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Multi-agent systems for simulating spatial decision behaviors and land-use dynamics

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Abstract A new method to simulate urban land-use dynamics is proposed based on multi-agent systems (MAS). The model consists of a series of environmental layers and multi-agent layers, which can interact with each other. It attempts to explore the interactions between different players or agents, such as residents, property developers, and governments, and between these players and the environment. These interactions can give rise to urban macro-spatial patterns. This model is used to simulate the land-use dynamics of the Haizhu district of Guangzhou City in 1995—2004. Cellular automata (CA) were also used for the simulation of land use changes as a comparison. The study indicates that MAS has better performance for simulating complex cities than CA.

Keywords: multi-agent systems, cellular automata, complex systems, cities, land use.

1 Introduction

Urban dynamics is a complex process which is influenced by a series of driving forces. Modeling urban land use changes can help to understand the mechanisms of urban evolution and examine existing urban theories[1−4]. One type of these models is based on the 'top-down' approach. These models are usually defined by strict mathematical equations which can only yield deterministic results. These deterministic models have difficulties in simulating complex urban behaviors[5]. Statistical models have been widely used to establish urban models using land use and social economic data[6]. System dynamic models based on the theories on control, system and information can reflect the relations between the complex structure, function and mobile action[7]. However, it also has limitations because of the lack of spatial details[7,8].

Cellular automata (CA) have attracted increasing attention as a powerful modeling tool for simulating geographical phenomena. Studies have demonstrated that very complex behaviors and global patterns can be generated by applying some simple local rules in CA models[9]. This 'bottom-up' approach is well adapted to the simulation of the evolution of urban systems[10]. CA have been applied to the simulation of artificial cities as aids in thought experiments for verifying urban theories[10]. They can be also used to simulate realistic cities by predicting future land use changes for urban planning[11]. However, the evolution of urban systems is affected by both physical and social factors[12]. Existing CA models have limitations because they do not consider the influences of social and human factors explicitly in urban simulation[13]. There are different players in urban systems and these players are significantly shaping the evolution of spatial structures of cities. These players may include residents, property developers, and governments.

The limitations can be overcome by incorporating multi-agent systems (MAS) in urban simulation. MAS are the integration of complex adaptive system theory, artificial life techniques and artificial intelligence techniques. There are many experiments in using MAS to analyze and simulate complex systems[14]. Some experiments have been carried out to apply this technique to simulating urban systems[13,15−20]. The immobility problem can be solved by adding mobile agents in the modeling process. In this kind of simulation, urban dynamics is determined by the interactions between a series of agents, such as urban residents, governments, and developers. The behaviors of these agents are also influenced by their surrounding environments and resources. For example, Benenson uses a multi-agent simulation model to simulate the population dynamics in a city, in which inhabitants can change their residential behavior depending on the properties of their neighborhood, neighbors and the whole city[18]. This model was further extended to simulate the dynamics of the ethnic residential distribution in the Yaffo area of Tel Aviv[13]. Ligtenberg developed a spatial planning model by combining MAS with CA[19]. The model can allow agents to acquire knowledge from CA to make decisions about the future of a spatial organization in a certain area. Otter simulated the location decisions of two main types of agents[20], namely households and firms. The model can show that human behavior at the microlevel in a spatial context is crucial in the formation of land use patterns.

The above models basically use a few types of agents to simulate spatial-temporal dynamics. It is still an initial stage in the application of MAS in urban modeling. In this study, a multi-agent system integrated with GIS will be developed to simulate the residential development in the Haizhu district of Guangzhou City. A more complete set of agents will be defined to simulate residential development. The model consists of several types of agents—residents, governments and property developers. These agents will interact with each other by a series of actions, such as communications, cooperation and competitions. Their decision-making behaviors will eventually change their surrounding environment and cause land use changes. However, these influences are mutual since agents' behaviors are also subject to the constraints of environment, which can be defined by GIS. The interactions between various agents and between agents and their surrounding environment can give rise to the orderly spatial structures. It is expected that more realistic land use change patterns can be simulated.

