develop an intelligent and flexible planning support system, within which three types of agents, including interface agents who improve the user–system interaction, tool agents to support the use and management of models, and domain agents to provide access to specialized knowledge, were created (Saarloos et al. 2008). Researchers also utilize ABM to simulate urban development processes. As described by a CityDve model, the economic activities of agents (e.g., family, industrial firms, and developers) that produce goods by using other goods and trade their goods on the markets have been simulated to visualize urban development processes resulting from urban policies (Semboloni et al. 2004).

In China, one of the countries around the world whose urbanization is taking place at an unprecedented rate, the conflict between human activities and urban environments is very serious. Agent-based simulation has easily gained much attention from Chinese researchers. Some of these researchers have improved traditional urban growth models by building up a set of spatial-temporal land resource allocation rules and developing a dynamic urban expansion model based on a multi-agent system (MAS) to simulate the interactions among different agents, such as residents, farmers, and governments (Zhang et al. 2010). This work is able to reflect basic urban growth characteristics, explain the reasons for the urban growth process and explain the effects of agents' behavior on urban growth. MAS simulations have shown a higher precision than cellular automata models, which suggests that these models could provide land use decision-making support to government and urban planners. Meanwhile, other researchers have focused on solving urban transportation problems using ABM. One example is a qualitative model of a multi-lane environment that has been built to simulate several cars acting in a multi-lane circuit (Claramunt and Jiang 2001). This work is an illustrative example of a constrained frame of reference. The potential of this model is that it was illustrated and calibrated using an agent-based prototype, within which the modeling objects were individual cars.

Residential Motility Simulation

In a study of ABM challenges for geo-spatial simulation, seven challenges for ABM work were illustrated, including the purpose of model building, the independent theory of model rooting-in, and interactions among agents (Crooks et al. 2008). Within this work ABMs have been utilized to model different urban systems problems, such as residential location, urban emergence evaluation, and residential segregation. Similar studies have been carried out on this topic such as a MASUS model (Multi-Agent Simulator for Urban Segregation) which provides a virtual laboratory for exploring the impacts of different contextual mechanisms on the emergence of segregation patterns (Feitosa et al. 2011). A population dynamic model in which inhabitants can change their residential behavior depending on the properties of their neighborhood, neighbors and the whole city has been built (Benenson 1998). A micro-simulation model for residential location choice has been developed, in which the Monte Carlo method was employed to model individual decision rules and an Artificial Neural Network (ANN) theory has been utilized to determine individual location choice (Raju et al. 1998). It is apparent that the principle of ABM has brought numerous researchers into the field of residential mobility simulation. Since residential location has been abundantly simulated, some researchers have begun to consider the environmental influences and landscape changes caused by household residential location choice. A framework called HI-LIFE, to be used for simulating and modeling residential demand for new housing by considering household interactions taking life cycle stages into account was argued for in 2009 (Fontaine and Rounsevell 2009). Within this work household residential location choices have been simulated to predict regional landscape pressure in the future. Furthermore, an ABM framework integrating spatial economic and policy decisions, energy and fuel use, air pollution emissions and assimilation has been developed for urban sustainability assessments (Zellner et al. 2008).

Land and Housing Market Simulations

For researchers to use ABM to simulate land and housing markets is quite usual now. In research by D. C. Parker, a local land market was portrayed as a special conceptual residential market, and the stakeholders and households were agents within it. This research combined traditional deductive optimization models of behavior at the agent level with inductive models of price expectation formation (Parker and Filatova 2008; Filatova et al. 2008). As implemented in this research, households make decisions on their housing behavior by evaluating the house utility and finally determining their willingness to pay for it. Another researcher simulated relocation processes and price setting in an urban housing market through modeling households' decision-making on relocation based on perceptions of housing market probabilities (Ettema 2011). In this study, utility was also an important factor for households' preference evaluations.

Such simulations can be quite helpful for local governments making policies affecting urban housing and land markets or making decisions about related policies. However, there is still little exploration into planning behaviors using ABM approaches.

Simulation of Planning Behaviors in the Planning Process

Limitations of Current Urban Models

We reviewed some typical simulations of urban policy or urban phenomena based on the ABM approach described above. These studies are typically aimed at helping planners or decision makers work out special planning policies. Within these models, urban policies are mostly imported as simulation factors, viewing the policies as preconditions for simulation. These simulations concentrate mainly on representing possible urban changes that could be influenced by policy implementation. However, there is too little information about how a policy making process could be implemented and how would it influence organizations. Thus, our focus has come to be how to support policy makers with practical planning behavior models, through which planning behaviors can be automatically introduced into complex organizational systems evolving in space and time.

The Garbage Can Model

To solve the problem discussed above, we introduce the garbage can model. The garbage can model of organizational planning behavior allows structuring of planning issues so that control is to be investigated, rather than merely imposed externally. It is thus particularly appropriate for investigating planning in organizations. Planning interventions or actions are at least partially substitutable for aspects of organizational design. Both affect the coordination of decisions. Thus to investigate planning, we must be able to manipulate aspects of organizational design and of planning interventions in that design. We first explain the original garbage can model and then introduce planning as an extension of the model.

