An Agent-Based Approach to Environmental and Urban Systems within Geographic Information Systems

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1 INTRODUCTION

Both environment and urban systems are complex systems that are intrinsically spatially and temporally organized. Geographic information systems (GIS) provide a platform to deal with such complex systems, both from modeling and visualization points of view. For a long time, cell-based GIS has been widely used for modeling urban and environment system from various perspectives such as digital terrain representation, overlay, distance mapping, etc. Recently temporal GIS (TGIS) has been challenged to model dynamic aspects of urban and environment system (e.g., Langran [25], Clifford and Tuzhilin [9], Egenhofer and Golledge [14]), in pursuit of better understanding and perception of both spatial and temporal aspects of these systems.

In regional and urban sciences, cellular automata (CA) provide useful methods and tools for studying how regional and urban systems evolve. Because of its conceptual resemblance to cell-based GIS, CA have been extensively used to integrate GIS as potentially useful qualitative forecasting models. This approach intends to look at urban and environment systems as self-organized processes; i.e., how coherent global patterns emerge from local interaction. Thus this approach differentiates it from TGIS in that there is no database support for space-time dynamics.

An agent-based approach was initially developed from distributed artificial intelligence (DAI). The basic idea of agent-based approaches is that programs exhibit behaviors entirely described by their internal mechanisms. By linking an individual to a program, it is possible to simulate an artificial world inhabited by interacting processes. Thus it is possible to implement simulation by transposing the population of a real system to its artificial counterpart. Each member of population is represented as an agent who has built-in behaviors. Agent-based approaches provide a platform for modeling situations in which there are large numbers of individuals that can create complex behaviors. It is likely to be of particular interest for modeling space-time dynamics in environmental and urban systems, because it allows researchers to explore relationships between microlevel individual actions and the emergent macrolevel phenomena.

An agent-based approach has great potential for modeling environmental and urban systems within GIS. Previous work has focused on modeling people-environment interaction [13], virtual ecosystems [21], and integration of agent-based approach and GIS [21]. Rodrigues and Raper [31] have employed spatial agents to distinguish those agents for geographic information processing. They have defined spatial agents as agents that make spatial concepts computable for the purpose of spatial simulation, spatial decision making, and construction of interface agents for GIS. Ferrand has applied agent technology to both complex diffusion processes and cartographic generalization.

This chapter explores this possibility with some practical application examples from urban and environmental systems. The remainder of the chapter is organized as follows. Section 2 briefly reviews current approaches of cell-based GIS and CA, as both have certain conceptual resemblances to agent-based approaches. Section 3 introduces the autonomous agent systems, fundamentals, and software platforms of multiagent simulation (MAS). Sections 4, 5, and 6 present a set of examples of urban and environmental modeling using MAS and, finally, section 7 draws the conclusions.

2 CELL-BASED GEOGRAPHIC INFORMATION SYSTEMS AND CELLULAR AUTOMATA MODELING

Because of its spatial structure, cell-based GIS—still considered to be a very important type of GIS—is very suitable for spatial analysis. In particular, its data structure is very similar to a satellite image; cell-based GIS is considered to be very important for the integration of satellite data in GIS. From the analytical point of view, the cell-based data format is often considered to be an intermediate process for vector GIS. To date, cell-based GIS has been widely used in the following areas [19]:

- map algebra,
- distance mapping,

- topographic feature extraction and surface description, and
- surface interpolation.

Map algebra probably is one of most conceptual framework for spatial modeling in cell-based GIS. It is a set of formal languages for spatial analysis and modeling. The idea was developed from the notion of a map, so it is often referred to as cartographic modeling [34]. A map is a commonly accepted metaphor for spatial representation. Indeed, it has been used in the map algebra for spatial representation and analysis. A map is a model of space in reduced scale which represents multiple characteristics. A map layer (or simple layer) is much like a conventional map, but each layer has one single characteristic, such as a street layer, a land use layer, etc. Each layer consists of numerous locations (or cells). A set of locations at a specified cartographic distance and/or directions from a particular location is defined as neighborhood. A set of locations with the same category is referred to as zone. Thus a layer and its components (locations, neighborhoods, and zones) constitutes the basic notions of map algebra, on which a range of operations is defined.

Based on the above-introduced notions, a range of operations have been defined for the purpose of spatial modeling and analysis. These operations, in terms of their scopes of imposed operations, can be categorized as five types:

- per-cell (local)
- per-neighborhood (incremental)
- per-neighborhood (focal)
- per-zone (zonal)
- per-layer (global)

Local operators are functions of a specific cell on one or more layers, i.e., to compute a new value for every location as a function of one or more existing values associated with that location. Per-neighborhood operations can be classified according to the nature of the spatial relationship between each neighborhood and its focus: incremental operations and focal operations. Incremental operators are functions of specific locations and the geometric condition represented at those locations. Focal operations are those that compute each location's new value as a function of the existing values, distance, and/or directions of neighboring (but not necessarily adjacent) locations on a specified map layer. Zonal operators are functions of irregular neighborhoods on one or more layers. Global operations are used for the generation of Euclidean distance and weighted cost distance maps, shortest path maps, nearest-neighbor allocation maps, for the grouping of zones into connected regions, for geometric transformations, for raster-vector interconversion, and for interpolation.