2 The integration of multi-agent systems with GIS

In this study, the Urban-Agent model consists of two major types of layers—immobile environmental layers and mobile agent layers. The environmental layers include land use types, accessibility, land price, facilities, ecology, and education. The environment is not uniform in space and time. GIS can provide valuable information for agents to make decisions. The agent layers are used to represent the mobile entities that can play a key role in forming the macro spatial structures for cities. Agents do not act independently, but make decisions through negotiations and cooperation with each other. These agents can not only adapt to the environment, but also change it. There are three major types of agents—residents, property developers and governments. Each major type of agents can be divided into subtypes according to their properties, such as incomes and capitals. For example, there are low-income residents and high-income residents. Each group of residents has unique preferences of choosing sites to purchase property.

These agents will influence each others in making decisions. First, resident agents choose the sites to purchase suitable flats to satisfy their needs as much as possible according to their financial capability. If there are too many buyers in the same location, the price will go up. If the rising price goes behind their affordable threshold, they will move to other places to buy flats.

Property developers will adjust their investment strategies according to the purchasing behavior of residents. Their simple objective is to make the profit as much as possible. However, they must get the approval from governments before a site can be developed.

2.1 The environmental layers

Land use: Land use is the most important factor in the simulation. It provides the environment for agents to make decisions. It is also subject to changes with regard to agents' activities. Agents will have different decision behavior for different land use types. For example, a developer is unlikely to apply the development of site if it belongs to forest or water. Instead, it is more likely that he will apply for the development of a site if it is surrounded by a large number of already developed sites.

Traffic accessibility: Accessibility is related to the convenience that a site can be reached by various transport tools. It is related to its geographical location (e.g. distance to roads and town centres) and the conditions of road networks. The attractiveness of a site based on the accessibility can be represented as follows:

$$E_{\text{traffic}} = c_1 \cdot A_1 \cdot e^{-B_1 \cdot D_{\text{road}}} + c_2 \cdot A_2 \cdot e^{-B_2 \cdot D_{\text{hway}}} + c_3 \cdot A_3 \cdot e^{-B_3 \cdot D_{\text{center}}} \tag{1}$$

where E_{traffic} expresses the accessibility of transportation, c_1, c_2 and c_3 represent the coefficient to the distances, and $c_1 + c_2 + c_3 = 1$, A_1, A_2 and A_3 are the intensity of spatial influence, B_1, B_2, B_3 is the declined coefficient to explain the spatial influence, D_{road} is the distance to express roads, D_{hway} is the distance to highways, and D_{center} is the distance to urban centres.

Land price: Land price determines apartment price which is the major concern for a potential buyer. Higher income residents can afford to buy good quality apartments in the locations of higher land price. Constrained by the financial capability, lower income residents can only choose the place of cheaper apartment price (land price) to live.

Public facilities: The provision of public facilities is another important factor to affect the decision of a potential buyer. The sites will be more attractive if they have closer distance to the facilities, such as hospitals, gardens, commercial centres and entertainment centers.

Environmental quality: The attractiveness of a site is also related to its surrounding environment. It is based on two indicators, the area of green land in the neighborhood and the proximity to rivers. People would like to live in the locations with more green land in the neighborhood. The area of green land in the neighborhood can be calculated by using a 9×9 moving window in the classified satellite image. A closer distance to rivers will have more attractiveness because of having better signs. It is easy to calculate the proximity to rivers for each site by using common GIS functions. Finally, the total attractiveness of a site related to the environmental aspects is obtained by using this following equation:

$$E_{\text{green}} = \begin{cases} 100 & \text{if} \quad N(H(L_{ij})) = 0, \\ \dfrac{N(G(L_{ij}))}{N(H(L_{ij}))} & \text{else}, \end{cases} \tag{2}$$

where E_{green} is the greenness of a site, L_{ij} is location of a cell within the two-dimensional space of $n \times m$, $i \in [1, N]$, $j \in [1, M]$, $N(G(L_{ij}))$ is expressed as the number of green land within the neighborhood using a window of 9×9; $N(G(L_{ij}))$ is the number of residential area within the same window.

It is also preferable to have a better sign of water. The similar utility function can be defined and the final assessment of environmental quality can be carried out using the following equation:

$$E_{\text{environment}} = C_g \cdot E_{\text{green}} + C_w \cdot A_w \cdot e^{-B_w \cdot D_w}, \tag{3}$$

where $E_{\text{environment}}$ is environmental quality according to the greenness and the proximity to water, C_g, C_w is separately expressed as the coefficient which green land and water affect the environment, A_w is the spatial impact of water, B_w is the declined intensity of water, D_w is the distance to water.

