AGENT-BASED APPROACH TO MODELLING ENVIRONMENTAL AND URBAN SYSTEMS WITHIN GIS

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ABSTRACT. Both environmental and urban systems are complex systems. Over the past years, GIS have been widely used for modelling environmental and urban systems from a variety of perspectives such as digital terrain representation and overlay analysis using cell-based GIS. Similarly, simulation of urban and environmental dynamics has been achieved with the use of CA-based GIS. In contrast to these approaches, agent-based approach provides a much more powerful set of tools. This allows researchers to set up a counterpart for real environmental and urban systems in computers for experimentation. The concept of self-organisation and the related potential for simulating behaviour in space and time can be contrasted with GIS or new TGIS approaches in which the real world is observed, modelled and represented from a static observer point of view. In this paper, I first outline the agent-based approach as developed in its outset from Distributed Artificial Intelligence (DAI). To illustrate the potential of the agent-based approach in the context of urban and environmental modelling, I provide a set of example scenarios where reactive agents have been used within cellular spaces. To date, only reactive techniques have been employed in cellular spaces; therefore I suggest in the conclusion the use of deliberate or cognitive agents in these models.

KEYWORDS: Multi-agent simulation, visual fields, pedestrian movement, and spatial diffusion

1. INTRODUCTION

Both environmental and urban systems are complex systems. Geographic Information Systems (GIS) provide a technical platform to deal with such complexity in terms of the modelling and visualisation of the phenomena under study. Digital terrain representation, overlay and distance mapping techniques have been widely used in modelling urban and environmental systems over the past years (Goodchild *et al.* 1996, Burrough 1998). The pursuit of a better understanding of the more dynamic spatial and temporal aspects of urban and environmental systems has also been tackled to some extent by Temporal GIS (TGIS) (e.g. Langran G. 1992, Clifford and Tuzhilin 1995, Egenhofer and Golledge 1998).

Cellular Automata (CA) provides useful methods and tools for the study of regional and urban systems evolution. Because of its conceptual resemblance to cell-based GIS, CA has been extensively studied as a potential useful tool for modelling and visualising dynamic phenomena (White 1998). The CA approach considers urban and environmental systems as self-organised processes within which coherent global patterns may be emerged as a result of local interaction. Thus the concept of self-organisation and the related potential for simulating behaviour in space and time can be contrasted with GIS or new TGIS approaches in which the real world is observed, modelled and represented from a static observer point of view.

Initially developed from Distributed Artificial Intelligence (DAI), agent-based approach has emerged as a valuable tool in the exploration of space-time dynamics. The idea underlying agent-based approach is that programs exhibit behaviours described entirely in their internal mechanisms. By linking an individual to a program, it is possible to simulate an artificial world inhabited by interacted processes. Thus it is possible to implement simulation by transposing the population of a real system to its artificial counterpart. Each member of the population is represented as an agent who has built-in behaviours. This approach is likely to be of particular interest in modelling space-time dynamics within environmental and urban systems since it allows researchers to study the relationships between micro-level individual actions and the emergent macro-level phenomena.

The agent-based approach shows great potential for modelling environmental and urban systems within GIS. Previous work in this area has been focused on modelling people-environment interaction (Deadman and Gimblett 1994), virtual ecosystems (Gimblett 1994), and the integration of agent-based approach into GIS (Box 1999). In addition, Rodrigues and Raper (1996) have employed spatial agents to highlight their presence in geographic information processing. They have defined spatial agents as those that make spatial concepts computable for the purpose of spatial simulation, spatial decision making, and construction of interface agents for GIS.

The purpose of this paper is to explore the possibilities of the agent-based approach through some practical examples from urban and environmental systems. The remainder of this paper is organised as follows: Section 2 introduces the autonomous agent concept and the fundamentals of Muli-agent Simulations. Section 3 presents an experiment to investigate how human movement is affected by urban structure within an artificial space. Section 4 explains how the agent-based approach is used to solve problems which otherwise require intensive computational effort. Two final examples (watershed and wild fire) are provided in section 5 to illustrate spatial diffusion within environmental systems. Section 6 draws the conclusions.

