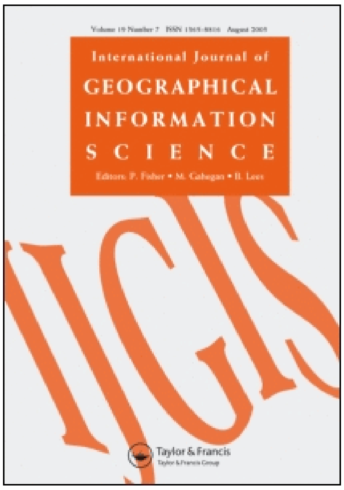

International Journal of Geographical Information Science
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713599799

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First published on: 12 March 2010

To cite this Article Liu, Xiaoping , Li, Xia , Shi, Xun , Zhang, Xiaohu andChen, Yimin(2010) 'Simulating land-use dynamics under planning policies by integrating artificial immune systems with cellular automata', International Journal of Geographical Information Science, 24: 5, 783 — 802, First published on: 12 March 2010 (iFirst)

To link to this Article: DOI: 10.1080/13658810903270551
URL: http://dx.doi.org/10.1080/13658810903270551

International Journal of Geographical Information Science
Vol. 24, No. 5, May 2010, 783–802

Simulating land-use dynamics under planning policies by integrating artificial immune systems with cellular automata

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(*Received 1 April 2009; final version received 20 August 2009*)

Cellular automata (CA) have been increasingly used in simulating urban expansion and land-use dynamics. However, most urban CA models rely on empirical data for deriving transition rules, assuming that the historical trend will continue into the future. Such *inertia* CA models do not take into account possible external interventions, particularly planning policies, and thus have rarely been used in urban and land-use planning. This paper proposes to use artificial immune systems (AIS) as a technique for incorporating external interventions and generating alternatives in urban simulation. Inspired by biological immune systems, the primary process of AIS is the evolution of a set of 'antibodies' that are capable of learning through interactions with a set of sample 'antigens'. These 'antibodies' finally get 'matured' and can be used to identify/classify other 'antigens'. An AIS-based CA model incorporates planning policies by altering the evolution mechanism of the 'antibodies'. Such a model is capable of generating different scenarios of urban development under different land-use policies, with which the planners will be able to answer 'what if' questions and to evaluate different options. We applied an AIS-based CA model to the simulation of urban agglomeration development in the Pearl River Delta in southern China. Our experiments demonstrate that the proposed model can be very useful in exploring various planning scenarios of urban development.

Keywords: artificial immune system; urban planning; cellular automata; urban simulation

1. Introduction

Cities are complex systems characterized by self-organization, self-similarity, emergence, and a non-linear behavior of land-use dynamics (Barredo *et al*. 2003). Urban expansion is consequently a complex process that involves multiple actors with different behaviors at various spatial and temporal scales (Lambin and Geist 2001, Barredo *et al*. 2003, He *et al*. 2006). Urban expansion is difficult to model using traditional 'top-down' models, as these models are largely static and linear, not so capable of dealing with the complexity in urban systems (Li and Liu 2007).

Cellular automata (CA), a branch of artificial life research (He *et al*. 2006), are a type of 'bottom-up' models. Its general idea is to apply transition rules to local subsystems and let all

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ISSN 1365-8816 print/ISSN 1362-3087 online

DOI: 10.1080/13658810903270551
http://www.informaworld.com

the local evolutions display the global pattern (White and Engelen 1997, He *et al*. 2006). CA have become a convenient and effective instrument to simulate non-linear and stochastic processes in complex systems (He *et al*. 2006). In spatial analysis, CA have been used to represent spatial interactions among subsystems and generate complex global patterns with simple local rules (Shi and Pang 2000, Liu *et al*. 2007). CA have many advantages for modeling complicated geographical phenomena (Torrens and O'Sullivan 2001). First, complex global spatial patterns can be generated by a set of simple local rules. This 'bottom-up' approach coincides with complexity theories stating that a complex system comes from the interactions of simple subsystems (Couclelis 1985, Liu *et al*. 2007). Second, CA provide process analysis functions for simulating the evolution of complex geographical systems (Torrens and O'Sullivan 2001). Lastly, the spatial framework of CA is perfectly matched to raster GIS (geographic information system), remote sensing, and digital photogrammetry, so a CA model can be easily coupled with GIS and remote-sensing analysis (White and Engelen 1994). CA have been considered to be a powerful tool for urban process modeling (Couclelis 1997), and in the last two decades there has been an increasing number of studies on using CA to simulate urban expansion and land-use dynamics (White and Engelen 1993, Batty and Xie 1994, Clarke and Gaydos 1998, Wu 1998, Li and Yeh 2000, 2002). Studies have shown that a 'bottom-up' model like CA is more appropriate to represent the spatial process of urban expansion (White and Engelen 1993, Batty and Xie 1994, Li and Yeh 2000, Wu 2002).

Tobler (1970) was perhaps the first to approbate the advantage of CA models in solving complex geographical problems (White and Engelen 1993, Li and Yeh 2004). He applied CA models to simulate the expansion of Detroit City in the Great Lakes area in the USA (Tobler 1970). At the end of the 1980s, Couclelis (1988) put forward the theoretical framework for geography-oriented CA and applied it to the simulation of urban expansion (Couclelis 1985, 1989) and population dynamics (Couclelis 1988). Batty is one of the pioneers who presented a class of urban models called DUEM and used it to simulate urban dynamics in the city of Buffalo (Batty and Xie 1994, 1997). White *et al.* (1997) developed a CA model to simulate the land-use pattern of Cincinnati, Ohio; Clarke *et al.* (1997) have been successful in integrating remote-sensing data and CA to simulate the development of the San Francisco Bay and Washington by using SLEUTH model; Li and Yeh (2000) were among the pioneers to integrate CA and GIS and used the integrated system to simulate the rapid urban expansion in the Pearl River Delta, China. Although many CA models have been built over the last 20 years, few models are operational as a tool to support land-use planning. This particular lack of applications may be related to the fact that so far most urban CA models derive their transition rules largely from empirical data, assuming that the historical trend of urban development will continue into the future. Such *inertia* simulations of CA do not take into account possible external interventions – particularly planning policies that may intend to advocate certain development philosophies like *sustainability* – and are not able to generate alternative scenarios that are often required in planning for option evaluation. Recently, researchers have started to explore methodologies to incorporate planning objectives into CA models. Ward and Murray (1999) proposed a CA model that simulates local decision-making processes, which was integrated with an optimization framework that addressed issues of sustainable urban development. Yeh and Li (2003) proposed a neural-network-based CA model that can be developed to simulate development alternatives for urban planning. Deal and Schunk (2004) built the land-use evolution and impact assessment model, which can integrate cellular micro-models and regionalized macro social-economic model into a single model framework. Ward *et al.* (2003) developed a land-use planning model by integrating a regional scale optimization model with a local-scale CA model. These studies show that CA have a great potential as a planning tool for urban development.