The original formulation of the garbage can model of organizational choice considers four elements: choices, solutions, problems, and decision makers (Cohen et al. 1972). Choices are situations in which decisions can be made, that is, commitments are made to take certain actions. In organizations, votes to spend money or signatures on forms to hire or fire persons are examples of actions on choices. Solutions are actions that might be taken, such as tax schedules that might be levied or land developments that might be approved. Solutions are things that choices can commit to enact, things we have the capacity to do directly. Problems are issues that are likely to persist and that decision makers are concerned with resolving, such as homelessness, unfair housing practices, congested highways, or flooding. Note that choices enact solutions; they do not solve problems. We cannot merely choose not to have homelessness. We cannot "decide a problem." We can choose to spend money on shelters or to hire social workers, which may or may not affect the persistence of homelessness as a problem. Decision makers are units of capacity to take action in choice situations.

A garbage can is a choice opportunity where the elements meet in a partially unpredictable way. Solutions, problems, and decision makers are thrown into a garbage can and something happens. There is, however, no simple mapping of decision makers to problems or of solutions to problems. Further, an organization has many interacting garbage cans, many interacting choice opportunities. The original model was used to investigate universities as an example of "organized anarchy." Structure as control can be increased from this starting point, however, which makes possible the investigation of a wide range of types and degrees of organizational structure (e.g., Padgett 1980). Planning and organizational design are at least partially substitutable strategies for affecting organizational decision making. Organizational design and planning are both means for "coordinating" related decisions. Thus the garbage can model provides a useful starting point for investigating planning behaviors in organizations.

The major assumption of the models is that streams of the four elements are independent of each other. Solutions may thus occur before the problems these solutions might resolve are recognized. Choice opportunities may occur because regular meetings yield decision maker status, independent of whether solutions are available.

Cohen et al. (1972) reported their results by focusing on four statistics: decision style, problem activity, problem latency, and decision difficulty. The three decision styles were resolution, oversight, and flight. Resolution meant that a choice taken resolved all the problems that were thrown into the garbage can at that choice opportunity. If a decision was taken for a choice to which no problems were attached, it was classified as oversight. All other situations constituted flight. Cohen et al. were able to demonstrate the sensitivity of organizational behavior to various access structures and decision structures.

The decision process was quite sensitive to net energy load. Net energy load is the difference between the total energy required for a problem to be resolved and that available from decision makers. With the general formulation of a decision process considering net energy load, Cohen et al. (1972) ran a simulation addressing four variables: net energy load, access structure, decision structure, and energy distribution. Different net energy loads, roughly analogous to organizational capacity in the form of decision makers relative to organizational demand, should yield differences in organizational behavior and outcomes. Access structure is the relationship between problems and choices. A zero-one matrix defines which problems can be resolved by which choices. Different access structures vary in the number of choices that can resolve particular problems. Decision structure defines which decision makers can address which choices and thus how the total energy capacity of the organization can be brought to bear in resolving choices.

Planning Behaviors in Garbage Can Models

The original garbage can model implies that the organization does not have control over the occurrence of problems and choices. In particular, the organization is not capable of generating choice opportunities to deal with problems that have just arisen in a given time step. The arrival of choice opportunities and the arrival of problems are both random. One way of introducing planning to the model is to allow the organization to purposefully create choice opportunities for resolving problems. This choice–problem dependence is a matter of degree with one extreme being the case of the original garbage can and the other extreme a complete mapping of arriving problems to created choice opportunities. This is equivalent to being able to compare garbage cans and choose one to act in at each time period of the simulation. What effect would the ability to choose among choice opportunities over time so as to match current problems have on the simulation results?

Lai (1998, 2003) ran a prototypical simulation to illustrate this approach. He assumed that, at a given time step, the planner is able to acquire complete information about the structure of the organization, except for the arrival of problems in that time period. The planner knows the decision structure and access structure, and the relationships among the elements. Thus the planner can predict which decision makers and problems will be in which garbage cans (choice opportunities) and how much energy will be accumulated in and spent by decision makers in each one. Choice opportunities in this case are related choices that the planner can select from based on the difference between the energy required to make a decision and the energy available from decision makers. The planning criterion is thus to select the choice opportunity (the garbage can) that results in the smallest energy deficit. Planning thus defined involves choosing the entry times for choices, without considering problems, decision makers, or solutions. Simulation results were sensitive to interventions based on this definition of planning. In the pilot study, such planning resulted in increasing the efficiency with which choices were made, meaning more choices were made with less energy expended, but fewer problems were resolved. Problems, choices, and decision makers tended to remain attached to each other in the case where planning occurred more than in the case without planning.

Lai's work was only tentative because of the small size of the simulations. Also, his scheme is only one way of introducing planning into the original model. Control as structure over other elements could also be considered. A combination of partial controls in experimental design on the four elements might yield planning possibilities that would result in more useful analyses of simulation results. Regardless of these details, Lai (1998, 2003) was able to demonstrate the possibility of gleaning instructive results for understanding planning effects because he showed that it is possible to add structure to decision making without increasing the organization's ability to resolve problems. The result suggests that this simulation modeling approach incorporates sufficient degrees of freedom to discover counter-intuitive results.