Distance mapping involves calculation of Euclidean distance, isotropic cost distance, and directional path distance, from or to a set of source locations. It can help to generate a buffer zone of geographic objects such as

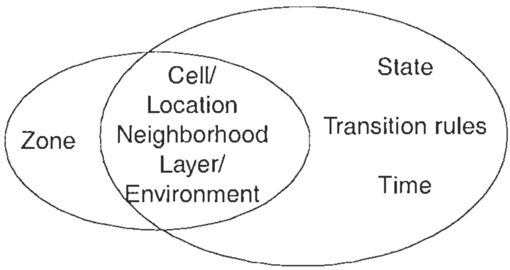

FIGURE 1 Basic notions of CA with overlaps to those of cell-based GIS.

rivers and roads. Topographic feature extraction and surface description have wide application in hydrological modeling such as the derivation of watershed, stream networks, flow accumulation, and flow length. Cell-based GIS is often used for surface interpolation. All these functionalities involve expensive computation.

Cell-based GIS provides a valuable tool for spatial modeling and analysis, which has wide application in urban and environmental systems. However, it inherently lacks the ability to deal with the temporal dimension. As stated by Takeyama and Couclelis [33], map algebra does not deal explicitly with spatial relations and interaction among locations. In contrast, CA, initially developed from computer science, are essentially designed for spatial interaction and dynamic phenomena. It shares with cell-based GIS a number of concepts, such as cell, neighborhood, and environment. Additionally CA provide three more notions to handle dynamics, i.e., transition rules, states, and time (fig. 1).

States or cell states represent the states of each cell, e.g., dead or alive. Transition rules are the heart of CA since they represent the process as time goes by. A typical example of transition rule (Life) reads as "if a cell is off, it turns on if exactly three of its neighbors are on. If a cell is on, it stays on if exactly two or three neighbors are on; otherwise it turns off." Thus interaction not only occurs at the space level but also on the time scale.

Because of its ability to deal with both space and time, CA have been widely used for space-time dynamics modeling in the context of GIS. In this connection, the most influential application field is urban dynamics. However, cities are even more complex and are beyond the capability of standard CA. Thus, in order to deal with more complex situations, standard CA have been extended in various ways, by considering, for instance, more states, a larger neighborhood, and more complex transition rules. Various efforts have been made to use CA for space-time dynamics, including among others:

- *CA for urban and regional dynamics.* Urban and regional systems are essentially dynamics and complex processes and CA have been intensively used in the context of simulating and predicting these dynamic processes (see White [36] for an overview). Both standard CA and extended CA have used and have been proposed for very complex urban and regional dynamics. These efforts provide deeper insights into urban and regional systems from both the microlevel and the macroscale.

- *CA for environmental modeling.* Environmental modeling is probably one of promising application areas of GIS, particularly in modeling space-time phenomena such as wildfire propagation [8] and ecosystem [6]. Burrough [5] has recently done a comprehensive overview of dynamic modeling as a set of tool kits for geocomputation.
- *Integration of GIS and CA.* Full integration of GIS and CA has also been considered. For instance, Wagner [35] has examined the similarities of CA and raster GIS, and the potential to implement one to another is demonstrated. Of particularly interest is the effort made by Couclelis and Takeyama [11] who proposed a general mathematical framework for the integration of GIS and CA based on the notion of proximal space [11].

However, many geographic phenomena, essentially involved with space-time dynamics, can be thought to have emerged from individual interactions. Usually there is more than one type of agents involved, which is beyond the capacity of CA modeling. In this respect, autonomous agents seem to have a high possibility for extension to modeling space-time dynamics.

2.1 AGENT-BASED MODELING

What is an agent or autonomous agent? It has been a very controversial topic these days. Based on a comprehensive survey on the existing definitions of autonomous agent, Franklin and Graesser [18, p. 25] have formalized an autonomous agent as "a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to affect what it senses in the future." Thus an autonomous agent could be humans, other animals, autonomous mobile robots, artificial life creatures, and software agents. A few things are quite important for an agent.

First of all, an agent is only adapted to its own environments; if an agent leaves the environment, it may no longer be an agent. We know that a certain kind of animal lives in a certain kind of natural environment. Change of the environment will dramatically change their adaptation (which is limited). In other words, different agents have different environments. Real-world agents live in the real world; software agents "live" in computer operating systems, databases, networks, etc.; artificial life agents "live" in artificial environments such as on a computer screen or in its memory [18]; and spatial agents live in geographic space. Generally, two kinds of environments are identified for different modeling situations. A distributed environment is a CA-like space

TABLE 1 Properties of agents (after Franklin and Graesser [18]).

Property	Meaning
reactive	responds in a timely fashion to changes in the environment
autonomous	exercises control over its own actions
goal-oriented/ proactive/ purposeful	does not simply act in response to the environment
temporally continuous	is a continuously running process
communicative/ socially able	communicates with other agents, perhaps including people
learning/ adaptive	changes its behavior based on its previous experience
mobile	able to transport itself from one machine to another
flexible	actions are not scripted
character	believable "personality" and emotional state

which consists of a set of cells, whereas a centralized environment has a unique structure [16].