2. AGENT-BASED APPROACH

2.1 Agent

What is an agent or autonomous agent? It has been a very controversial topic these days. Based on a comprehensive survey of the existing definitions, Franklin and Graesser (1997, pp. 25) have provided a formal description of the autonomous agent. That is "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 effect what it senses in the future". Thus an autonomous agent could be humans, animals, autonomous mobile robots, artificial life creatures, and software agents.

A few distinctive characteristics are of major importance for an agent. Firstly, agents are environment dependent: once an agent leaves the environment to which it is adapted, it may no longer be considered as an agent. We know that certain animal species live in specific natural environments; any change in the environment they inhabit will dramatically influence their capacity for adaptation (which is limited). In other words, different agents belong to different environments. Real world agents live in the real world; software agents "live" in computer operating systems, databases, or networks; artificial life agents “live” in artificial environments such as a computer screen or its memory (Franklin and Graesser 1997); spatial agents live in geographic space. Generally, two kinds of environments have been identified for different modelling situations. Distributed environment is a CA-like space, which consists of a set of cells, while centralised environment has a unique structure (Ferber 1999).

Secondly, sense and acts are two important properties of an agent, which determine how they behave inside their environment. Agents can be classified as reactive agents and cognitive (or deliberative) agents. They stand respectively at the low and high ends of being agents depending on the range and sensitivity of their sense and the range and effectiveness of their actions. In response to what is sensed, agents undertake actions autonomously. The differences between reactive agents and cognitive agents can be further characterised through the following illustration. When humans navigate in a complex urban system, they may be considered to belong to the high end of being agent in that they not only interact each other as reactive agents but they are also capable of memorising what they have sensed. Moreover, they may also undertake global planning tasks by using relevant sources of information like maps and their own previous experience. Agents act on their own agenda, and no leaders, dictator or co-ordinators may be identified within an agent system.

Table 1: Properties of agents (After Franklin and Graesser 1997)

Property	**Meaning**
Reactive	Responds in a timely fashion to changes in the environment
Autonomous	Exercises control over its own actions
goal-oriented/ pro-active/ 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 behaviour 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

In the above definition, an agent is considered to be a system. In order to describe an autonomous agent, it is essential to describe its environment, its sensing capabilities and its actions. On the other hand, an agent can also be treated as a part of an environment with a variety of properties (Table 1). The range of properties within a particular environment represents the low- to high-end sequence of intelligibility attributed to the autonomous agents at play. Therefore agents are objects equipped with spatial communication mechanisms that allow them to interact with each other.

There is a special kind of agent called “real life agent” who aims at simulating its real world counterpart by means of animated visualisation. SimCity – a computer game for children of all ages – is a very good example in point. Agents in SimCity can be various vehicles, pedestrians, or other objects endowed with senses and able to act upon the city environment. Within this program, real life agents are directly visible to the user. Such a property provides the scientists with the possibility to construct an exploratory simulation of real life and to use the computer as a laboratory where the informational structure of complex systems can be explored out.

2.2 Multi-Agent Simulations

Multi-agent simulation (MAS) is an agent system with multiple agents. By utilising multi-agent simulation rather than multi-agent systems (Ferber 1999), it is intended to stress the SimCity-like agent systems, which combine the capacities of visualisation and modelling together. Moreover, MAS usually may be customised to allow researchers the possibility of setting a range of parameters for exploratory purposes.

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

$$< agents, objects, environments, communications >$$

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, move and act, and where signals (sounds, smell, etc.) propagate; and *communications* are the set of all communication categories, such as voice, written materials, and signs. Behaviours are generated through agent interaction or communication with other objects and their environment(s), and can therefore be seen as properties of objects and/or environments, although they are usually considered to be the properties alone. Thus MAS has a close link to the approaches of cell- and CA-based GIS (Figure 1).