Transition rules are essential in urban CA. These rules are represented by the parameters and weights associated with the spatial variables involved in the simulation (Liu *et al*. 2008). Usually, empirical data are used to derive these parameters and weights according to calibration procedures. Some calibration techniques have been proposed to determine these parameter values, such as visual test (Clarke *et al*. 1997), multiple criteria evaluation (Wu and Webster 1998), logistic regression (Wu 2002), and fuzzy set (Liu and Stuart 2003). Recently, artificial intelligence techniques have been increasingly incorporated in urban CA models, including artificial neural networks (ANNs) (Li and Yeh 2002) and kernel-based learning machines (Liu *et al*. 2007). However, ANN does not give insight into the relations actually used in modeling, leaving the user uninformed about the possible lack of causality in the relations that are used in the model. Kernel-based model is also constrained by the use of implicit transition rules and the need of intensive computation. Most of these methods assume that transition rules are constant in the spatiotemporal dimension. However, the static transition rules may not be suitable for simulating complex geographical phenomena at a large regional scale, because these rules cannot capture the influences of unexplained variables and thus reflect complex relationships.

In this paper, we examine the potential of artificial immune systems (AIS) as a technique for incorporating external interventions into the transition rules of CA. AIS is a computational intelligence method first proposed by Jerne (1974). Inspired by natural biological systems, AIS mimics the form and function of biological antibodies in learning and memorizing new information, recalling previously learned information, and performing pattern recognition in a highly decentralized fashion. Since it was proposed, AIS has been used in many applications such as pattern recognition (Carter 2000), intelligent optimization (Chun *et al*. 1997), machine learning (Timmis 2000), adaptive control (Kumark and Neidhoefer 1997), and fault detection (Dasgupta and Forrest 1995). However, applications of AIS in geosciences are far less reported, except application in remote-sensing classification (Zhong *et al*. 2007). Actually, the features of self-adapting, self-learning, and memorizing of AIS make it promising in solving complex geographical problems. AIS is appropriate to recognize land-use dynamics, the antigens are used to describe urban dynamics and the antibodies are like media to store urban dynamics information extracted from antigens through 'training'. The information stored in the antibodies is then applied to the queried data to recognize them. Furthermore, AIS is especially appropriate to urban planning, since it is a good way to incorporate external interventions such as planning objectives because of its mutation mechanism. If planning objectives are embedded into the mutation process, which control the orientation of mutation, the antibodies will gradually 'evolve' toward the predefined planning objectives and finally reach the planner's intentions.

This paper presents a new method on the use of AIS to construct transition rules for urban CA modeling. The 'antibodies' form a problem solver and their *evolutions* are more suitable for representing *dynamic* transition rules. The use of discrete 'antibodies' can provide a powerful tool to capture the complexities exhibited in many geographical phenomena, which may have exceptions, irregularities, and variations. Particularly, we demonstrate how an antigen–antibody process can be used to derive transition rules that address both historical data and planning policies. The next section introduces some basics of AIS, followed by a section detailing the AIS' derivation of transition rules for urban CA models. The second half of the paper presents a case study of simulating urban agglomeration development in the Pearl River Delta in southern China. Some conclusions we draw from this work about using AIS-based urban CA models are put at the end of this paper.

2. Basics of AIS

There is an increasing interest in using biological immune systems as a metaphor for developing computational intelligence approaches. From a computing standpoint, biological immune systems are parallel, self-adapting, self-learning, self-organizing, distributed, and capable of complex behaviors (King *et al.* 2001). Inspired by theoretical immunology and observed immune system functions, AIS emerged as a computational intelligence technique for solving complex problems (Tarakanov and Dasgupta 2000).

A biological immune system consists of a complex of cells, molecules, and organs that aim to protect the biological body against infection. The defense mechanism is based on the adaptive immune responses, in which antibodies evolve to obtain stronger capability of dealing with certain antigens (de Castro and Timmis 2002). This type of response is explained by the clonal selection principle (Burnet 1959), which states that only those antibodies with high affinities to certain antigens are selected to proliferate. The selection continues and the affinities of antibodies to the antigens get improved from generation to generation. This is also referred to as the maturing process of antibodies.

An AIS implements an information memorizing and processing mechanism similar to that of a biological immune system. It imitates a biological system by adapting a set of 'antibodies' through responding to a set of *known* 'antigens', and then by using 'matured antibodies' to process *unknown* 'antigens'. The *known* 'antigens' serve as the training set, in which each 'antigen' contains both problem description and solution. The 'antibodies' form a problem solver (e.g., a classifier) and their adaptations or evolutions are essentially the training process. Once the 'antibodies' are 'matured', that is, the problem solver is trained, they can be used to solve new problems represented by unknown 'antigens'.

AIS is feasible, a finite number of 'antibodies' recognize an effectively infinite number of *known* 'antigens' (Perelson and Oster 1979), that is to say, the number of 'antibodies' can be much smaller than the number of *known* 'antigens', so basically this is a way to derive generalized 'rules'. Specifically in a land-use CA model, 'antigens' are the cells to be classified in the simulation and 'antibodies' are the classifiers that will assign different land-use types to cells based on their features.

3. Using AIS to construct transition rules for CA

As a machine-learning technique, an AIS can derive transition rules for CA from historical data. This section describes the basic process of using AIS to construct transition rules for land-use CA. In the next section, we will discuss the details of using AIS to incorporate external interventions into CA land-use modeling.

3.1. Definition of antigen in geographical CA

In the proposed AIS-based CA model, each antigen contains information about the cell. The antigen is represented as a vector consisting of two parts: attributes (features) and state conversion (solution). The attribute part includes proximity variables and a variable of land-use type. The proximity variables may cover distance to road, distance to city center, distance to railway, etc. Similar to other studies (Wu 2002, Li and Yeh 2006, Liu and Li 2008), the neighborhood is not included in the attribute part of the antigen because the neighborhood density changes along with the simulation. The state conversion part records if the state of the cell will be converted or not (e.g., urbanized or not). Formally, an antigen can then be represented as follows:

$$Ag = (a1, a2, \&, aN, ; S) \tag{1}$$

where $a_1, a_2, \cdots, a_N$ are the attributes of antigen Ag and N is the total number of the attributes; S is a Boolean variable that uses 1 to represent the state of being urbanized and 0 for otherwise. Note that the attributes should be normalized so that their values are comparable. In this study, we normalized all the attributes to the range of 0–1.