Secondly, sense and action are two important properties of an agent, which determine how they behave in their environment. Agents can be named as reactive agents and cognitive (or deliberative) agents, which are respectively the low and high end of being agents, according to the range and sensitivity of their sense, and the range and effectiveness of their actions. In response to what is sensed, agents take action autonomously. The differences between reactive agents and cognitive agents can be further characterized as follows. Humans, when they navigate in a complex urban system, can be treated as the high end of being agent, in that they not only interact with each other as reactive agents, but also remember what they have sensed, and they can also do some global planning by the use of maps, relevant sources of information, and even previous experience. Agents do things with their own agenda and, in an agent system, none of them acts as a sort of leader or coordinator.

An agent is treated in the above definition as a system. To describe an autonomous agent, it is necessary to describe its environment, sensing capabilities, and actions. On the other hand, an agent can also be treated as a part of an environment, which has a variety of properties such as reactive, autonomous, goal-oriented, temporally, continuous, communication, learning, mobile, flexible, and character (table 1, Franklin and Graesser [18]). The range of properties is ordered in the sequence of intelligibility, from low to high end of being autonomous agents. So agents are not just objects; they are those objects with spatial communication mechanisms that allow them to interact each other.

There is a special kind of agent called a "real-life agent" which aims to simulate the real-world counterpart by means of intuitive visualization. SimCity system is a very good example in this respect. It is a computer game for children of all ages. Agents in SimCity could be various vehicles, pedestrians, and other objects with senses which can act on city environments. So real-life agents are directly visible to users. This property provides the possibility for scientists to construct an exploratory simulation of real life, and to use the computer as a laboratory for studying the informational structure of complex systems.

3 MULTIAGENT SIMULATIONS

Multiagent simulation (MAS) is an agent system with multiple agents. By using multiagent simulation rather than multiagent systems [16], we intend to stress the SimCity-like agent systems which combine the capacities of visualization and modeling together. In contrast to SimCity, MAS usually can be customized in an exploratory way, which means end users can set a range of parameters for exploratory purposes.

Such simulations can be summarized as a set of the following elements: agents, objects, environments, and communications. These are described by the quadruplet:

$$\langle \text{agents, objects, environments, communications} \rangle$$

where *agents* are the set of all the simulated individuals; *objects* are the set of all represented passive entities that do not react to stimuli (e.g., buildings, street furniture in urban environments); *environments* are the topological space where agents and objects are located, where they can move and act, and where signals (sounds, smell, etc.) propagate; and *communications* are the set of all communication categories, such as voice, written materials, signs, etc. Behaviors are generated by the ways in which agents interact or communicate with other objects and their environment(s), and thus can be seen as properties of any of these although they are usually considered to be properties of agents. Thus an MAS can be thought of as the combination of CA and autonomous agents (fig. 2).

A MAS provides a platform for space-time dynamics. We are developing agent-based dynamic models in a number of different contexts. The MAS treats a population of interacting objects in a decentralized or distributed manner, each agent having an independent behavior but with the ability to communicate (with each other). Two types of agent can be identified: reactive agents whose behavior depends entirely upon how they react to their environment; and cognitive agents with plans or protocols who usually interact with one another, are influenced by their environment, but whose behavior is largely self-driven. In the examples sketched here, we will deal exclusively with

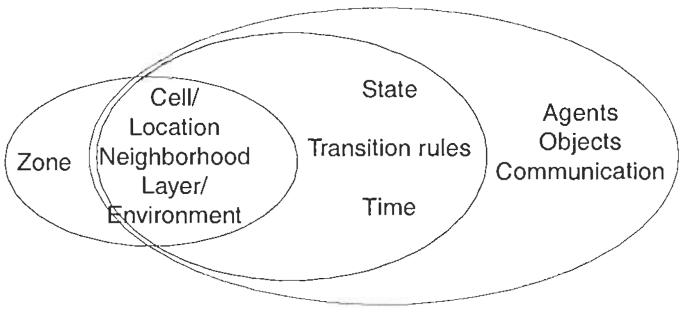

FIGURE 2 Notions of MAS and those of cell-based GIS and CA.

reactive agent-based models where the environment is extremely important to the simulation of behavior.

Over the past years, much effort has been made in order to provide a easily used software platform for scientists to undertake studies on complex systems. Among others, the Swarm project [26] is one of the ambitious projects, which intends to construct an MAS platform for exploring various complex systems. It is designed to serve as a generic platform for modeling and simulating the complex behavior of space-time dynamics. It provides a set of classes for defining agents' behavior, properties, etc. using the computer language Objective-C. Based on Swarm system, various projects have been undertaken, e.g., Transims [32] and Sugarscape [15]. However, Swarm does not, in contrast to what it promised, provide an easily used platform for MAS for noncomputer experts. Attempts have been made to provide a more easily used platform for average users based on Swarm engine [22].