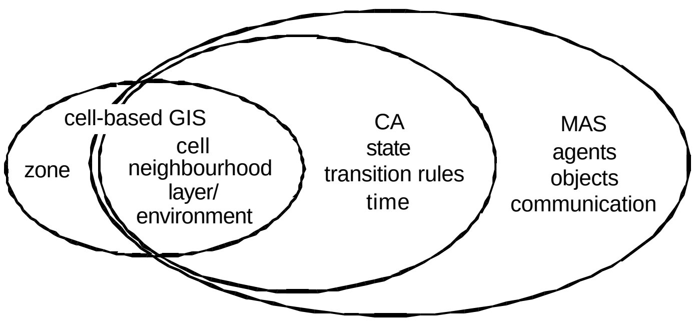


Figure 1: Notions of MAS and those of cell-based GIS and CA

Over recent years, much effort has been made to create MAS platform on which scientists may be able to undertake studies on complex systems. The SWARM project (Langton et al. 1995), among others, is one of these ambitious undertakings. It is designed to serve as a generic platform for modelling and simulating complex space-time dynamics. It provides a set of classes for the definition of agents' properties and behaviours using computer language objective C. Various projects have been made on the SWARM system, e.g. TRANSIMS (Smith et al. 1995). However, SWARM is not an easy-use platform for non-computer scientists. Attempts have been made to provide a simple platform based on SWARM engine (Gulyás et al. 1999).

StarLogo is another MAS platform with the exploratory capability to facilitate experimentation for the real-world complex systems (Resnick 1997). It has been developed from Logo, a programming language for children (Papert 1980). The newly developed StarLogo has dramatically expanded its ability to simulate complex systems. Various applications have been developed, using StarLogo, to simulate real-world 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 a CA-like space whose each cell is called patch; interaction can be occurred between turtles as well as between turtles and patches through visual or chemical senses. Turtles exhibit behaviours such as speed up/down, movement and directional change in response to what they sense. It should be noted that observer is not a leader or co-ordinator, it is just responsible for creating agents within the virtual world. In other words, global patterns created by agents are not due to the co-ordinated work of observer. The architecture of the system can be pictured as in Figure 2.

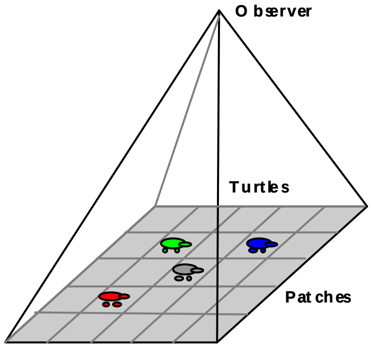


Figure 2: The patch-turtle-observer model

Many space-time dynamics in environmental and urban systems can be characterised as the interaction at both space and time dimensions. Individuals (whether human or vehicular) within an urban system interact with each other and their surrounding environment before making a decision on movement. For example, a typical driving behaviour can be defined as, "a car speeds up if there are no cars ahead; otherwise, it slows down or overtakes." It is this kind of simple behaviour that leads to traffic congestion (Resnick 1997). With MAS, many space-time dynamics can be modelled.

3. PEDESTRIAN MOVEMENT IN URBAN SYSTEMS

The patterns of people's movement in urban systems represent one of the most important areas of research within urban studies. Human movement has been of big concern to a range of disciplines such as traffic engineering, urban design and planning. Spatial configuration is considered essential to the characterisation of such complex phenomena. Moreover, it is commonly accepted that spatial configuration represents the basic drive for people's movement within urban systems (Hillier 1996). It is found that well-connected streets attract large numbers of people, and that well-integrated streets tend to channel large movement of people.

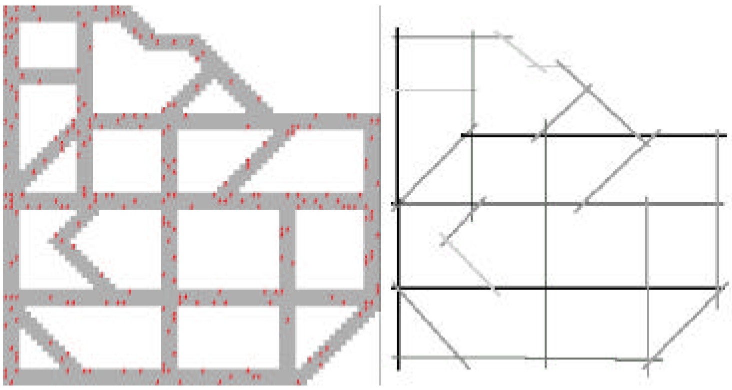
From the ecological psychology (Gibson 1979) point of view, human behaviour in urban systems can be thought of as a stimulus-reaction model, i.e. what is perceived determines the way in which we as human beings act. Thus the people's movement can in some sense be considered to be a self-organised phenomena arising through the interaction between among people and their environment. There are of course some other factors like cultural constraints, security factor, and genders, which influence the above equation (Claramunt 1999).