3.2. *Antibody initialization and affinity calculation*

An antibody can also be formalized as a real-valued vector:

$$Ab = (R_1, R_2, \ldots R_N;\ S) \tag{2}$$

where $R_1, R_2, \ldots R_N$ refer to the attributes (features) of antibody in terms of a series of spatial variables and proximity variables. Here an antibody is initialized with a random number. Specifically, each R in Equation (2) is initially set to be a random number between 0 and 1. S is a Boolean variable in which the urbanized is 1 and the non-urbanized is 0.

Affinity refers to the binding degree of an antibody with an antigen. The affinity between an antigen and an antibody can be measured by the distance between the two vectors in the attribute space. In this study, affinity is calculated as follows:

$$Af_{gb} = \frac{1}{1 + d(Ag, Ab)} \tag{3}$$

where Af_{gb} is affinity and $d(Ag, Ab)$ is the distance between an antigen and an antibody.

In this study, $d(Ag, Ab)$ is calculated using an Euclidean distance:

$$d(Ag, Ab) = \sqrt{\sum_{i=1}^{N} (a_i - R_i)^2} \tag{4}$$

3.3. *Clonal selection and mutation*

During the evolution, the antibodies are evaluated using an affinity function and ranked in a descending order based on their affinity values. The m antibodies with the highest affinities are selected for the cloning operation. For each selected antibody to be cloned, the higher its affinity is, the larger the number of clones will be generated for it. The total number of clones generated for all these m selected antibodies is given by the following equation:

$$M_c = \sum_{h=1}^{m} \mathrm{round}\left(\frac{G^* M}{h}\right) \tag{5}$$

where round(.) is the operator that rounds its argument toward the closest integer, M is the total number of antibodies, G is a multiplying factor to control the total number of antibodies of the new generation, and h is the antibody current rank where $h \in [1, m]$, m is the number of selected antibodies for the cloning operation.

Each term of this sum corresponds to the clone size of each selected antibody. For example, for $M = 200$ and $G = 0.5$, the highest affinity antibody will produce 100 clones, while the second highest affinity antibody produces 50 clones, and so on. After cloning, the clones are mutated to increase their diversity. The degree of mutation for an antibody is inversely proportional to the affinity of that antibody: The higher the affinity the lower the degree of mutation. The mutation performed in this study can be represented as follows:

$$R_i^t = \begin{cases} R_i^{t-1}, & \text{if} \quad Af_{gb}/B \geq r \\ R_i^{t-1} - (1 - e^{-d(Ag,\, Ab)})(R_i^{t-1} - a_i), & \textit{if} \quad Af_{gb}/B < r \end{cases} \tag{6}$$

where t is an indication of generation, and thus R_i^{t-1} is an attribute value of an antibody of the last generation and R_i^t is its counterpart in the new generation; B is a constant greater than 1 for controlling the antibody's mutation probability; r is a random number within (0–1); and a_i is the corresponding attribute value of a training antigen.

Through clonal selection, antibodies with low affinities will gradually be replaced by new antibodies that are clones of those antibodies with high affinities. These clones will then go through mutations that contain a certain degree of randomness in order to maintain the diversity of the antibody library so that new areas of the search space can be explored. In this way, the antibodies in the antibody library will gradually obtain increasingly higher affinities to the sampled antigens, a process called *affinity maturation*. The clonal selection and mutation repeat until a termination criterion is met or a predetermined generation number is reached.

3.4. *Estimating the probability of urban development using AIS*

In the AIS-based CA model, empirical data from remote sensing and GIS (spatial distance variables) are used to create the antigen library (i.e., the sample set). On the other hand, the first generation of antibodies are created and initialized with random numbers. The antibodies gradually get 'matured' through the clonal selection and mutation, as discussed in Section 3.3. This process corresponds to the training stage in many other machine-learning methods. The 'matured' antibodies can identify and memorize antigen structures. When classifying an unknown cell in CA (in the form of an unknown antigen), first the affinity between each antibody and the cell is calculated using Equation (3), and then the k antibodies with the best affinities to the cell are used to determine the class (state) of the cell. Commonly, the voting method is used, that is, the cell is assigned the majority class (state) of its k best antibodies, which can be represented as follows:

$$\hat{f}(i) \leftarrow \arg\max \sum_{j=1}^{k} \delta(s, f(Ab_j)), \quad \begin{cases} \delta(s, f(Ab_j)) = 1, & \text{if} \quad s = f(Ab_j) \\ \delta(s, f(Ab_j)) = 0, & \text{if} \quad s \neq f(Ab_j) \end{cases} \tag{7}$$

where k is the total number of the best antibodies (with highest affinities) to the queried cell and s is the finite set of target class value. In this study, s represents the state of a cell (e.g., 1 for urbanized and 0 for non-urbanized). $f(Ab_j)$ is the class (state) of antibody j.

This method adopts a simple voting scheme in which the final result is determined by$f(Ab_j)$. Equation (7) only yields a Boolean value: a cell will be converted (urbanized) or not. In CA, however, conversion probability is often used to produce more plausible simulation results (Wu 2002, Li and Liu 2006). In this study, a roulette wheel algorithm is used to estimate the conversion probability:

$$P(i) = \frac{\sum_{j=1}^{k} Af(Ab_j, i) \cdot \delta(f(Ab_j), 1)}{\sum_{j=1}^{k} Af(Ab_j, i) \cdot \delta(f(Ab_j), 1) + \sum_{j=1}^{k} Af(Ab_j, i) \cdot \delta(f(Ab_j), 0)} \tag{8}$$

where $Af(Ab_j, i)$ is the affinity of antibody j to the queried cell i. This equation indicates that the contribution of an antibody is determined by its affinity to the queried cell.Equation (8) only concerns about the attributes of the queried cell. However, in reality a cell may also be significantly influenced by other cells in its neighborhood. For example, more urbanized cells in the neighborhood will increase the conversion probability of the cell under concern (Batty and Xie 1994, Li and Liu 2006). In this study, the neighborhood influence is incorporated as follows:

$$\Omega(i) = \frac{\sum_{3\times 3} N(\text{urban}(i))}{3\times 3 - 1} \tag{9}$$

where $\sum_{3\times 3} N(\text{urban}(i))$ refers to the total number of urbanized cells in a 3×3 neighborhood window around the cell under concern. It is noted that neighborhood density changes along with the simulation.

Furthermore, constraints such as rivers, steep slopes, and protected farm lands can be incorporated into the probability estimation (White *et al*. 1997, Li and Yeh 2000, Liu and Li 2008). The final conversion probability can then become

$$P_{\text{dev}}(i) = A \cdot P(i) \cdot C(i) \cdot \Omega(i) \tag{10}$$

where $C(i)$ is the combined constraint, $\Omega(i)$ is the percentage of urbanized cells in the neighborhood, and A is an adjusting factor.