StarLogo [30], a MAS platform with exploratory capability, provides an experimental counterpart of real-world complex systems. It was developed from Logo, a programming language for children [28]. Now the new developed StarLogo has dramatically expanded the simulation of complex systems; various applications have been developed for simulating real-life phenomena such as bird flocks, traffic jams, ant colonies, and market economies (for a set of extendible models, see homepage on ⟨http://www.ccl.tufts.edu/cm/models/⟩). StarLogo consists of three characters: turtles, patches, and observer. Turtles are actually autonomous agents living in CA-like space, each cell of which is called a patch; interaction can occur between turtles, or between turtles and patches through visual and chemical senses. In response to what is sensed, turtles can move around with behaviors such as speed up/down, and heading differently. It should be noted that the observer is not the leader or coordinator, but simply responsible for creating agents in the virtual world. In other words, global patterns created by agents are not due to the coordinated work of the observer. The architecture of the system pictured in figure 3 indicates

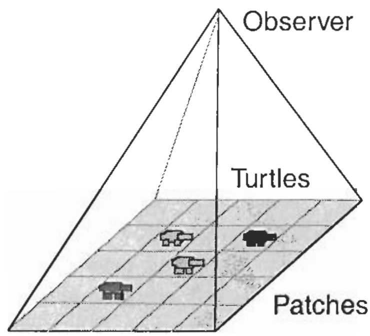

FIGURE 3 The patch-turtle-observer model.

in spatial terms that turtles react to patches, but both turtles and patches are subject to the controls posed by the observer.

We have applied this model to many different kinds of problems, all of which involve some kind of motion or movement. Here we will describe three different processes that depend on moving agents in response to the attributes of their environment which are coded in patches. We will present traditional models of motion in a spatial environment based on traffic which we have developed for pedestrian movement, models of flow dynamics which relate to how watersheds and rivers are formed, and models of how agents can be used to explore the geometry of local environments in buildings through ideas pertaining to what can be seen relative to the view (see Itami [23] for intervisibility analysis).

Many space-time dynamics can be characterized as the interaction at both space and time dimensions. For human or vehicle movement in an urban system, each individual interacts with each other within the neighborhood and the environment to make a movement decision. For example, a driving behavior can be simply defined as, "a car speeds up if there is no cars ahead, otherwise slowdown or overtakes." These behaviors lead to traffic congestion [30]. With an MAS, many space-time dynamics can be modeled.

4 PEDESTRIAN MOVEMENT IN URBAN SYSTEMS

The patterns of people's movement in urban systems characterize one of the very important research areas in urban studies. It has been a big concern in a range of disciplines such as traffic engineering, urban design, and planning. Attraction and spatial configuration are traditionally considered to be very important in characterizing the complex phenomena. It is considered to be very important that spatial configuration is the basic driver for people's movement in urban systems. Often it is found that streets which are well connected attract more people. In other words, integrated streets tends to have more people movement and, on the other hand, segregated streets tend to have less people movement.

Within an urban system, there are two elements that have some direct effect on people movement. From the ecological psychology [20] point of view, human behavior in urban systems can be thought of as a stimulus-reaction model; i.e., what is perceived determines how to act. Thus people's movement can be considered in some sense to be self-organized phenomena through interaction between each other and their environment.

In the model following, we intend to set up a counterpart of pedestrian movement in an urban system, in order to explore this complex phenomena. The aim is to investigate how people's movement is affected by urban morphological structure. Here the structure is described by space syntax, with an integration value describing the properties of urban structure. In the simulation system, the virtual pedestrians have no sense of global structure. They just explore the open space locally and learn themselves from what they have explored. At every moment, we collect pedestrian flows in each street segment for the analytical purposes. The procedure can be described as follows:

Step 1: create a number of pedestrians in the center of an urban system.
Step 2: let all pedestrian move around without encountering obstacles; count the pedestrian rates in each street segment.
Step 3: visually check if all pedestrians have distributed all around; if yes, output pedestrian rates for analysis; if no, go to **step 2**.

As an example, consider figure 4, which shows a small urban system with a relatively regular grid structure of an urban system. Let us first use space syntax to analyze the structure. The analysis result is shown in (a), where the structure parameter of local integration is colored by a spectrum legend; i.e., red represents highest value and blue represent lowest value. Figure 4(b) is a snapshot of the simulation process. The detailed scatter plot is shown in figure 5, where the r-square tends to be 0.7.

Now we slightly change the simulation, and let only one live pedestrian in the system, to see how the shortest paths emerge from locations. In the same urban system, pedestrians can be modeled as working out the route from a starting point or origin called (A) to a preset destination (B), as we show in figure 6. As each pedestrian reacts locally to what is in the surrounding neighborhood, we can compute the crow-fly distance from the point reached in the path so far to the ultimate destination, and then move the agent toward this point in terms of the local geometry which usually poses many obstacles to moving in a straight line. At each stage the crow-fly distance is recomputed, and the agent adapts locally. This process is a crude simulation of the dynamic programming algorithm used to compute shortest paths, first suggested by Bellman and Dijkstra. A typical path is shown in figure 6.