In the following model, I intend to set up a counter part of pedestrian movement within an urban system in order to explore the complex movement phenomena. The aim is to investigate how people's movement is affected by urban structure. Here the structure is described by space syntax (Hillier and Hanson 1984, Hillier 1996, Jiang, Claramunt and Batty 1999), with integration value describing the properties of urban structure. In the simulation system, the virtual pedestrians have no sense of global structure and they just explore the open space locally and learn from what they have explored. Simultaneously, pedestrian flows are observed in each street segment for analysis purpose. The procedure can be described as follows:

Step 1: generate a number of pedestrians from the centre of an urban system; define their moving behaviour to avoid collisions.

Step 2: let all pedestrians move around without encountering obstacle; measure flow rates in each street segment.

Step 3: visually check if all pedestrians have distributed themselves all around the urban system; if they have (yes), output pedestrian rates for analysis; if they have not (no), go to **step 2**.



(a) (b)

Figure 3: A snapshot of pedestrian simulation and local integration

As an example, let us first use space syntax to analyse the structure of a small urban system shown in figure 3 (a). The analysis result is shown in figure 3 (b), where structure parameter local integration is represented by the darkness of lines, i.e. dark grey represents highest value and light grey represents lowest value. The left side of the figure is also a snapshot of the simulation process. The detailed scatter plot between local integration and pedestrian rates collected from the simulation is shown in figure 4, where r-square tends to be 0.7 (Jiang 1999).

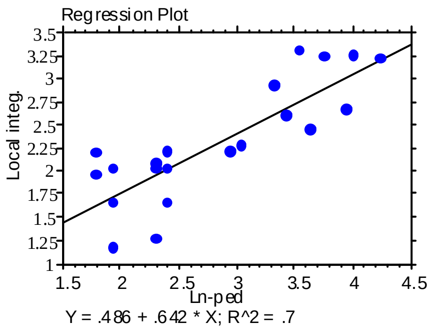


Figure 4: The regression plot between local integration and pedestrian rates

Now let's change the simulation slightly and let only one pedestrian alive in the system to see how shortest paths are emerged from local interactions. In the same urban system, pedestrians can be modelled to calculate the way from a starting point or origin called (A) to a pre-set destination (B) as show in Figure 5. As each pedestrian reacts locally to what is in the surrounding neighbourhood, 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 towards this point in terms of the local geometry. This usually poses many obstacles to moving in a straight line. At each stage the crow-fly distance is recomputed, the agent adapting 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 5.

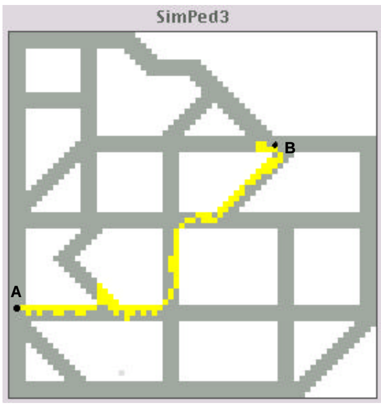


Figure 5: A shortest path emerging from local interactions

As an exploratory platform, the program allows us to experiment on the behaviours of agents repeatedly. Surprisingly, most of times, the agent or pedestrian works out the routines, which may differ slightly but represent – at least in principle – the shortest paths. For simulation purpose, we set the destination as the only parameter and then let the agent explore the space by means 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 sides of a street block, it is highly likely the agent will be stuck, and will not be able to work out a routine. This issue can be resolved by incorporating some global knowledge in the agent. One option would be to let the agents interact continuously with patches and thus afford them visibility properties, as being discussed in the following section, to guide their navigation.