4. AIS-based CA by incorporating planning interventions

As discussed in the previous section, an AIS-based CA model can perform *inertia* simulation if the historical trend in urban development continues in the future. In addition and more importantly, an AIS is 'open' for allowing some kinds of interventions. This allows the user to easily incorporate the inputs of planning policies into the transition rules through intervening antibodies' evolution. In other words, the user has the control to make antibodies to evolve into a certain form that will construct transition rules by reflecting planning objectives. In a land-use simulation, this means that the simulation does not have to be *inertia* that is totally based on the historical trend, but can also incorporate policies specified by planners. Through altering the structure and parameter values of the AIS-based CA model, we can generate different simulated scenarios to answer 'what if' questions and explore and evaluate various options (Figure 1).

There are many possible urban growth patterns, which are the main concerns of urban planning. Urban forms are closely related to the efficient use of energy, capital, and land

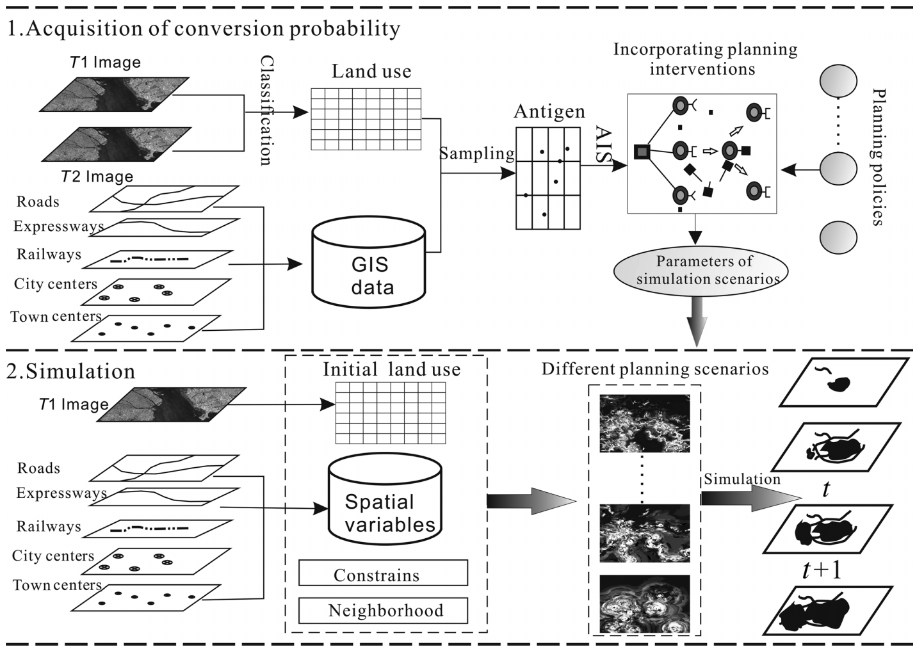

Figure 1. AIS-based CA model for urban planning.

resources (Banister *et al.* 1997, Burchell *et al.* 1998). With an AIS-based CA model, the user can design the selection and mutation mechanisms to incorporate planning intentions for different urban development forms. In this section, we use the 'city center' growth as an example to demonstrate how to embed planning policies into the AIS.

4.1. Incorporating planning policy by mutation

The 'city-center' growth means that the urban development is around city centers, resulting in a monocentric form. This form reflects compact developments that are restrained within small areas around cities. The 'city-center' policy has a clear planning intention to improve efficiencies in land and energy utilizations. This planning policy can be easily incorporated into the AIS by introducing constant thresholds about the distance to city into the mutation mechanism. Specifically, we increase the mutation probability for an urbanized antibody if its distance to a city is greater than a specified threshold; and meanwhile decrease the probability for a non-urbanized antibody if it is distant to cities. This simple idea can be easily implemented by altering Equation (6) as follows:

$$R_i^t = \begin{cases} R_i^{t-1}, & if \;\; Af_{gb}/B \geq r \text{ and } R_i^{t-1} \leq T_1 \\ R_i^{t-1} - (1 - e^{-d(Ag,\, Ab)})(R_i^{t-1} - a_i), & if \;\; Af_{gb}/B <= r \text{ or } R_i^{t-1} > T_1 \end{cases} \tag{11}$$

$$R_i^t = \begin{cases} R_i^{t-1}, & if \;\; Af_{gb}/B \geq r \text{ and } R_i^{t-1} \geq T_2 \\ R_i^{t-1} - (1 - e^{-d(Ag,\, Ab)})(R_i^{t-1} - a_i), & if \;\; Af_{gb}/B <= r \text{ or } R_i^{t-1} < T_2 \end{cases} \tag{12}$$

Equation (11) is for an urbanized antibody and Equation (12) is for a non-urbanized antibody. In Equations (11) and (12), T_1 and T_2 are two constants serving as the thresholds about the distance to city, and they indicate that the thresholds can be different for urbanized and non-urbanized cells. With Equations (11) and (12), the mutation process is not only controlled by affinity that represents the inertia trend, but also by user-specified thresholds that represent external interventions or planning policies.

Some other planning intentions, for example, restraining development to be close to roads and restraining development to be close to towns, can be embedded into the mutation process in the same way, only replacing the distance to city in Equations (11) and (12) with their corresponding variables (e.g., the distance to road and the distance to town).

4.2. Incorporating planning policy by clonal selection

The clonal selection process can also take into account planning policies. To achieve that, rather than to use only the affinity value to determine if an antibody will be selected for cloning, the user can use a combined value that includes both the affinity and the measurement representing the policy. Furthermore, the user can specify the weights for the two components in the combined value. The values that determine the selection of an antibody as antibodies are calculated as follows:

$$As = \alpha^* Af_{gb} + \beta^* \mathrm{e}^{-d} \tag{13}$$

$$As = \alpha^* Af_{gb} + \beta^* \mathrm{e}^{d} \tag{14}$$

Equations (13) and (14) are for urbanized antibodies and non-urbanized antibodies, respectively. *As* is the value that determines the selection of an antibody as antibodies with large *As* will be selected and retained in the antibody library. Variable d is the distance variable. The second component is the measurement for addressing the city-center growth policy. The weights of α and β reflect the relative importance of the affinity and the planning policy, respectively. They are specified by the user. For example, the greater the ratio β/α, the more important the planning policy in determining the selection.

Through the altered mutation and selection discussed above, antibodies for class 'urbanized' will gradually 'mature' and their values of the distance to certain features (e.g., city) will gradually decrease. Meanwhile, antibodies for class 'non-urbanized' will gradually 'mature' and their values of the distance to certain features will gradually increase. The planning policy is embedded into the antibodies according to this clonal selection process.