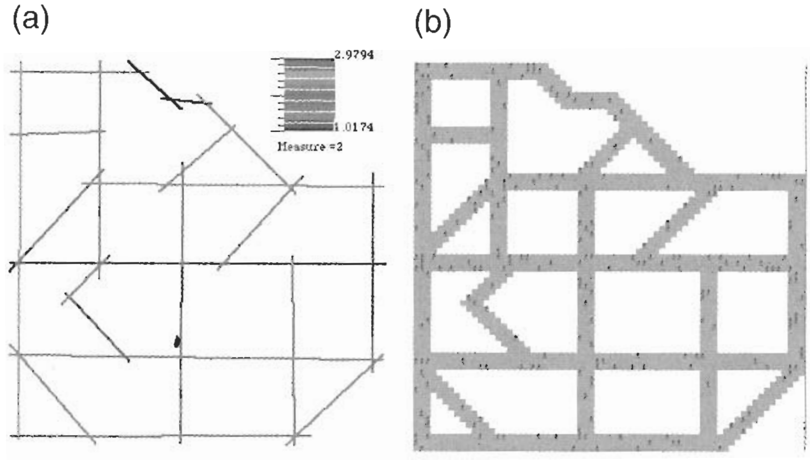

FIGURE 4 A small urban system with a relatively regular grid structure of an urban system.

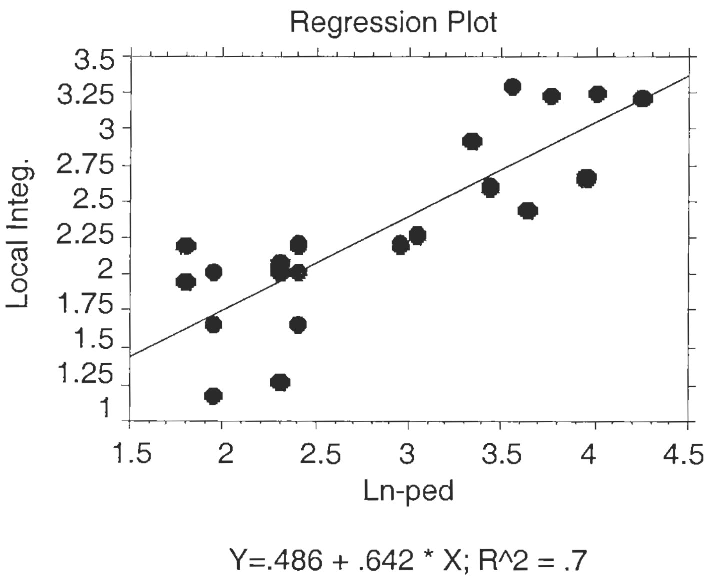

FIGURE 5 The regression plot between local integration and pedestrian rates.

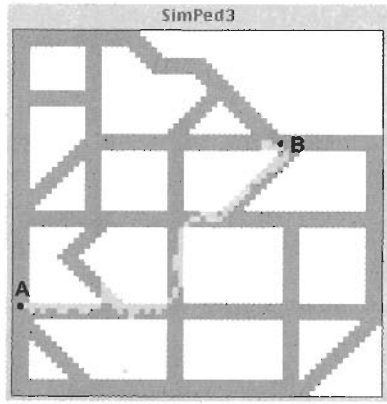

FIGURE 6 A shortest path emerging from local interactions.

As an exploratory platform, the program allows us to experiment repeatedly with the behaviors of agents. Surprisingly, each time the agent works out the route, the routines differ slightly, but in principle are the shortest paths. In the simulation, we only set the destination, and then let the agent explore the space in terms of local interaction. It should be noted that the shortest path does not emerge every time. For instance, if we set starting point and destination at opposite side of a street block, most likely the agents will be confused, and have problems working out a routine. Incorporating some global knowledge in the agent solves this problem. One option would be to apply the following visibility parameter to patches; i.e., the agent continuously interacts with patches and obtains visibility properties to guide its navigation.

5 VISUAL FIELDS IN URBAN SYSTEMS

A view shed, or what can be seen from a certain location, has been a very important issue in environmental modeling. View-shed analysis using the digital terrain model (DTM) has long been one of standard functions of the GIS. However, visual field in urban systems has not received as much attention in the GIS community. In contrast, researchers in architecture and urban studies have paid much attention to how people perceive space. Visual fields are determined by local geometry, moving agents systematically through space in contrast to computing geometric lines of sight [2]. It has been a very important to understand how people perceive and understand and move around their environment. For instance, Hillier's space syntax covered in the above section is based on the notion of visibility, and Peponis et al. [29] have taken this a step further by expanding the partition space into an infinite number of convex spaces in terms of visual perception.

In the fields of robotics and computer vision, visual fields have been very important for robot navigation—i.e., path planning [7, 27]. For instance, before beginning a forward movement, a robot has to check whether the movement is safe. The same check is performed repeatedly during the movement to prevent collisions. In the above example about pedestrian movement, we have used a conflict avoidance procedure, but that was a local check, which means that the pedestrian only can see one step away.

Computation of visual field is a very intensive task [12], because it involves computing the line of sight or possible occlusions between obstacles. Instead it appears that agent-based approaches provide a fascinating platform to achieve the task. The idea is that we fill the space with agents and that we get each agent to explore their environment as far as they can before they come to an obstacle that impedes their path. They make this exploration in every direction or rather in enough directions to cover the entire space which is represented as a raster. In essence the technique depends upon setting as many agents as there are raster cells in the open space between obstacles—rooms, buildings etc.—and then exhaustively computing all areas which they can visit from their particular starting point. Later on with what we have explored, we can explore the space dynamically to show the visual fields from each location. The algorithm is described as follows,

Step 1: fill all open space with agents.
Step 2: alpha = 0.
Step 3: let all agents move to this direction of alpha; and accumulate distance until hit the spatial obstacle.
Step 4: alpha = alpha + increment.
Step 5: check if alpha = 360 if yes, stop; if no go back to **step 3**.