Education benefits: Distance functions are also used to represent the convenience of accessing education facilities, such as schools and libraries. More benefits can be achieved if there is a closer distance to these facilities.

2.2 Agents and their decision-making strategies

Agents are entities capable of making decisions and possessing self-determination, which can represent animals, mankind or organizations, etc. An entity is not limited to a single individual, but also can be expressed as a group of individuals. In this analysis, an agent can represent a number of residents or families by a proportion. Each type of agents has unique features. For example, government agents have the feature of macro planning without spatial attribute. It is difficult to define the exact location of developer agents. The locations for resident agents were randomly selected at the initial stage. They will choose the site to reside according to the interaction between three kinds of agents.

(i) Resident agents and decision-making. There are two kinds of residents——new residents moving in from outside and existing residents relocating new places to live. The behaviors of these mobile residents will affect the investment strategies of property developers. The interactions between these agents are responsible for the formation and evolution of urban structures, such as social and ethnic segregation, self-organization and urban expansion. A utility function is defined to assess if a site is suitable for an agent to reside. The assumption is that an agent will tend to maximize the utility function as much as possible when it is looking for a place to reside. According to dynamically random utility model[21], the utility function is defined as

$$U(t,ij) = a \cdot E_{\text{environment}} + b \cdot E_{\text{education}} + c \cdot E_{\text{traffic}} + d \cdot E_{\text{price}} + e \cdot E_{\text{convenience}} + \varepsilon_{tij}\,, \qquad (4)$$

where $a+b+c+d+e=1$, $E_{\text{environment}}$, $E_{\text{education}}$, E_{traffic}, E_{price}, $E_{\text{convenience}}$ are the factors of environmental quality, education benefits, accessibility, land price and public facilities for location L_{ij}. The parameters of a, b, c, d and e are the preferences (weights) of a type of resident agent (t) for each factor. ε_{nij} is a stochastic term.

Site selection and relocation of a flat reflect residents' standpoints on values (Table 1). Different types of resident agents will show dissimilar-interests in the decision-making process.

A discrete selection model can be used to represent the site selection and relocation for residency. It is considered that the randomly fluctuant item ε_{ij} in the utility model satisfies the rule of Weibull scatter[21−23], that is, $F(\varepsilon_{tij}) = \exp(-\exp(-\varepsilon_{tij}))$. According to McFadden's theorem [22,23], the probability of location L_{ij} selected by resident agent t is equal to the probability that the utility (attraction) of L_{ij} is more than or equal to any other location's attraction.

Table 1 The factors of affecting residential development

Residents' standpoints on values	Factors
Attributes of location	Accessibility of traffic Convenient common utilities Education resource Quality of physical environment Price of housing
Social attributes	Income Occupation Family structure (whether having child or not) Age Education degree

$$P(t,ij) = \Pr(U(t,ij) \geq U(t,i'j')) = \frac{\exp(U(t,ij))}{\sum_t \exp(U(t,ij))}\,, \quad (5)$$

where $\Pr(U(t,ij) \geqslant U(t,i'j'))$ is expressed as the probability that the attraction of location L_{ij} is more than or equal to any other location's attraction, $\sum_t \exp(U(t,ij))$ is all the exponential attractions of locations to be selected. The equation above reveals that residents will select locations by the rule of maximum utilities.

The Monte Carlo method is used to decide the final selection of a location for residency. This can allow a stochastic variable to be added to the modeling process. After a satisfied location has been identified by a resident agent, there are three situations: (1) the location has been already occupied by another resident agent; (2) the location is available; and (3) the location has not been developed.

The third situation is the essential part of this study. If undeveloped sites have been required to develop by the resident agents, the developer agents will consider their willingness. The developer agents will assess the potential profit. They will apply for the development of these sites if the profit is greater than a threshold value. The sites will then be developed when the application has been approved by the government agents. This interaction process can give rise to the orderly spatial patterns for urban development.