4. VISUAL FIELDS IN URBAN SYSTEMS

Viewshed has become a topic of great importance in environment modelling. Viewshed analysis using Digital Terrain Model (DTM) has long been one of standard functions of GIS. However, the notion of a visual field within urban systems has not received much attention from GIS community. A visual field or isovist is defined as a visual area that is wholly visible across the system from a defined vantage-point (Benedikt 1979). This concept is of utmost importance in understanding how people perceive space, conceive it, and further react to the environment.

In the fields of robotics and computer vision, visual fields have been of crucial importance for robot navigation and path planning (Cameron and Probert 1994; Moutarlier and Chatila 1991). For instance, before beginning a forward movement, a robot has to check whether movement is safe. The same check is performed repeatedly during the movement to prevent collisions. In the above example about pedestrian movement, I have used conflict avoidance procedure, but that was at local level, which means that our virtual pedestrians can only see one step away. But we are able to improve the pedestrians' visibility by calculating visual fields.

Computation of visual field is a very intensive task (Davis and Benedikt 1979), because it involves computing the line of sight or possible occlusions between obstacles. Instead it appears that agent-based approach provides a fascinating technique to achieve the task. The idea is to fill the space with agents and 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 in 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 we can explore the space dynamically with what we have already explored to show the visual fields from each location. The algorithm is described as follows,

Step 1: fill all open space with agents

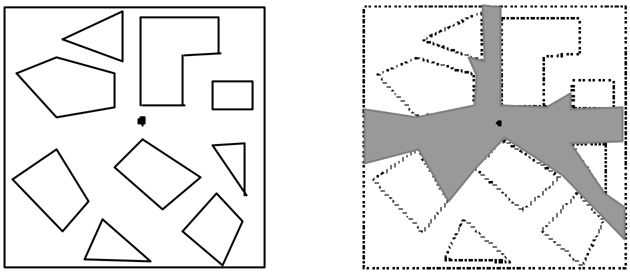
Step 2: alpha = 0

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 it does (yes), stop; if it does not (no), go back to **step 3**.

As an example, figure 6 (a) shows part of an urban system where the blocks are supposed to be spatial obstacles such as buildings. After the computation pre-process shown above, each space location has got parameters which show how much one can see in every direction from the standing point of view. A series of visual fields may be seen on screen dynamically by positioning the mouse in different places. A typical one is shown in figure 6 (b).



(a) (b)

Figure 6: The visual fields dynamically shown using the agent-based approach

The above model has been applied to some real urban systems such as Wolverhampton town centre and London Tate Gallery (Batty and Jiang 2000). Together with the model, we have constructed spatial properties like most visible space in the systems. This proves that the agent-based approach is very efficient in what regards the computation of visual fields. However, because of adaptation of cellular space, gaps in visual field display cannot be totally avoided no matter how fine grid adapted.

Gibson's (1979) optical flow is considered to be of critical importance in human spatial behaviour related to the visual perception of the environment. However, it is indeed difficult to visualise an optic flow. Benedikt and Burham (1984) have investigated how Gibson's optical flow can be objectively simplified as isovists, and it is found that isovists do affect human perception in urban environments. Since isovists can be considered the equivalent of a global sense, it is possible to extend agent's sense from local to global by means of interaction with environment. Moreover, since visual fields are storied as a patch variable with which agents can interact, such combination could lead to the creation of more deliberate or cognitive agents for the simulation of pedestrian movement.

6. WATERSHED DYNAMICS AND WILD FIRE DIFFUSION IN ENVIRONMENTAL SYSTEMS

There are many phenomena in environmental systems that can be characterised interaction between agents and environment. Spatial diffusion such as air pollution, heat diffusion and water floods can be considered interactions between those objects such as pollutants, heat, and water with their respective environments. In the examples that follow, I will try to illustrate two such interactions within environmental systems.