As an example, figure 7 illustrates part of an urban system where the blocks are supposed to be spatial obstacles such as buildings. After the computation preprocess shown above, each location of the space has a parameter which shows how much one can see from the standing point of view. As the mouse moves around, a series of visual fields will be seen dynamically on screen. One typical series is shown in figure 7 (b).

The above model has been applied to some real urban systems such as Wolverhampton town center and London Tate Gallery. With the model, we have constructed spatial properties such as most visible space (see Batty and Jiang [1] for details). Various models have demonstrated that agent-based approaches to the computation of visual fields have been very efficient and effective. However, there exist some problems. For instance, because of the cellular space adaptation, there is an unavoidable gap in the displayed visual field, regardless of the fineness of the adapted grid.

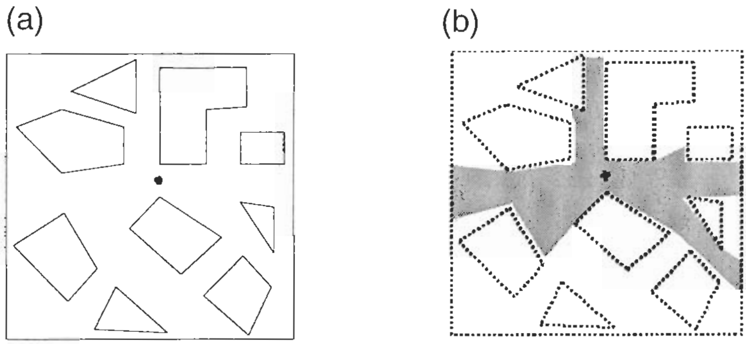

FIGURE 7 The visual fields dynamically shown using agent-based approaches.

In the visual perception of environment, Gibson [20] proposed the idea of an optic array which is considered to be critical in human behavior. However, it is indeed difficult to visualize an optic array. Benedikt and Burham [3] have investigated how Gibson's optical arrays can be objectively simplified as isovists. It is also found that isovists, indeed, do affect human perception in urban environments. Since isovists can be considered in a global sense, it appears to be possible to extend an agent's sense from local to global through interaction with the environment. In the mean time, the visual fields are stored as a patch variable with which agents can interact, and this could lead to more deliberate or cognitive agents.

6 WATERSHED DYNAMICS AND WILDFIRE DIFFUSION IN ENVIRONMENTAL SYSTEMS

There are many phenomena in environment systems that can be characterized as a kind of interaction between agents and environment. For example, spatial diffusion such as air pollution, heat diffusion, and water floods can be considered as interaction between those objects, such as pollutants, heat, and water, with their respective environments. In the following discussion, we discuss two examples from environmental systems.

The first example is about watershed dynamics. We first generate a terrain, and smooth the surface and apply color to make it appear more realistic. Then we create a group of water droplets and let them randomly distribute over the surface. We use greedy search strategies to find the lowest location within a neighborhood. The key step is to use a greedy search to find local maximum (minimum). The procedure can be described as follows:

Step 1: create a random terrain surface and color it.

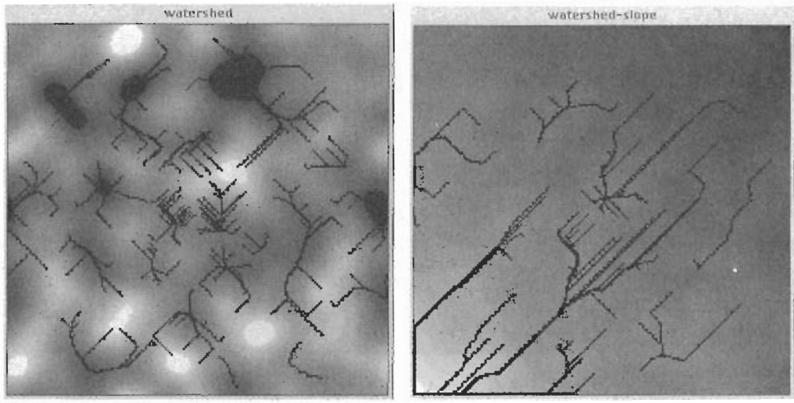

FIGURE 8 Stream networks created from the local interaction of agents with their environment.

Step 2: create a number of water droplets and randomly locate them on the terrain surface.
Step 3: use a greedy search to find the highest elevation and move to the local minimum.
Step 4: check if all water droplets are in local minimum; if yes, stop; if no, go to **step 3**.

As an example, we assume an idealized terrain in which the patches code the height of a surface without any vegetation or forest cover. Stream networks are created by dropping water randomly onto the terrain, and then treating each droplet as an agent whose heading (direction of flow) is computed as a function of elevation in its neighborhood. Figure 8 shows two different terrain models and stream networks that were generated. In the experiment, there are a number of things we can explore. For instance, we can change the number of water droplets, we can change terrain surface, and we can change radius of the greedy search.