(ii) The agent of property developers and its decision behavior. Property developers play an important role in shaping urban development. They need to consider the preferences of residents in buying flats and the policies of governments. Their objectives are to achieve a certain amount of profit that is greater than an expectation value. This will decide whether a site will be developed or not. The formula is

$$D_{\text{profit}} = H_{\text{price}} - L_{\text{price}} - D_{\text{cost}}, \tag{6}$$

$$D_{\text{profit}} \begin{cases} > D_{\text{threshold}}, & \text{developed,} \\ < D_{\text{threshold}}, & \text{undeveloped,} \end{cases} \tag{7}$$

where D_{profit} represents the investment returns, H_{price} is the price of housing, L_{price} is land price, D_{cost} stands for cost for building houses, $D_{\text{threshold}}$ is threshold of profits expected by property developers.

Finally, property developers must submit their development applications to government authorities for approval. The authorities will examine these development plans before the approval can be issued.

(iii) Government agent and its decision behavior. Planning authorities will decide if an application for land development is successful or not according to a number of factors. Firstly, existing land use is a major factor to determine land use conversion. Different land use will have different approval probability for land development. For example, land development is not allowed in ecological sensitive areas. The probability for land development in wetland areas or mountainous areas is extremely low. Secondly, the approval probability is also related to development plans. It is more likely that an application can be approved if there are no conflicts with existing planned land use.

Although the initial approval probability is decided by governments, it is subject to changes with the influences from residents and property developers. For example, the probability will increase if a location has been applied for development many times. The adjusted probability can be calculated as follows:

$$P_{\text{accept}_{ij}^*} = P_{\text{accept}_{ij}} + g \cdot \Delta P_1 + h \cdot \Delta P_2$$
$$(i \in [1,n], j \in [1,m]), \tag{8}$$

where $P_{\text{accept}_{ij}^*}$ shows the probability of location L_{ij} accepted by government, $P_{\text{accept}_{ij}}$ explains the probability of government's original acceptation, g is the total number of the location applied for by property developers, ΔP_1 is the probability increase related to property developers, h represents the site number approved by government agents within a 3×3 window, ΔP_2 is the probability increase related to government agents.

3 Application

3.1 Study area and data

The Haizhu district of Guangzhou City has been selected for testing the proposed model. The model is used to simulate the land-use dynamics in 1995—2004. The test area used to have a large part of agricultural land, but most of it has been converted into urban land use. The simulation and prediction of the fast urban expansion can provide useful information for land use planning and management.

Landsat TM images dated on 30 December, 1995 and on 13 June, 2004 were used to obtain training data about actual land use conversion. GIS data were also used to represent the independent factors that determine land use changes. These data were digitized from the maps of urban planning, land price, land use, and public facilities. Social and economic data (e.g. population) were also collected from statistical yearbooks.

All the spatial data were converted into raster grids with a resolution of 100 m, registered and overlaid with each other. Each grid is composed of $n\times m$ cells. The GIS layers of land-use, transport, land-price, public facilities, environmental quality and education resources are superposed seamlessly in the space grid of two dimensions. These layers have no moveable properties and can be considered as the environment factors. In multi-agent layers, the agents are moveable and they represent different types of decision-makers who affect urban land-use changes in actual cities. These different types of agents interact with each other so that they understand their environment in common and then take actions in affecting the environment. Moreover, the environmental layers are also dynamic, which will ultimately affect the behaviors of multi-agents. The multi-agents can take the corresponding measures and actions to balance the need for urban development and the need for environmental protection.

3.2 Model simplification

Since the collection of some input data is very difficult, the proposed model should be simplified before implementation. Only the registered population was used to represent the resident agents in the simplified model. Most of the floating population lacks the economic capability to purchase flats because of the uncertainty of working places and financial capability. Therefore, floating population may not play a big role in influencing property markets. To the decision behavior of residents, we only pay more attention to the third condition mentioned in 2.2(i). An important part of the model is to simulate resident agents in choosing locations for buying flats. New residents are the main forces for causing urban expansion in the study area. The increase population in 1995—2004 will be used as the major factor in influencing residential development.