Incorporation of Spatial Relationships

All planning behaviors have to be conducted within a certain urban space. Thus, there is no doubt that when planners try to make a plan there will be an interaction between the urban area and planning behaviors. How to better represent the spatial process of planning behavior is now a problem. In this session, we first review how spatial processes are explored using CA and ABM approaches in current research reports and then present two examples for discussion on how spatial datasets can be integrated into ABM simulations. We present a possible solution using a Prisoner's dilemma game to simulate spatial evolution in planning behaviors, such as planning in organizations promoted by the Garbage can model.

Spatial Process of Urban Modeling

Urban Modeling and Spatial Processes

In urban modeling, spatial processes can be simulated through automata. There are automata of different types, but simply put, each automaton can be defined as a discrete processing mechanism with internal states. When the state of one automaton has been changed by its own characteristics or through input from outside conditions, such as urban policies, this change will be transmitted to other automata through a predetermined transition rule. Thus, researchers can represent a spatial process by defining the spatial features of automata and the transition rule between them. A typical application of this principle is CA simulation, in which a real urban space is modelled as a cell in the simulation. Each cell has its own spatial characteristics, and urban policies can be input as simulation conditions. Changing conditions will finally result in a cell state change. This type of model has been used in research simulating strategic spatial plans, with cells' spatial attributes including landscape, land-use zoning, slope, urban plan, and land price (Ma et al. 2010). These attributes will determine the state value of a cell, and so, along with the transition rule, determine any changes of state it may undergo.

Spatial processes within ABM can be achieved through the interaction between agents and space. Spatial information for a simulation model can be gained by coupling geographic information systems with the model. Some researchers in this field have argued that a simulation approach named the geographic automata system, in which a MAS can be combined with CA and which takes advantages of GI Science to model complex geographic systems that are comprised of infrastructure features and human objects (Torrens and Benenson 2005). Within geosimulation, the most common implementation of multi-agent models is for the agents to act as objects within a spatial framework (Albrecht 2005; Benenson and Torrens 2004). This approach also can be employed for residential mobility simulation (Torrens 2007).

As most simulations of residential location do, the spatial features of a cell are utilized to calculate the location utility for agents. Thus, the interaction between agents and space can be within the simulation model. As in the research on residential pressure on landscape change we reviewed before, regional space is represented by a regular lattice of grid cells indexed by their geographic coordinates (i, j) in the matrix space $\{I \times J\}$. Each cell is considered to be a homogenous land unit with key spatial information including three groups, *like available properties, land accessibility, and environmental amenities*. Interaction between agents and space takes place as agents choose their new location by evaluating the utility of cells. Household location change will further change the landscape of a cell. Thereby, landscape pressure can be evaluated (Fontaine and Rounsevell 2009).

GIS and Spatial Datasets

The ABM simulations can (e.g., Jiang 2000) be run on a platform combining geographic information systems and ABM or CA, the former being the ArcGIS system of ESRI whereas the latter is an agent-based or CA software such as StarLogo, created by MIT or AUGH, developed by Cecchini (1996). Two examples of such coupling are provided here. In the first example, a land-use change model was constructed with the StarLogo software programmed by MIT coupled with GIS (Lai and Han 2009). The research assessed the probability of development based on economic property right indices, and the probability of possible land uses allowed in the zoning system was embedded in the simulation rules. Finally, the research used parameters developed over 100 generations of a genetic algorithm method to calibrate the simulation model. The main results from this research are as follows: (1) Using the parameters gained from the genetic algorithm method, the model was indeed able to simulate, at least partially, the pattern of land uses for the Taipei metropolitan area. (2) The zoning system in the simulated area does influence the appearance and pattern of land uses. It limits the development of industrial land use and affects the fractal pattern of commercial land use. (3) After comparing the spatial patterns of simulation results and conducting one-way ANOVA analysis, it can be concluded that zoning affects specific locations, but not the fractal pattern of land uses.

Figure 4.1 shows the logic of how the use type of a particular parcel (cell) is determined. Note that the use types are checked against zoning regulations in which mixed uses are allowed. Figure 4.2 is a sample illustration of the simulation and Fig. 4.3 is the interface.

In the second example, research was conducted, grounded on a microscopic simulation approach to studying how decisions made locally give rise to global patterns (Lai and Chen 1999). CA provide the simplest bottom-up way to study discrete systems and complex urban spatial systems. Based on the coupling of a CA model and GIS of a small town in central Taiwan, Minjian Township, the research focused on an agent-based simulation approach to considering land-use and transportation networks as two traits of the evolution of complex urban spatial systems.