The second example is about wildfire diffusion that has been discussed elsewhere by Resnick [30]. Since it is a very typical example for environmental systems in GIS, we briefly discuss the example as evidence to support our position. How does wildfire spread over the forest? It depends on many factors. One critical factor is the density of trees; i.e., if the forest is dense enough, the fire is likely to spread all over; otherwise, it is likely to extinguish. So the exploration of fire diffusion with different forest density could be very interesting in investigating spatial diffusion phenomena. Using a different adaptation than Resnick, we assume that the fire is the agents and the forest is the en-

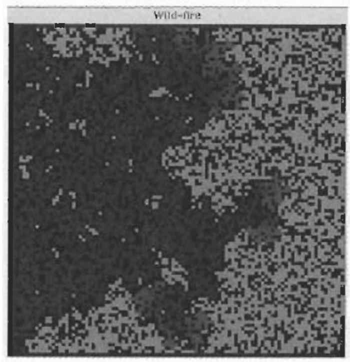

FIGURE 9 A snapshot of fire diffusion in forest with density of 61%.

vironment. Thus the fire diffusion can be thought of as spatial interaction between fire and trees. A simple fire behavior can be described as

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IF a cell is surrounded by more than one tree
THEN [fire diffuse]
ELSE [fire is extinguished]
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As an example, figure 9 shows a fire diffusion pattern assuming a density of 61%.

From both the watershed and fire examples, we have reached a conclusion, as in the above example, how the local action gives rise to a global pattern. Obviously this example is far from complete, since factors such as gravity or speed of flow have not yet been considered. In addition, the fire diffusion example could consider wind factor or different types of trees in order to generate a more robust model.

7 CONCLUSIONS

Agent-based approaches have been shown to have many advantages over existing approaches for modeling environmentation and urban systems problem. MAS provides an exploratory platform for users to test hypotheses behind the space-time dynamics. It provides a platform for researchers to experiment and play what-if games with complex spatiotemporal processes, i.e., using a computer as a laboratory for the study of complex, adaptive systems. In this chapter, we have explored and illustrated the potential of the MAS as useful tools for space-time dynamics. We have shown its advantages over existing approaches such as cell-based GIS and CA, not only for space-time dynamics but also for some tasks which need expensive computation. Future work should attempt to go beyond the limitation of reactive agents, to have cognitive or deliberative agents incorporated in the MAS. Future work also implies a fully integration of the MAS and the GIS.

REFERENCES

[1] Batty, M., B. Jiang, and M. Thurstain-Goodwin. "Local Movement: Agent-Based Models of Pedestrian Flows." Working Paper Series, CASA, 1998.

[2] Benedikt, M. L. "To Take Hold of Space: Isovists and Isovist Fields." *Envir. & Plan. B* **6** (1979): 47–65.

[3] Benedikt, M. L., and C. A. Burnham. "Perceiving Architectural Space: From Optical Arrays to Isovists." In *Persistence and Change*, edited by W. H. Warren, R. E. Shaw, and N. H. Hillsdale, 103–114. Hillside, NJ: Lawrence Erlbaum, 1984.

[4] Berry, J. K. "Cartographic Modeling: The Analytical Capabilities of GIS." In *Environmental Modeling with GIS*, edited by M. F. Goodchild, B. O. Parks, and L. T. Steyaert, 58–74. New York: Oxford University Press, 1993.

[5] Burrough, P. A. "Dynamic Modeling and Geocomputation." In *Geocomputation: A Primer*, edited by P. A. Longley, S. M. Brookes, J. McDonnell, and B. MacMillan, 165–191. Chichester, UK: Wiley, 1998.

[6] Camara, A. S., R. Ferreira, and P. Castro. "Spatial Simulation Modeling." In *Spatial Analytical Perspectives on GIS*, edited by M. Fisher, H. J. Scholten, and D. Unwin. London: Taylor & Francis, 1996.

[7] Cameron, S., and P. Probert. *Advanced Guided Vehicles: Aspects of the Oxford AGV Project.* London: World Scientific, 1994.

[8] Clarke, K. C., and G. Olsen. "Refining a Cellular Automaton Model of Wildfire Propagation and Extinction." In *GIS and Environmental Modeling: Progress and Research Issues*, edited by M. F. Goodchild, L. T. Steyaert, B. O. Parks, C. Johnstone, D. Maidment, M. Crane, and H. Glendinning, 333–338. Fort Collins, CO: GIS World, 1993.

[9] Clifford, J., and A. Tuzhilin, eds. *Recent Advances in Temporal Databases.* Berlin, Springer-Verlag, 1995.

[10] Couclelis, H. "Cellular Worlds: A Framework for Modeling Micro-Macro Dynamics." *Envir. & Plan. A* **16** (1985): 141–154.

[11] Couclelis, H. "From Cellular Automata to Urban Models: New Principles for Model Development and Implementation." *Envir. & Plan. B: Plan. & Design* **24** (1997): 165–174.