The model also needs to determine the suitable investment locations for property developers. The main reason for property developers to choose the locations is to satisfy the profit criterion. However, detailed data about the profit making is unavailable. However, most of the property developers tend to select the areas with resident gathering and small developing risk for their investment[24]. These well-developed neighborhoods have good public facilities and require no further investment. The neighborhoods with fewer people gathering should require additional capital to construct public infrastructure. There are higher costs and risks to invest in these places. The influence from the neighborhood was taken as a criterion of investment. The amount of already developed cells is summed by using a 3×3 window:

$$P_{\text{dev}_{ij}} = \frac{\sum_{3\times3} N(\text{urban}(ij))}{3\times3-1}. \tag{9}$$

If $\sum_{3\times3} N(\text{urban}(ij)) = 0$, then let $P_{\text{dev}} = 0.05$, where the variable P_{dev} is the developing probability for property developers; $\sum_{3\times3} N(\text{urban}(ij))$ is the pixels belonging to residential land use within 3×3 neighbor window.

In the simplified model, government agents have only the role of controlling land development at a macro level. Therefore, the probability of the location L_{ij} to be selected by the t resident, permitted by government and to be developed by property developers can be expressed as

$$P_{ij}^{t} = A\cdot P(t,ij)\cdot P_{\text{accept}_{ij}^{*}}\cdot P_{\text{dev}}, \tag{10}$$

where A is the parameter to rectify the model, $P(t,ij)$ is the probability for the t resident to select the location L_{ij} under the circumstance of best profit, $P_{\text{accept}_{ij}^{*}}$ is the probability of location L_{ij} accepted by government agents, P_{dev} is the probability for property developers to develop the location L_{ij}.

3.3 Application of model

(i) Classification of resident agents and the weight to be computed. Detailed attributes about residential agents can be obtained by using social and economic data. This study considers two major attributes, income and household size, which are obtained from the *Statistical Yearbook of Guangzhou* in 2004, and the fifth national census respectively. These attributes can be used to define the decision behavior of the resident agents.

Each agent has unique features of decision behavior. The model may become too complicated to implement by using these distinct agents. These agents can be classified into a few groups so that the model can be more practical. These attributes will be classified into a number of groups. Residents' income can be classified into three groups—low income (< 9600 yuan RMB/year), middle income (> 9600 yuanRMB/year and < 60000 yuanRMB/year) and high income (> 60000 yuanRMB/year). Household size can also be classified into two groups—without children and with children. A total six classes of residents can then be obtained by using these two classified attributes. The population proportion for these six groups can be calculated according to the *Statistical Yearbook of Guangzhou* in 2004, and the fifth national census (Table 2).

Table 2 The proportion of each type of resident agents

	Type of resident agents					
Home structure	Without children			With children		
Income	Low	Middle	High	Lowl	Middle	High
Proportion	9%	39%	9%	6%	31%	6%

Different types of residents have different preferences in the location choice of residency according to their inherent attributes. These preferences can be reflected by using weights. The first step is to define the initial weights based on experts' experiences. Then an entropy method can be used to readjust these weights so that subjective bias can be removed as large as possible[25].

These factors should be normalized before these weights can be applied. There are two types of factors —positive and negative. Positive factors (e.g. accessibility of transportation, facilities, education resource and environmental quality) and negative ones (the price of housing) were normalized by using a fuzzy function. For the positive factors, the half-ascending trapeziform model was used to quantify:

$$a'_{mk}=\begin{cases}1 & a_{mk}\geqslant Max_k;\\ \dfrac{a_{mk}-Min_k}{Max_k-Min_k}, & Min_k\leqslant a_{mk}\leqslant Max_k;\\ 0 & a_{mk}\leqslant Min_k.\end{cases}\qquad(11)$$

For the negative factors, the half-descending trapeziform model was used as follows:

$$a'_{mk}=\begin{cases}1 & a_{mk}\leqslant Min_k;\\ \dfrac{Max_k-a_{mk}}{Max_k-Min_k}, & Min_k\leqslant a_{mk}\leqslant Max_k;\\ 0 & a_{mk}\geqslant Max_k;\end{cases}\qquad(12)$$

where a_{mk} is the attribute of the kth factor at location m, Max_k, Min_k are the maximum and minimum of the kth factor, a'_{mk} is the normalized value.