The first example relates to watershed dynamics. We first need to create a random terrain surface, smooth out it and colour it in order to create a realistic representation. We then generate a group of water droplets and scatter them randomly over the surface. The key step to this approach is to use greedy search, to find local maximum (minimum) within a neighbourhood then let water droplets head that direction. The procedure can be described as follows,

Step 1: create a random terrain surface and colour it

Step 2: generate a number of water droplets and randomly locate them over the terrain surface

Step 3: use 'greedy search' to find the lowest elevation and move to the local minimum

Step 4: check if all water droplets have been placed in the local minimum
if they have (yes), stop; if they have not (no), go to **step 3**.

As an example, we assume an idealised 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 neighbourhood. Figure 7 shows two different terrain models and stream networks generated. In the experiment, there are a number of things we can explore. We can change the number of water droplets, the terrain surface, and the radius of 'greedy search' to see how stream networks change.

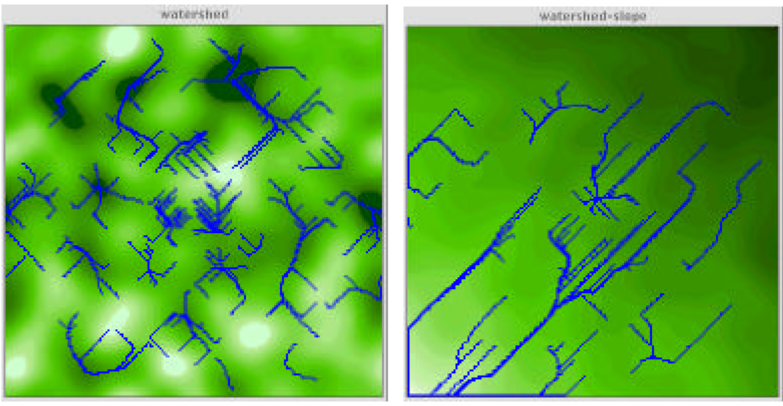


Figure 7: Stream networks created from the local interaction of agents with their environment

The second example relates to wild fire diffusion, which has been discussed elsewhere by Resnick (1997). Since it is very typical in the study of environmental systems within GIS, I brief the example as another evidence to support the discussion. How does wild fire spread over the forest? It depends on many factors, a critical factor being tree density, i.e. if the forest is dense enough, the fire is likely to spread over; otherwise, it is likely to be distinguished. Therefore fire diffusion in forests showing different tree densities could be extremely interest to the study of the spatial diffusion phenomena. If we assume that the fire is an agent and the forest is the environment, fire diffusion can be thought of as spatial interaction between the fire and the trees. Simple fire behaviour can be described as:

IF a cell is surrounded by more than one tree
THEN [fire diffuse]
ELSE [fire is distinguished]

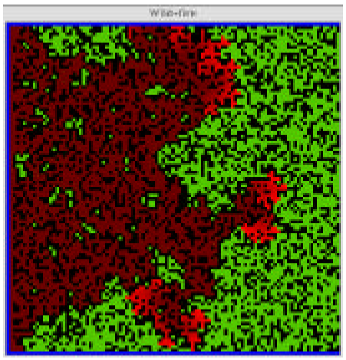


Figure 8: A snapshot of fire diffusion in forest with density of 61%

Let's assume the tree density to be of 61% for illustration purposes. Figure 8 shows the resulting fire diffusion pattern. Both the watershed and the wild fire example show again how local interaction gives rise to a global pattern. Obviously, such examples are far from complete, since factors such as gravity or speed of flow have not yet been considered. Equally, factors such as wind or forest composition could be considered in the fire diffusion example to achieve a more robust model.

6. CONCLUSIONS

The parallel processing agent-based approach has shown various advantages over existing approaches such as cell-based GIS and CA in modelling environmental and urban systems. Such an approach can be used for both simulation and computation purposes. MAS provides an exploratory platform to test hypotheses behind the space-time dynamics as well as to experiment with 'what-if' games within complex space-time processes, i.e. using the computer as a laboratory for the study of complex adaptive systems. Besides, it can be used to achieve some computational intensive tasks through the collective work of individual agents. Future work should focus on removing the limitations of reactive agents, implementing the use of cognitive or deliberate agents and achieving their full integration into GIS.

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