5. Model implementation and results

5.1. Study area and spatial data

The proposed AIS-based CA model was applied to the simulation of urban agglomeration development in the Pearl River Delta in southern China. The study area is about 41,157 km^2 in size, consisting of a hierarchy of cities with different scales of population and economic development. Recent years have witnessed a considerable urban expansion due to the fast economic development in this area. In this paper, the cellular space is represented as a regular

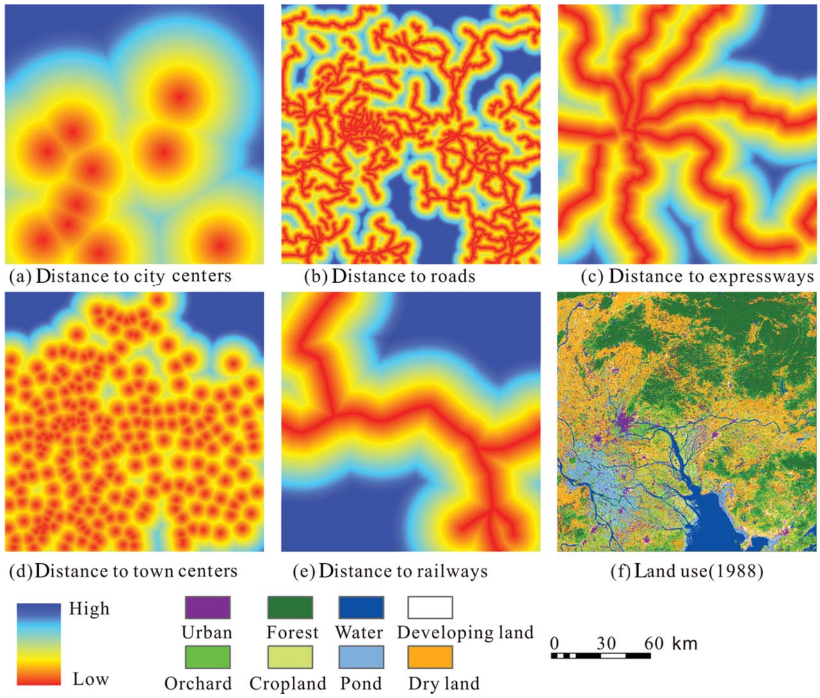

Figure 2. Various spatial variables prepared by a raster GIS.

lattice of two dimensions. The cellular state is a Boolean variable, which uses 1 to represent the state of being urbanized and 0 for otherwise.

The actual land-use types in the years of 1988, 1993, 1996, 1999, and 2002 were obtained by the classification of the TM satellite images. These empirical data were used to derive transition rules. A series of spatial variables related to land development in 1988, 1993, 1996, and 1999 were prepared using GIS function. Figure 2 shows the actual land-use and spatial variables in 1988. These spatial distances were calculated using the *Eucdistance* function in ArcGIS. Then, a sampling procedure was employed to retrieve only a portion of the original data as antigens by using a stratified sampling method (Congalton 1991), which ensures that sampling effort can be distributed in a rational pattern so that a specific number of observations are assigned to each category to be evaluated. The antigen library consists of two classes of antigens: urbanized and non-urbanized.

The antigen library was updated to reflect the possible change in relationships by using additional satellite images, the 1996 and 1999 TM images. Studies have indicated that the land-development patterns of the study area have changed significantly in different periods because of the variations in economic growth and land-use policies (Li and Liu 2006). At the same time, the attribute part of the antigen, including proximity variables, was updated by using these renewed variables in 1988, 1993, 1996, and 1999, which indicates that antigens can reflect the dynamics of land use over time.

The proposed AIS-based CA model was implemented using Visual Basic 6.0 and ArcObjects. ArcObjects provides access to spatial data as well as tools for distance calculation and focal operations. Visual Basic was used to calculate the transition rules and integrate the different components in the model.

5.2. Simulation of urban agglomeration development in the Pearl River Delta

Transition rules obtained by using the AIS algorithm were applied to the simulation of urban development in the Pearl River Delta. The antigen library contains a total of 9308 antigens, including 4505 urban antigens and 4803 non-urban antigens. On the other hand, the first generation of antibodies was created and all their attributes were initialized with random numbers. The evolution of the antibodies started with the calculation of affinity between each pair of antigen and antibody using Equation (3). There is no agreement on the optimal number of antibodies selected for cloning operation (King *et al.* 2001). The 200 antibodies were empirically derived after performing an exhaustive set, and the total number of clones generated for all these selected antibodies is given by Equation (5). Finally, the antibodies with higher affinity were retained in the antibody library, while the antibodies with low affinities were replaced by new antibodies mutated through Equation (6). As shown in Figure 3, the affinity becomes stabilized after the time of evolution is greater than 100, and the affinity is 0.991 at this time, which indicates the maturity of the antibodies. Therefore, the process stops when affinity reaches 0.991.

To test the capabilities of the evolving antibodies in identifying antigens, another 8370 samples were acquired through randomly sampling the remote-sensing classification data. The test with these samples indicated that the identifying capabilities of the antibodies were gradually improved as the antibodies are evolving. After 100 times of iteration, the capability tends to get stable (Figure 4).

The mature antibodies were then applied to the simulation of urban development with the land use of 1988 as the initial state. The simulation was conducted in discrete temporal steps. A sufficient number of steps are required to reveal the effects of spatial interactions and produce details in the resulting spatial patterns. Although there is no consensus on the optimal number of steps, 100–200 iterations are common in practice (Wu 2002, Li and Yeh 2004, Liu *et al*. 2008). The observation interval between remote-sensing images is generally far greater than the iteration interval of CA simulation. It may be ideal if the observation interval is equal or *close to the iteration interval* so that derived transition rules can be used directly in urban simulation (Li and Yeh 2004). As a result, it is necessary to determine the amount of land-use conversion in the iteration interval in CA models. The number of iterations of CA models during the period of iteration is determinate according to the research of Li and Yeh (2004). In our experiments, the urban development in the period of

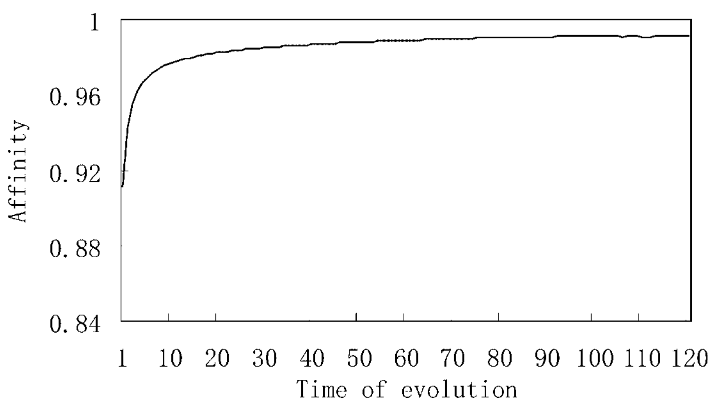

Figure 3. The processes of affinity maturation for antibodies.