An entropy method can then be applied to obtaining a more objective weight for each normalized factor. Entropy is always used to measure the uncertainty in information theory. Higher uncertainty will be associated with a lower value of the entropy. The entropy can be calculated by the following equation:

$$E_k=-N\cdot\sum_{m=1}^{M}(f_{mk}\cdot\ln f_{mk}),\qquad(13)$$

where M is the total number of the observation, $N=\dfrac{1}{\ln M}$, $f_{mk}=\dfrac{|a'_{mk}|}{\sum_{m=1}^{M}|a'_{mk}|}$, providing when $f_{mk}=0$, $f_{mk}\cdot\ln f_{mk}=0$, then the adjusted weight can be presented as follows:

$$H_k=\frac{1-E_k}{K-\sum_{k=1}^{K}E_k},\qquad(14)$$

where K is the number of all these factors.

The adjusted weights can be computed as

$$w_z=u_z\cdot H_z/\sum_{z=1}^{K}u_z\cdot H_z,\qquad(15)$$

where u_z is the initial weight defined by experts, H_z is its entropy, w_z is the adjusted weight.

From eqs. (13) and (14), it can be seen that a higher difference within a factor will yield a lower value of entropy and a higher value of weight. This indicates that this factor should have a large contribution to the decision. The weights for different groups of resident agents are obtained in Table 3. These adjusted weights will be used for the calculation of eq. (4).

(ii) Application and results. Satellite TM images were used to collect the information about urban expansion in 1995—2004. Land use classification was carried out by using the 1995 and 2004 TM images. The land use in 1995 was used as the initial stage and the land use in 2004 was used to verify the simulation. It is assumed that every newly urbanized cell can accommodate one resident agent. The total number of the resident agents is determined according to the amount of urban cells. The flow chart of the model is shown in Fig. 1. The procedures of running the model are as follows:

(1) Determining the total number of resident agents according to the actual amount of urban expansion in

Table 3 Weight for different groups of resident agents

Type of residents	Weight				
	Accessibility	Housing price	Facility	Environmental quality	Education resources
Low income without children	0.287	0.447	0.095	0.058	0.113
Low income with children	0.209	0.393	0.048	0.049	0.301
Middle income without children	0.268	0.206	0.139	0.276	0.111
Middle income with children	0.215	0.241	0.093	0.187	0.264
Higher income without children	0.324	0.058	0.104	0.394	0.120
Higher income with children	0.265	0.094	0.052	0.302	0.287

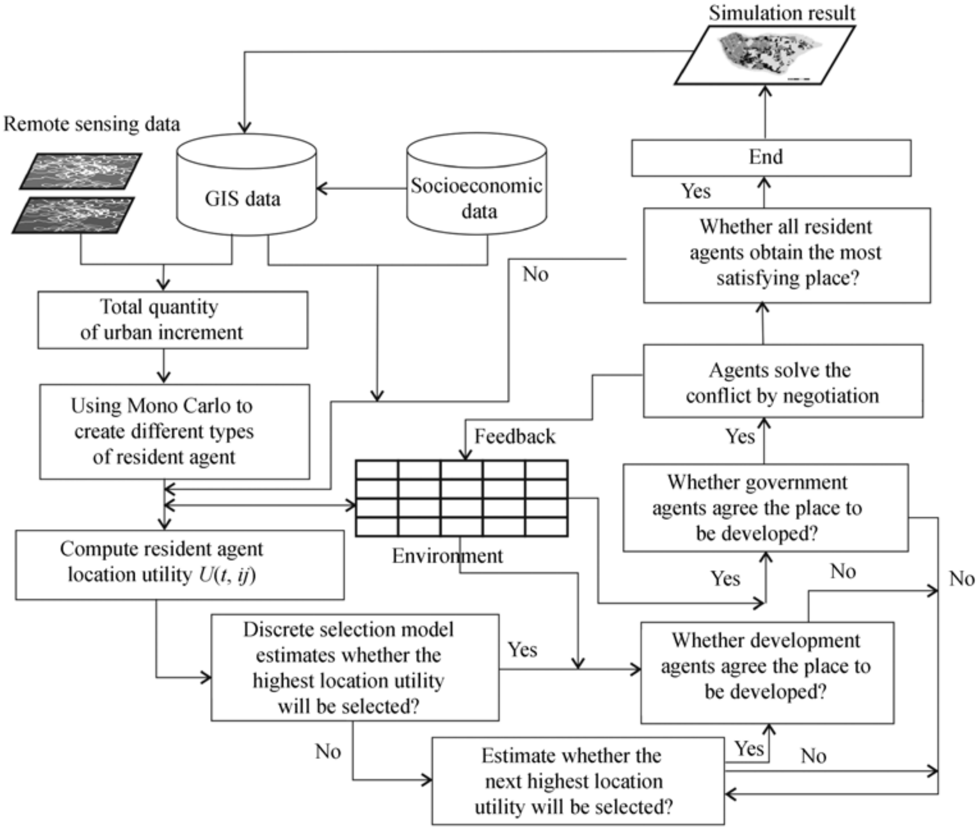

Fig. 1. Simulating the evolution of complicated land use systems based on multi-agents.