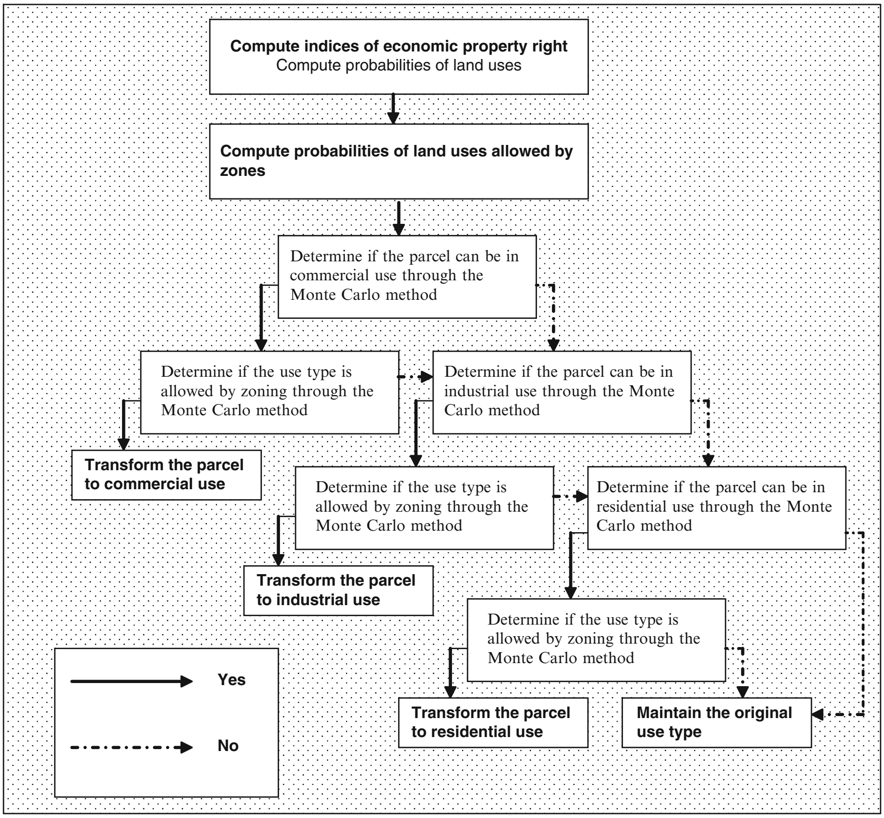

Fig. 4.1 Logic of computing and determining land-use transitions

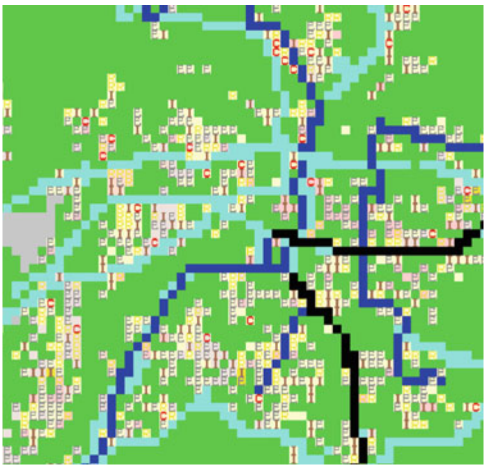

Fig. 4.2 Sample simulation plot (Black = road; blue = transit line; I = industrial; C = commercial; R = residential; E = vacant)

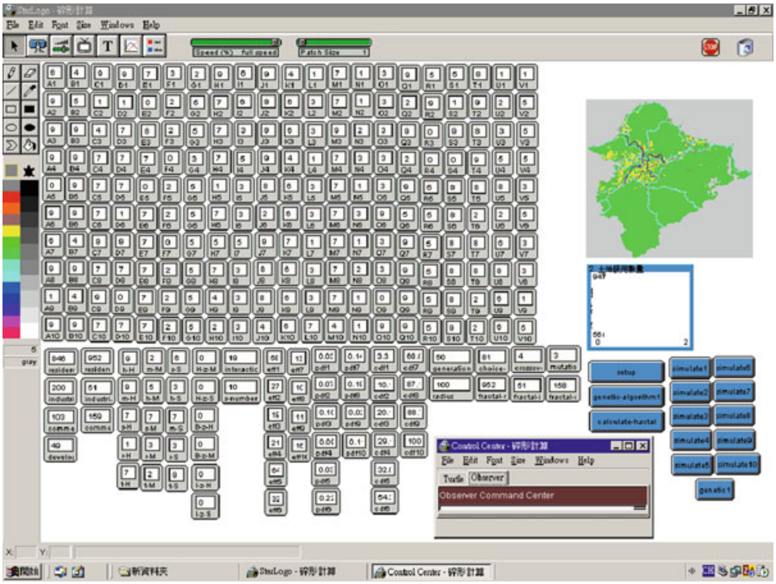

Fig. 4.3 Simulation interface. Rules of the genetic algorithm (*upper buttons*) and the simulated maps and necessary data (*lower buttons*) are displayed

The simulation views land development decisions as simple rules characterized by degrees of complexity and diversity. Three factors, the numbers of transition rules (N), the diversity of transition rules (D), and the numbers classifications of the transition rules (n), are derived from theories of measures of complexity and evolution in general system theory (GST). Simulating systems behavior based on the transition rules classified and sorting out the results by the three factors shows that when the diversity of rules increases, the urban structure will grow in a complex, fractal way. Figure 4.4 shows the simulation framework and two illustrations of the simulation are given in Fig. 4.5. Note that the simulation was run on the AUGH platform (Cecchini 1996). Both rules of the simulation in Fig. 4.5 are for high diversity, measured by and derived from different levels of complexity.