[12] Davis, L. S., and M. L. Benedikt. "Computational Models of Space: Isovists and Isovist Fields." *Comp. Graphics & Img. Proc.* **11** (1979): 49–72.

[13] Deadman, P., and R. Gimblett. "The Role of Goal-Oriented Autonomous Agents in Modeling People-Environment Interactions in Forest Recreation." *Math. & Comp. Model.* **20(8)** (1994): 121–133.

[14] Egenhofer, M. J., and R. G. Golledge, eds. *Spatial and Temporal Reasoning in GIS.* New York: Oxford University Press, 1998.

[15] Epstein, J., and R. Axtell. *Growing Artificial Societies: Social Science from the Bottom-Up.* Princeton, NJ: Princeton University Press, 1996.

[16] Ferber, J. *Multi-agent Systems: An Introduction to Distributed Artificial Intelligence.* Reading, MA: Addison-Wesley, 1999.

[17] Flake, G. W. *The Computational Beauty of Nature: Computer Explorations of Fractals, Chaos, Complex Systems, and Adaptation.* Cambridge, MA: MIT Press, 1998.

[18] Franklin, S., and A. Graesser. "Is It an Agent, or Just a Program?: A Taxonomy for Autonomous Agents." In *Intelligent Agents III: Agent Theories, Architectures, and Languages*, edited by J. P. Muller, M. J. Wooldridge, and N. R. Jennings, 21–35. Berlin: Springer, 1997.

[19] Gao, P., C. Zhan, and S. Menon. "An Overview of Cell-Based Modeling with GIS." In *GIS and Environmental Modeling: Progress and Research Issues*, edited by M. F. Goodchild, L. T. Steyaert, B. O. Parks, C. Johnstone, D. Maidment, M. Crane, and H. Glendinning, 325–331. Fort Collins, CO: GIS World, 1993.

[20] Gibson, J. J. *The Ecological Approach to Visual Perception.* Boston: Houghton Mifflin, 1979.

[21] Gimblett, R. "Virtual Ecosystems." *AI Appl. Natl. Res., Agric. & Envir. Sci.* **8(1)** (1994): 77–81.

[22] Gulyás, L., T. Kozsik, P. Czabala, and J. B. Corliss. "Telemodeling—Overview of a System. Short paper presented at "Teleteaching '98," part of IFIP World Computer Congress, held September 1998, in Vienna-Budapest. 1998. Available at ⟨http://www.syslab.ceu.hu/telemodeling/index.html⟩.

[23] Itami, R. "Mobile Agents with Spatial Intelligence." This volume.

[24] Jiang, B. "Multi-agent Simulations for Pedestrian Crowds." In *Simulation Technology: Science and Art*, edited by A. Bargiela and E. Kerckhoffs, 383–387. Also in *Proceedings of the 10th European Simulation Symposium and Exhibition*, held October 26–28, 1998, in Nottingham.

[25] Langran, G. *Time in Geographic Information Systems.* London: Taylor & Francis, 1992.

[26] Langton, C., M. Nelson, and R. Burkhart. "The Swarm Simulation Systems: A Tool for Studying Complex Systems." Santa Fe Institute, Santa Fe, New Mexico, USA. 1995. ⟨http://www.santafe.edu/projects/swarm/⟩.

[27] Moutarlier, P., and R. Chatila. "Incremental Free-Space Modeling from Uncertain Data by an Autonomous Mobile Robot." In *Geometric Reasoning for Perception and Action*, edited by C. Laugier, 200–213. Berlin: Springer-Verlag, 1991.

[28] Papert, S. *Mindstorms: Children, Computers and Powerful Ideas.* New York: Basic Books, 1980.

[29] Peponis, J., J. Wineman, M. Rashid, S. Bafna, and S. H. Kim. "Describes Plan Configuration According to the Covisibility of Surfaces." *Envir. & Plan. B: Plan. & Des.* **25** (1998): 693–708.
[30] Resnick, M. *Turtles, Termites, and Traffic Jams: Explorations in Massively Parallel Microworlds.* Cambridge, MA: MIT Press, 1997.
[31] Rodrigues, A., C. Grueau, J. Raper, and N. Neves. "Environmental Planning using Spatial Agents." In *Innovations in GIS 5*, edited by S. Carver, 108–118. London: Taylor & Francis, 1996.
[32] Smith, A. P., M. Dodge, and S. Doyle. "Visual Communication in Urban Planning and Urban Design." CASA Working Paper 2. University College, London, 1–19, Torrington Place, Gower Street, London, 1998.
[33] Takeyama, M., and H. Couclelis. "Map Dynamics: Integrating Cellular Automata and GIS through Geo-Algebra." *Intl. J. Geograph. Infor. Sci.* **11(1)** (1997): 73–91.
[34] Tomlin, C. D. "Cartographic Modeling." In *The Accuracy of Spatial Databases*, edited by D. J. Maquire, M. Goodchild, and S. Gopal, 115–122. London: Taylor & Francis, 1991.
[35] Wagner, D. F. "Cellular Automata and Geographic Information Systems." *Envir. & Plan. B: Plan. & Design* **24** (1997): 219–234.
[36] White, R. "Cities and Cellular Automata." *Discrete Dynamics in Nature and Society* **2** (1998): 111–125.