1995—2004 classified from remote sensing data.

(2) Using Monto Carlo method to create resident agents according to the actual proportion of various types of residents (Table 2).

(3) Using formula (4) and Table 3 to compute location utility for each type of resident agents. Selecting the locations with the highest utility values and estimating development probability for these places according to the communication between residents, property developers and government using equation 10.

(4) Determining whether the locations of the highest utility values will be developed by using the Monto Carlo method. If yes, the location will be marked and go to step 1 to start the next round of selection again. If no, the next highest location will be evaluated until residents requirements are satisfied.

The input data for the simulation include the maps of land use in 1995, urban development plan for 1996—2010, transport, land price, utilities, environmental quality, and education resources. The proposed model was used to simulate the urban dynamics of the study area. Fig. 2 shows the simulation results.

The simulated urban land use (Fig. 3(a)) can be compared with the actual urban land use in 2004 (Fig. 3(b)). Very plausible results have been obtained by using this proposed model. However, there are still some differences between the simulated and actual patterns. It is found that the actual development is in a more regular pattern, but the simulated development tends to be a little bit chaotic. In the simulation, some new development took place in the places of green land and vegetable fields. These locations are easily accepted by residents, but not approved by government and developers agents, according to formula 10. Although there are low values of development probability for these places, a few locations can still be accepted according to the Monto Carlo method. This can lead to some chaotic patterns in the simulation.

The increase of residential areas from 1995 (T = 0) to 2004 (T = 1400) is shown in Fig. 4. The increase is at the cost of losing green land and vegetable fields.

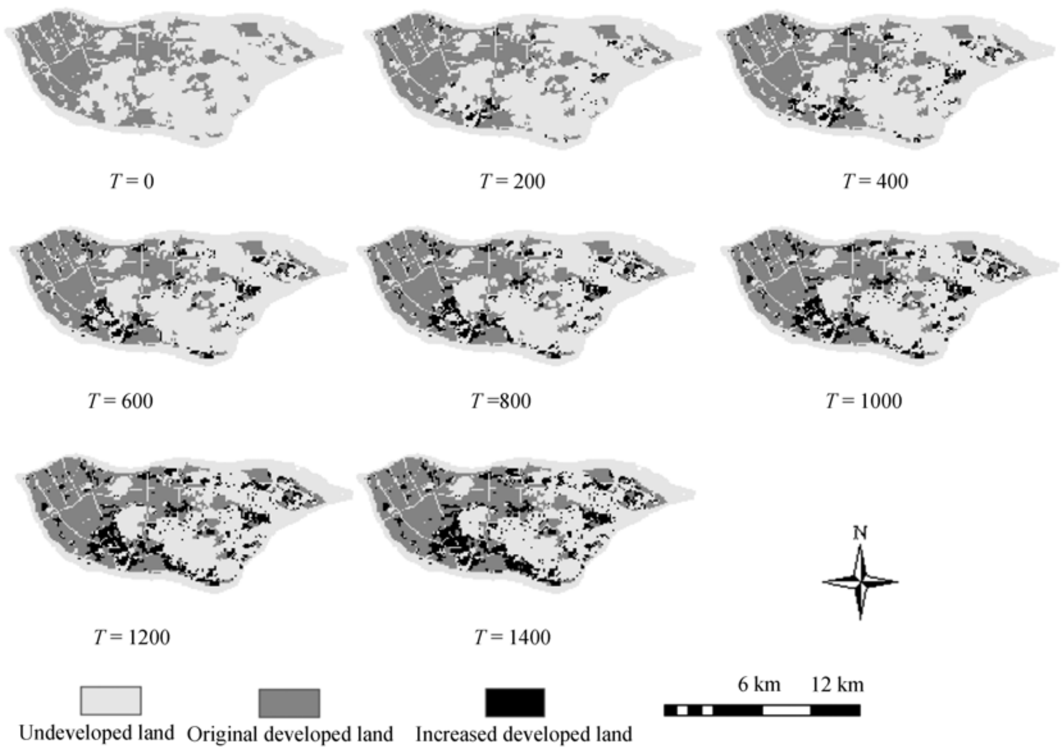

Fig. 2. Simulating spatial evolvement of residential areas.