Space Evolution in Planning Behavior

Prisoner's Dilemma Game in Space

Planning in the context of urban development, both physical and social, must acknowledge the significance of spatial effects of association and competition. Recent work on evolution of behavior, characterized as games in space, provides one starting point for incorporating space in simulations (Nowak 2006). Here, we first present the model of Nowak and May (1993) and then introduce planning to the

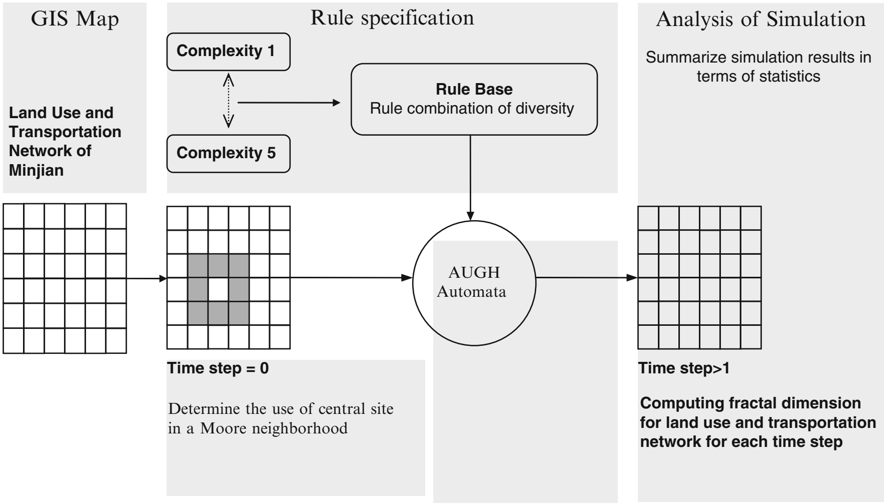

Fig. 4.4 Simulation framework (complexity 1 through 5 represent degrees of complexity as measured by fractals)

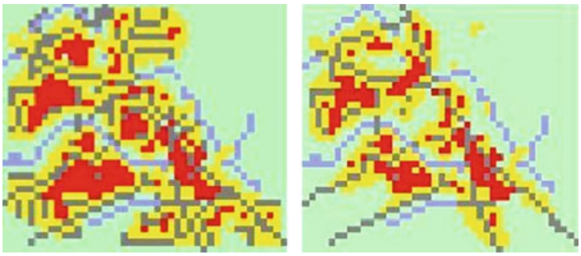

Fig. 4.5 Coupling of a CA model with GIS to explore land use and transportation interaction (yellow = residential; red = commercial; gray = road; blue = river)

model. Allen and Sanglier (1981) considered some aspects of urban spatial evolution in a similar framework.

Nowak and May (1993) investigated the spatial evolution of a set of actors in a square lattice as actors in a sequence of prisoner's dilemma games. The prisoner's dilemma game presents each player with two options: cooperate or defect. The payoffs are determined by the combination of plays such that the values of the payoffs for player one decrease in the following order DC > CC > DD > CD where C signifies cooperate and D signifies defect. The first strategy is the action of player one, and the second is the action of player two. Player two faces a symmetric situation. The dilemma is that it is in each player's individual interest to defect regardless of the action of the other, but in doing so they both end up worse off, since DD has a lower payoff for each player than CC. Interaction among players (agents) in a spatial configuration based on this simple decision rule generates complex spatial patterns given different relative payoff levels. The effects of spatial configurations can be investigated by comparing the results of non-spatial sequences of prisoner dilemma games.

Arthur (1989, 1994) interpreted a similar sequence in terms of increasing returns to market share. He showed that if the payoff for adopting a strategy increases with the number of agents adopting the same strategy, it is impossible to predict the eventual evolutionary outcome of the resulting trajectory of market share. One typical illustration of this phenomenon is the adoption of particular computer software packages. The payoff increases with the number of other adopters because of the greater likelihood of additional compatible packages, knowledgeable users, and continuing upgrades. Similarly, consumers seem to have made choices about Betamax versus VHS in video formats at least partially on the basis of likelihood of available videotapes to play rather than on picture quality.

Planning in a Spatial Evolution Game

The payoff in the prisoner's dilemma game will then vary depending on the number of agents in the "neighborhood" choosing a particular option: cooperate or defect. This combination can be described using the fractal concept of space (see Mandelbrot 1983; Batty and Longley 1994; Batty 2005). This approach allows simulations to characterize spatial relations across continuous dimensions, which can represent a richer variety of urban geographic relationships or organizational structures more effectively than Euclidean space.