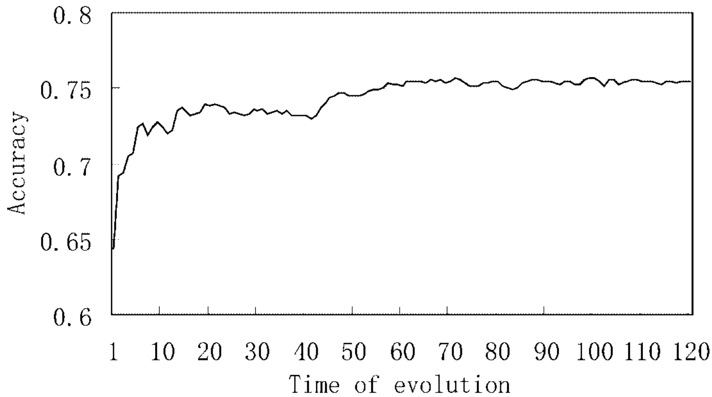

Figure 4. The improvement process of identification capabilities for antibodies.

1988–1993 and 1993–2002 was simulated by running the model for 200 and 400 iterations, respectively.

Following Clarke *et al.* (1997) and White *et al.* (1997), we conducted visual inspections to compare the simulation results and the actual situations derived from the TM data. It is found that the simulated pattern and the actual one are very similar (Figure 5). A confusion matrix was calculated to quantify the concordance between the simulated and the actual development patterns (Table 1), as suggested by Li and Liu (2006). This matrix was obtained based on a cell-on-cell spatial overlay of the two layers. The matrix reveals that the total accuracies of the simulations are 85.3 and 81.3% for 1993 and 2002, respectively.

5.3. *Simulating development alternatives for urban planning in the Pearl River Delta*

In urban planning, a compact urban form is usually advocated as it improves efficiencies in land and energy utilizations (Jenks *et al.* 1996, Li *et al.* 2008). Disorderly urban sprawl has been widely criticized in both developed and developing countries. The planning and management of urban growth need the quantitative measurement of urban forms. Land development has taken place in a rather fragmented form in the Pearl River Delta (Li and Yeh 2004). The simulation of land development can allow planners to explore and evaluate different planning options. Some planning policies or interventions can be incorporated in the simulation for promoting more compact urban forms. The simulation explores six planning scenarios: (1) ‘city-center’ growth: the developments are around city centers, resulting in a monocentric form in an urban area; (2) ‘road-concentrated’ growth: the developments are concentrated along roads; (3) ‘expressway-concentrated’ growth: the developments are concentrated along expressways; (4) ‘town-center’ growth: the developments are around town centers, resulting in a polycentric form; (5) ‘city-center and expressway’ growth: the developments are concentrated both around city centers and along expressways; and (6) ‘town-center and road’ growth: the developments are concentrated both around town centers and along roads.

Specified mutation and selection processes were designed for each scenario. For example, 11–14 describe the mechanism of mutation and selection for antibodies under the scenario of ‘city-center’ growth. Similar to the ‘city-center’ growth, other planning scenarios were obtained by just modifying the parameters of Equations (11) and (12) (Table 2).

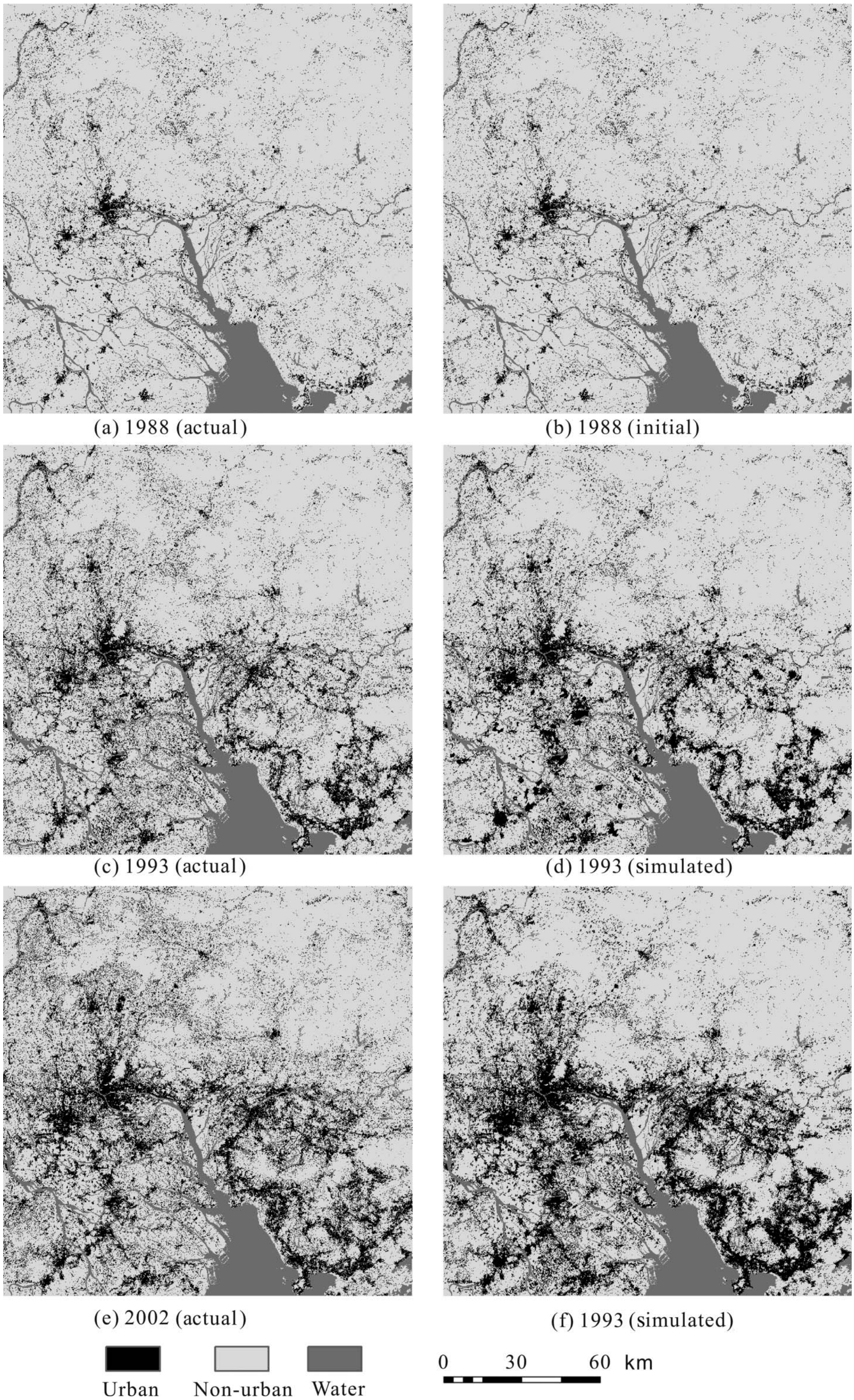

Figure 5. Simulated and actual urban development in the Pearl River Delta in 1988, 1993, and 2002.