Fig. 3. Simulated developed area (a) and actual developed area (b).

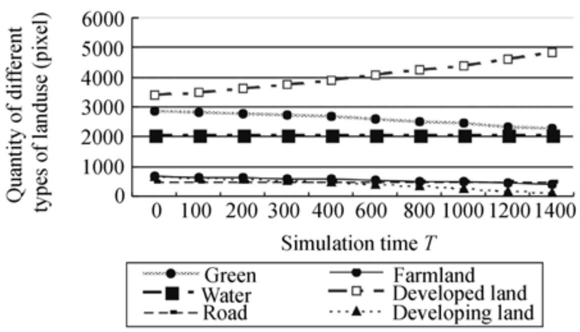

Fig. 4. The fluctuation of land use in the study area.

This will gradually result in the depravation of environment. The decrease of new development land is due to the increasing control from governments and the corresponding strategies of developers.

4 Model verification

Two methods were used to evaluate the simulation performance of the model——cell-by-cell comparison and aggregate comparison[26]. The comparison of the simulated and the actual residential areas using the cell-by-cell yields the total accuracy of 78.6% (Table 4), among which the accuracy for the changes is 67.9%. In this study, the aggregate comparison is based on Moran's I, which is focused on the whole pattern. In general, Moran's I, ranging from 0 to 1, is used to reveal the spatial self-correlation, which can reflect spatial centrality or decentralization[26,27]. The higher Moran's I is, the more compact the development patterns will be. Moran's I is 0.6644 for the simulated and 0.6878 for the actual (Table 5). This indicates that the both spatial patterns are very close.

Table 4 Accuracies of the simulation according to the cell-by-cell comparison

		Simulated		Accuracy (%)
		Undeveloped	Developed	
Actual	Undeveloped	2305	437	84.1
	Developed	452	954	67.9
Total accuracy				78.6

Table 5 Comparison of Moran's I

Moran's I		
1995 (Initial)	2004	
Actual	Actual	Simulated
0.6894	0.6876	0.6644

A further experiment is to use cellular automata (CA) to simulate urban development which can be compared to the agent-based model. The accuracy from the cell-by-cell comparison is 0.5103, and Moran's I is 0.5967 for the CA model. This indicates that the agent-based model can produce better simulation outcomes. It is because the behavior of various players in actual urban systems can be well incorporated in the agent-based model. CA models still have limitations to reflect non-physical factors.

5 Conclusions

Cities are complex systems with nonlinear and open features. Agent-based modeling can provide a useful tool for analyzing and simulating complex urban systems. It can conveniently incorporate the role of decision makers in the simulation process and produce more plausible results. It has a lot of advantages in simulating dynamic changes of urban land use. The essential of multi-agent models is how to define agents and their actions to reflect complicated systems. The number of agents should be properly chosen because using too many types of agents will lead to a more complicated model and longer computation time. Too few types of agents will also result in the loss of details of complex systems.

This paper proposes an agent-based model simplifying urban agents to some extent, selecting three main types of agents (resident agents, property developer agents, government agents). Different types of agent interact and negotiate with each other in the simulation process. They interact with the surroundings together and take measures to affect the environment. Meanwhile, the transformation of environment will also affect the behavior of multi-agents. Urban macro patterns can be generated by the interactions between the agents and environment.

Selecting the Haizhu District of Guangzhou City as a test area, this paper simulated the dynamic transformation of urban land use from 1995 to 2004, and the results were compared to the actual patterns obtained from remote sensing data. As a whole, the model can produce satisfactory results. The total accuracy of the simulation is 78.6% according to the cell-by-cell comparison. The use of Moran's I also reveals that the simulated pattern is quite close to the actual. When compared to CA model, the multi-agent model also has the advantages in simulating the complex residential development with better performance.

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