Consider a continuum of space-filling agents residing in a space of fractal dimension who act based on the payoff in the prisoner's dilemma game and the principles of garbage can simulation. Each agent makes one of two choices, defect or cooperate, as in the usual prisoner's dilemma game. The payoffs, however, are not fixed, but depend on the numbers of these choices adopted in the system. The payoffs for player one are depicted below, where (p,q) denotes the initial payoff or preference for choice p made by an agent interacting with another agent making choice q; r is the rate of change of return relative to the number of agents making a particular choice; and n(p) is the total number of agents choosing choice p. The rate r can be positive, negative, or zero, representing increasing, decreasing, or constant rates of return, respectively. Note that $a(d,c) > a(c,c) > a(d,d) > a(c,d)$ (Table 4.1).

The agent chooses for the next time step so that it yields the maximum payoff based on the choices among its neighbors at the current time step. The neighbors are the agents, including the agent under consideration, located within a radius R from

Table 4.1 Payoff matrix

Player 1/Player 2	Cooperate	Defect
Cooperate	$a(c,c) + rn(c)$	$a(c,d) + rn(c)$
Defect	$a(d,c) + rn(d)$	$a(d,d) + rn(d)$

the site where the agent is located in fractal space. The agent can also make a choice by selecting the maximum payoff among the agents located within its "neighborhood" or the square lattice over time period T. R and T are thus indicative of planning investment in space and in time according to our definition. That is, they denote the scope of related choices considered in space and time, respectively. Let M (R,k) be agents standing for the mass of the fractal sub-space with radius R and center k. We have M (R,k) = uR(D) where u is a uniform density and D is a fractal dimension (Mandelbrot 1983). The total payoff for an agent j located at the center of M(R,j) is the sum of the payoffs for that agent interacting with all agents i in M(R,j), including j itself. That is,

$$P(j,t,R,T) = \sum\sum[(a(c(j,t),c(i,t)) + rn(c(j,t))]$$

where P(j,t,R,T) = the cumulative payoff function for j over time period T at time t within M(R,j), and c(j,t) = the choice made by j at time t.

The first summation is over t of elements of the set T and the second is over i elements of the set M(R,j). The decision rule for any agent k at time t + 1 is to adopt the choice made by the agents in k's neighborhood that yields the maximum payoff. That is,

$$\mathrm{c(k,t+1) = c(j\ I\ Max\ P(j,t,R,T)),\ for\ j\ is\ an\ agent\ of\ M(R,k).}$$

This form of simulation of spatially structured behavior provides a basis for incorporating space into a simulation model similar to the garbage can model discussed above.

Idea for Integrating the Garbage Can Model with a Spatial Evolution Game for Planning Simulation

To incorporate the garbage can model into a spatial model, consider a continuum of decision makers (agents) in a fractal space. There are finite numbers of problems and choices. Define a decision structure of relationships among decision makers and choices, an access structure of relationships between problems and choices, and a solution structure between solutions and problems. These zero-one matrices of relationships have the same meaning and range of forms as in the original garbage can model and are givens external to each simulation run. These structures can be varied as described earlier to discover their effects on choice-making behavior.

The initial payoffs for all decision makers are the same, but these payoffs vary with respect to two variables in the simulation. The first variable is the number of agents that adopted that choice in the particular time step of the simulation. The second variable is the problems associated with that choice at that time. Because the problems arrive in a random sequence, the payoffs are subject to random

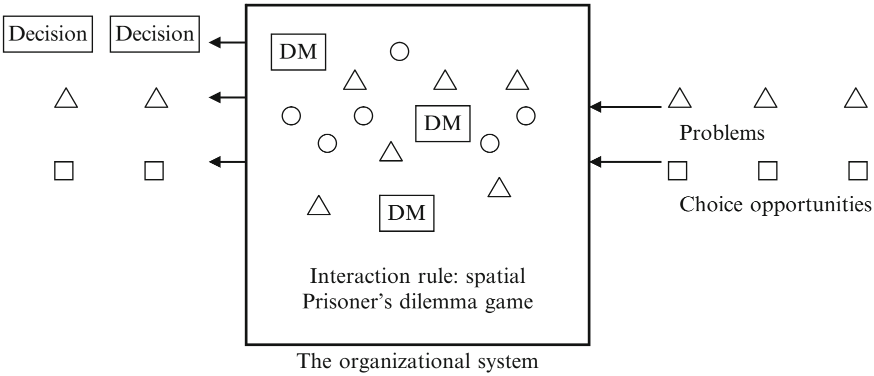

Fig. 4.6 Relationship between the garbage can model and the prisoner's dilemma game model (*DM* decision maker)

fluctuations and the evolution is not deterministic. The payoff table is therefore different from that of the prisoner's dilemma game because in the spatial version there is interaction among the agents involved. The decision rule for an agent adopting a particular choice is the same as that in our spatial model: the best choice is the one that yields the maximum payoff considering the choices among the agent's neighbors in space and time.

This spatial version of the prisoner's dilemma model can then be used to consider the effects of space on a garbage can model that also incorporates planning behaviors as suggested in Fig. 4.6. We have not yet run such simulations in a structured way so as to test the sensitivity of this model to spatial scope or temporal consideration of related choices. We can identify, however, the types of questions that might be addressed. Different types of organizational structures, from strictly hierarchical to "matrix" structures could be considered as partial substitutes for planning intervention. For example, does a hierarchical organizational structure benefit less from planning than a "matrix" organization? Does planning that is focused on considering more related choices (that is more garbage cans) yield more problem resolutions than planning focused on generating solutions for fewer choices (garbage cans)? What differences arise from increasing the size of the neighborhood in space relative to increasing the size of the neighborhood in time? A spatial version of the Garbage can model has been provided (Lai 2006), and the simulation framework suggested here can be considered as a sequel to that model.