Table 1. Simulation accuracies of the AIS-based CA model for the Pearl River Delta.

	1988–1993 (cells)		
	Simulated 1993 non-urban	Simulated 1993 urban	Accuracy
Actual 1993 non-urban	473,326	61,667	88.5%
Actual 1993 urban	32,454	70,953	68.6%
Total accuracy			85.3%
	1988–2002 (cells)		
	Simulated 2002 non-urban	Simulated 2002 urban	Accuracy
Actual 2002 non-urban	429,098	69,172	86.1%
Actual 2002 urban	49,974	90,155	64.3%
Total accuracy			81.3%

As shown in Figure 6, the average distance to city centers is gradually decreased at a large scale, which implies that the evolution of antibodies can fully and correctly represent planners' intention. In the simulation of *inertia* growth scenarios, urban development also shows a trend toward the city centers. However, this trend is not remarkable (Figure 6). Through altering the evolution process (training) of antibodies, planning policies can be integrated into the AIS algorithm, and the planner can generate different simulated scenarios to answer 'what if' questions and explore and evaluate various options.

Based on the six planning scenarios designed for urban development, by altering the mechanism of mutation and selection for antibodies, the planning policies were embedded into the AIS algorithm. Urban-development probability is calculated by using Equation (10). The urban-development pattern from 1988 to 2002 is then simulated by running this planning model with 600 iterations under different planning scenarios (Figure 7). It can be seen from Figure 7 that the simulated planning scenarios can well reflect the predefined planning policies.

The evaluation of urban morphology can help identify suitable planning schemes for producing compact development. The assessment is carried out by using some common landscape metrics, which can provide a detailed description of the accuracy of the model's historical simulations (Herold *et al.* 2003). In this study, these metrics include number of patches (*NP*), area-weighted mean patch fractal dimension (*AWMPFD*), patch edge density (*ED*), landscape shape index (*LSI*), and aggregation index (*AI*). These metrics can be calculated by using a landscape analysis package, FRAGSTATS 3.3. The indicators of *NP*,

Table 2. Values of different parameters under various planning scenarios in the Pearl River Delta.

Simulation scenarios	T_1	T_2	B
City center	60.0	124.0	1.5
Road-concentrated	46.0	82.0	1.5
Expressway-concentrated	54.0	102.0	1.5
Town center	43.0	78.0	1.5
City center and expressway	60.0	124.0	1.5
	54.0	102.0	1.5
Town center and road	43.0	78.0	1.5
	46.0	82.0	1.5

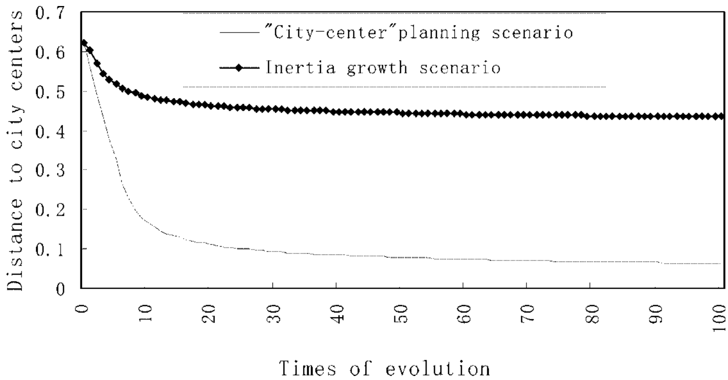

Figure 6. The change of average distance to city center for antibodies.

AWMPFD, and *ED* can be used for evaluation of landscape fragmentation; *AWMPFD* and *LSI* can be used for complexity measurement of landscape shape; and *AI* can be used for evaluation of landscape compactness.

NP can be calculated as follows:

$$NP = N \tag{15}$$

where N is the total number of patches. The bigger the *NP*, the higher the degree of landscape fragmentation.

AWMPFD is given as follows:

$$AWMPFD = \sum_{i=1}^{m}\sum_{j=1}^{n}\left[\frac{2\ \ln(0.5P_{ij})}{\ln(a_{ij})}\left(\frac{a_{ij}}{A}\right)\right] \tag{16}$$

where P_{ij} is the perimeter of the patch, a_{ij} is the area of the patch, and A is the total area of the landscape.

ED is represented by the following equation:

$$ED = 10^6 * \frac{E}{A} \tag{17}$$

where E refers to the total length of all patch edges and A refers to the total area of the landscape. The more fragmented the landscape, the higher the value of *ED*.

LSI is expressed as follows:

$$LSI = \frac{0.25E}{\sqrt{A}} \tag{18}$$

where E is the total length of all patch edges and A is the total area of the landscape. The more complex the landscape shape, the higher the value of *LSI*.

AI can be calculated by using the following equation:

$$AI = 100^{*}\left[\frac{g_{ii}}{\max(g_{ii})}\right] \tag{19}$$

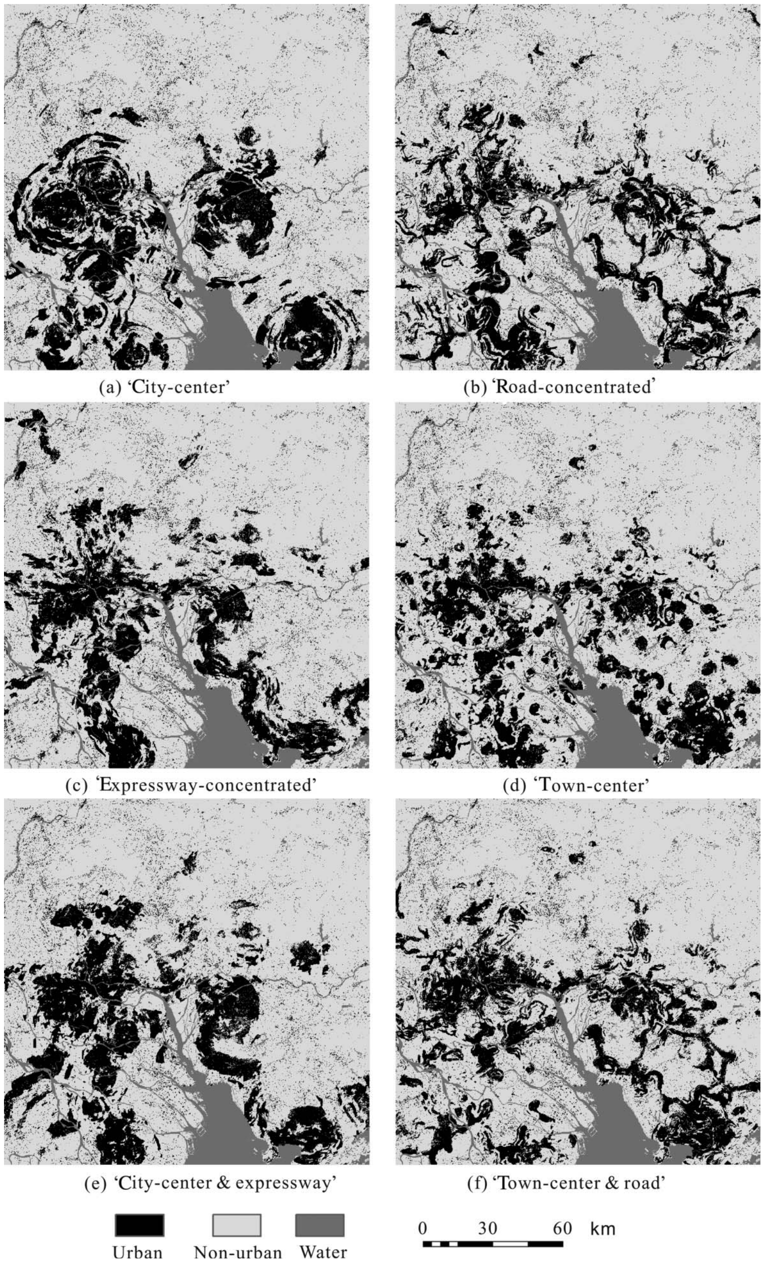

Figure 7. Simulated results of different planning scenarios in the Pearl River Delta.

where g_{ii} is the number of like adjacencies (joins) between pixels of patch type (class) i based on the single-count method. $\max(g_{ii})$ is the maximum number of like adjacencies (joins) between pixels of patch type (class) i based on the single-count method. If the same type of patches is highly joined together, AI would be very high.

Table 3 shows landscape indices of different simulation scenarios in the Pearl River Delta. Some interesting results can be found as follows:

Table 3. Landscape indices of different simulation scenarios in the Pearl River Delta.

Simulation scenarios	NP	AWMPFD	ED	LSI	AI
City center	10,583	1.283	10.447	37.564	91.622
Road-concentrated	11,459	1.294	11.373	41.893	87.786
Expressway-concentrated	10,981	1.291	10.779	39.755	90.422
Town center	11,284	1.293	10.949	41.292	87.639
City center and expressway	10,743	1.279	10.291	37.003	91.763
Town center and road	11,643	1.295	11.484	42.290	87.687
Actual development	20,840	1.345	23.404	85.152	78.937
Inertia growth scenario	18,260	1.341	21.606	84.588	80.269

(1) Urban forms resulted from ‘city-center’ and ‘city-center and expressway’ growth models appear to be more compact and less fragmented, while urban forms resulted from ‘town-center’ and ‘road-concentrated’ growth models appear to be more disordered and more dispersed.
(2) The actual urban form is very close to that of *inertia* growth scenario. This means that the AIS method can have a good performance in discovering reliable transition rules of CA models.

6. Conclusions

The preparation of various development scenarios is important in urban and regional planning. The simulation can help planners and decision makers test and compare what can be gained under different planning policies. CA models have been increasingly used in urban simulation. However, most urban CA models assume that the historical trend will continue into the future and ignore possible external interventions, particularly planning policies. Therefore, there are very limited studies in applying them to urban planning.

This study proposes a new kind of urban simulation models for generating development scenarios by integrating AIS, CA, and GIS. This proposed method can conveniently generate development alternatives through modifying the mutation mechanism according to different planning policies. Planning policies can be integrated into the AIS algorithm by altering the mechanism of antibody evolution. Antibody will ‘evolve’ gradually toward the predefined planning policies that are specified by urban planners. Altering the AIS-based CA model structure and input parameters, different growth scenarios can be generated and evaluated, and ‘what if’ questions can be answered. This proposed model can help planners and decision makers test and compare what can be gained under different planning policies. It provides a useful exploratory tool for testing various planning scenarios for urban development.

The proposed AIS-based CA model was applied to the simulation of urban agglomeration development in the Pearl River Delta in southern China. Fast urban expansion has occurred in the 1990s due to the fast economic development in the study region. The actual urban areas in the years of 1988, 1993, and 2002 were obtained by the classification of the TM satellite images, which is used to discover transition rules based on the AIS algorithm. The simulated and actual patterns are very similar through visual inspections and cell-by-cell comparisons. The Pearl River Delta consists of a hierarchy of fast growing cities, such as Shenzhen, Dongguan, and Guangzhou. However, the AIS-based CA can produce very plausible simulation results for this region, which indicates that this model is appropriate to simulate urban development in large regions.

Meanwhile, six different urban growth scenarios were designed in this study. The proposed AIS-based CA planning model was used to simulate urban development in the Pearl River Delta under different planning schemes (1988–2002). This model provides a useful method to create different urban forms such as 'city center', 'town center', and 'road-concentrated' growth patterns. A number of spatial metrics were used to measure the morphology of simulated results. Experiments demonstrate that the 'city-center' and the 'city-center and expressway' growth modes are more compact and less fragmented. In contrast, the 'town-center' and the 'road-concentrated' growth modes are disordered and dispersed. This study indicates that CA can not only provide useful knowledge in understanding urban development processes but is also able to assist land use planning by incorporating planning objectives in the simulation.

The proposed AIS-based CA model enables planners and stakeholders to assess the future outcomes of current planning policies in large regions and investment choices before they are put into action. However, these planning policies used in this model are development preferences at the scale of local transition rules. Future effort will be focused on integrating local-scale and global-scale planning policies into AIS-based CA model, such as socioeconomic factors associated with administrative boundaries and census district.

Acknowledgments

This study was supported by the National Natural Science Foundation of China (Grant No. 40901187), the Key National Natural Science Foundation of China (Grant No. 40830532), the National Outstanding Youth Foundation of China (Grant No. 40525002), and the Research Fund of LREIS, CAS (Grant No. 4106298).

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