Conclusions

We have proposed modified versions of two previously proposed simulation models to allow consideration of the effects of planning in complex, spatial, temporal organizational systems. We have extended the garbage can model of Cohen, March, and Olsen so as to consider a particular definition of planning behavior. Recent simulation runs suggest that the revised model is sensitive to these planning interventions. We have also proposed a revised version of the prisoner's dilemma spatial game taking into account space and planning. In particular we have considered increasing returns, planning investments, and fractal space. Such simulations can be coupled with GIS to yield policy implications for real world situations. The major work of running structured sets of simulations so as to discover and elucidate systemic principles remains.

Simulations of this type are of interest because of the abstract form of questions that can be considered. The intent is not to simulate concrete, specific cases, but to understand the functioning of systems. The simulation result is encouraging in that it implies planning interventions might increase the efficiency of choice making without increasing the number of problems resolved. This suggests that useful, counterintuitive properties might be discovered. Such systemic understanding must then be interpreted in concrete terms for organizational behavior.

References

Albrecht, J. (2005). "A new age for geosimulation," Transactions in GIS. 9(4): 451–454

Allen, P. M. and M. Sanglier (1981). "Urban evolution, self-organization, and decisionmaking," Environment and Planning A. 13: 167–183.

Arthur, W. B. (1994). Increasing returns and path dependence in the economy. Ann Arbor: The University of Michigan Press.

Arthur, W. B. (1989). "Competing technologies, increasing returns, and lock-in by historical events," The Economic Journal. 99: 116–131.

Batty, M. (1976). Urban modelling: Algorithms, calibrations, predictions. Cambridge, UK: Cambridge University Press.

Batty, M. (2005). Cities and complexity: understanding cities with cellular automata, agent-based models, and fractals. Cambridge, Massachusetts: The MIT Press.

Batty, M. (2008). Fifty years of urban modelling: macro statics to micro dynamics. In S. Albeverio, D. Andrey, P. Giordano and A. Vancheri, Editors, The dynamics of complex urban systems: an interdisciplinary approach. Physica-Verlag, Heidelberg, DE, 1–20.

Batty, M., H. Couclelis and M. Eichen (1997). "Urban Systems as Cellular Automata," Environment and Planning B: Planning and Design. 24(2): 159–164.

Batty, M. and P. Longley (1994). Fractal Cities. New York: Academic Press.

Batty, M., Y. Xie and Z. Sun (1999). "Modeling urban dynamics through GIS-based cellular automata," Computers, Environment and Urban Systems, 23(3): 205–233.

Benenson, I. (1998). "Multi-agent simulations of residential dynamics in the city," Computers, Environment and Urban Systems. 22(1): 25–42.

Benenson, I and P. M. Torrens (2004). "Geosimulation: object-based modelling of urban phenomena," Computers Environment & Urban Systems. 28: 1–8.

Cecchini, A. (1996). "Urban modeling by means of cellular automata: generalized urban automata with the help on-line (AUGH) model," Environment and Planning B. 23:721–732.

Chin, N. (2002). "Unearthing the roots of urban sprawl: A critical analysis of form function and methodology," Centre for Advanced Spatial Analysis (CASA) working paper series. London: University College London.

Claramunt, C. and B. Jiang (2001) "A qualitative model for the simulation of traffic behaviours in a multi-lane environment," Geographical Sciences. 11 (1): 29–42.

Clarke, K. C. and L. J. Gaydos (1998). “Loose-coupling of a cellular automaton model and GIS: long-term growth prediction for the San Francisco and Washington/Baltimore,” International Journal of Geographical Information Science, 12(7): 699–714.

Cohen, M. D., J. G. March and J. P. Olsen (1972). “A garbage can model of organizational choice,” Administrative Science Quarterly. 17(1):1–25.

Crooks, A., C. Castle and M. Batty (2008). “Key challenges in agent-based modelling for geo-spatial simulation,” Computers, Environment and Urban Systems. 32(6): 417–430.

Ettema, D. (2011). “A multi-agent model of urban processes: modelling relocation processes and price setting in housing markets,” Computers, Environment and Urban Systems. 35(1): 1–11.

Ewing, R. H., (1994). “Characteristics, causes and effects of sprawl: a literature review,” Environmental and Urban Issues. 21(2): 1–15.

Ewing, R. H. (1997). Is Los Angeles-style sprawl desirable? Journal of American Planning Association. 63(1): 107–126.

Fang, S., G. Gertner, Z. Sun and A. Anderson (2005). “The impact of interactions in spatial simulation of the dynamics of urban sprawl,” Landscape and Urban Planning. 73(4): 294–306.

Feitosa, F. F., Q. B. Le and P. L. G. Vlek (2011). “Multi-agent simulator for urban segregation (MASUS): A tool to explore alternatives for promoting inclusive cities,” Computers, Environment and Urban Systems. 35(2): 104–115.

Ferdinando Semboloni et al., (2004) “CityDev, an interactive multi-agents urban model on the web,” Computers, Environment and Urban Systems, 28(1–2): 45–64.

Filatova, T., D. C. Parker and V. D. A. Veen (2008). “Agent-based urban land markets: agent’s pricing behavior, land prices and urban land use change,” Journal of Artificial Societies and Social Simulation. 12(13), <http://jasss.soc.surrey.ac.uk/12/1/3.html>

Fontaine, C. M. and M. D. A.Rounsevell (2009). “An agent-based approach to model future residential pressure on a regional landscape,” Landscape Ecology. 24: 1237–1254.

Friend, J. and A. Hickling (2005). Planning under pressure: the strategic choice approach. New York: Elsevier Butterworth Heinemann.

Hopkins, L. D. (2001). Urban development: the logic of making plans. London: Island Press.

Jager, W. and H. J. Mosler, (2007). “Simulating human behavior for understanding and managing environmental resource use,” Social Issues. 63 (1): 97–116.

Jagera, W. (2007) "The four P’s in social simulation, a perspective on how marketing could benefit from the use of social simulation," Journal of Business Research, 60(8): 868–875.

Jiang, B. (2000). “Agent-based approach to modeling environmental and urban systems within GIS,” Proceedings of the 9th International Symposium on Spatial Data Handling. 1–12.

K A. Raju, P.K Sikdar and S.L Dhingra, (1998) “Micro-simulation of residential location choice and its variation,” Environment and Urban Systems, 22(3): 203–218

Lai, S.-K. (1998). “From organized anarchy to controlled structure: effects of planning on the garbage-can processes,” Environment and Planning B: Planning and Design. 25: 85–102.

Lai, S.-K. (2003). “Effects of planning on the garbage-can decision processes: a reformulation and extension,” Environment and Planning B: Planning and Design. 30: 379–389.

Lai, Shih-Kung (2006). “A spatial garbage-can model,” Environment and Planning B: Planning and Design, 33 (1): 141–156.

Lai, Shih-Kung and Chen, Yo-Jen (1999). “A dynamic exploration into land uses and transportation networks interaction based on cellular automata simulations,” paper presented at the 1999 International Symposium of City Planning, Tainan, Taiwan.

Lai, Shih-Kung and Haoying Han (2009). Complexity: New Perspectives on Urban Planning. Beijing: China Architecture and Building Press.

Li,X.,Yeh,A.G.O., (2000) “Modeling sustainable urban development by the integration of constrained cellular automata and GIS,” International Journal of Geographical Information Science, 14(2): 131–152.

Ligtenberg A., et al., (2010) “Validation of an agent-based model for spatial planning: A role-playing approach,” Computers, Environment and Urban Systems, 34(5):424–434.

Mandelbrot, B. B. (1983). The Fractal Geometry of Nature. New York: W.H. Freeman.

Ma Y., et al., (2010) “Urban Growth Simulation for Spatial Strategic Plan of Chuangdong Area, China,” 18th International Conference on GeoInformatics, pp 1–6.

Neuman, M., 2005, The compact city fallacy, Planning Education and Research 25(1), pp. 11–26.

Nowak, M.A. and R. M. May (1993) “The spatial dilemmas of evolution,” International Journal of Bifurcation and Chaos. 3(1): 35–78.

Nowak, M. A. (2006). Evolutionary Dynamics: Exploring the Equations of Life. Cambridge, Massachusetts: The Belknap Press of Harvard University Press

Padgett, J. F. (1980). “Managing garbage can hierarchies,” Administrative Science Quarterly, 25(4): 583–604.

Parker D. C. and Filatova T., (2008) “A conceptual design for a bilateral agent-based and market with heterogeneous economic agents”, Computers, Environment and Urban Systems, 32(6):454–463.

Saarloos D. J.M., Arentze T. A., Borgers A. W.J. and Timmermans H. J.P., (2008) “A multi-agent paradigm as structuring principle for planning support systems,” Computers, Environment and Urban Systems, 32(1): 29–40.

Schaeffer, P. V. and L. D. Hopkins (1987). “Planning behavior: The economics of information and land development,” *Environment and Planning A*, 19: 1211–1232.

Torrens P. M., (2007) “A Geographic Automata Model of Residential Mobility,” Environment and Planning B: Planning and Design, 34: 200–222

Torrens P. M. and Beneson I., (2005) “Geographic Automata Systems,” International Journal of Geographical Information Science, 19(4): 385–412

Wu, F., (2002) “Calibration of stochastic cellular automata: the application to rural–urban land conversions,” International Journal of Geograghic Information Science, 16(8): 795–818.

Zellner M. L. et al., (2008) “A new framework for urban sustainability assessments: Linking complexity, information and policy,” Computers, Environment and Urban Systems, 32(6): 474–488

Zhang H., Zeng Y.N., Ling B., Yu X.J., (2010) “Modelling urban expansion using a multi agent-based model in the city of Changsha,” Geographical Sciences, 20(4): 540–556.