Science in China Series D: Earth Sciences

Genetic algorithms for determining the parameters of cellular automata in urban simulation

LI Xia†, YANG QingSheng & LIU XiaoPing

School of Geography and Planning, Sun Yat-sen University, Guangzhou 510275, China

This paper demonstrates that cellular automata (CA) can be a useful tool for analyzing the process of many geographical phenomena. There are many studies on using CA to simulate the evolution of cites. Urban dynamics is determined by many spatial variables. The contribution of each spatial variable to the simulation is quantified by its parameter or weight. Calibration procedures are usually required for obtaining a suitable set of parameters so that the realistic urban forms can be simulated. Each parameter has a unique role in controlling urban morphology in the simulation. In this paper, these parameters for urban simulation are determined by using empirical data. Genetic algorithms are used to search for the optimal combination of these parameters. There are spatial variations for urban dynamics in a large region. Distinct sets of parameters can be used to represent the unique features of urban dynamics for various subregions. A further experiment is to evaluate each set of parameters based on the theories of compact cities. It is considered that the better set of parameters can be identified according to the utility function in terms of compact development. This set of parameters can be cloned to other regions to improve overall urban morphology. The original parameters can be also modified to produce more compact urban forms for planning purposes. This approach can provide a useful exploratory tool for testing various planning scenarios for urban development.

Cellular automata, genetic algorithms, planning scenarios, compact development

1 Introduction

Cellular automata (CA) were first introduced in 1948 by the mathematician von Neumann, with suggestions from his colleague, Ulam, to model complex dynamic systems, such as biological reproduction and crystal growth[1]. As a kind of dynamic models, CA are based on discrete time and space, finite states, and local rules. In the early stage, CA were used to demonstrate that universal machines could simulate themselves and, if they could do this, there lay the logic for their self-reproduction[2,3]. This logic is also the basis for digital computation, which was illustrated by Wolfram's researches on CA in the 1980s[4]. Wolfram demonstrated that complex behaviors of complex systems can be simulated by using some simple local rules of CA. It is interesting that a series of advantages can be identified for CA in modeling physical systems: (1) The correspondence between physical and computation processes are clear; (2) CA can produce more comprehensive results just by using simpler rules than complex mathematical equations; (3) it is convenient to use computers to model them without loss of precision; (4) they can simulate the actions of any possible physical systems; and (5) the forms of CA are most compact because they are irreducible[5].

CA have been increasingly used in the simulation of complex systems, such as biological reproduction, chemically self-organizing systems, propagation phenomenon, and human settlements. The application of two-dimensional CA is straightforward for simulating

Received March 12, 2007; accepted June 27, 2007
doi: 10.1007/s11430-007-0127-4
†Corresponding author (email: lixia@mail.sysu.edu.cn)
Supported by the National Outstanding Youth Foundation of China (Grant No. 40525002), the National Natural Science Foundation of China (Grant No. 40471105), and the Hi-tech Research and Development Program of China (863 Program) (Grant No. 2006AA12Z206)

cities and other geographical phenomena. CA have great potentials in simulating urban growth and exploring alternative development forms by using predefined rules. In the last two decades, a set of urban models based on CA techniques were reported with interesting outcomes[2,6−9]. For example, Batty and Xie[2] have shown how CA can deliberately articulate global patterns through some local processes. Their simulation is based on the suburban expansion of a peripheral municipality, the town of Amherst, in metropolitan Buffalo, White et al.[8] also provide a realistic example of CA simulation for the land-use pattern of Cincinnati, OH. A series of experiments for simulating fast urban growth in China have been also reported[10−12].

Traditional CA have been significantly modified when they are applied to the simulation of urban systems. Local rules are relaxed by using "action-at-distance" rules instead of using strict "locality" rules to address various influences of geographical variables. Moreover, CA are often linked to GIS for enhancing their functionality. This can overcome some of the limitations of current GIS and satisfy the data realism requirement of CA for modeling[11]. GIS have limitations in modeling spatiotemporal dynamics, but the integration of CA and GIS can significantly improve their modeling capability[6]. Space no longer needs to be uniform in CA since the spatial difference equations can be easily developed in the context of GIS[2].

In CA, many variables are involved for defining transition rules. Each variable is usually associated with a parameter that indicates its importance in simulation. These parameters significantly affect the outcomes of urban simulation[11,13]. It is essential to define proper parameter values when CA are used to simulate realistic cities. Some calibration techniques have been proposed to determine these parameter values. For example, computer search algorithms have been used to derive optimal parameter values according to the best fit between the observed data and various simulated results[14]. This method involves intensive computation by comparing numerous possible combinations of parameter values. Artificial neural networks have been incorporated into urban CA for deriving parameter values automatically[11]. However, it is difficult to comprehend the meanings of these parameter values because of the back-box approach of neural networks. Wu[13] provides a method to estimate the global development probability by using a logistic regression model. Data mining techniques can be used to retrieve transition rules[12].

However, existing methods are based on a uniform set of parameters for simulating urban dynamics in a whole region. This assumes that the relationships are fixed in the spatio-temporal dimension. In reality, the relationships may be complex between the state conversion and its geographical variables, and discrepancy can be created for the simulation based on a uniform set of transition rules. Heterogeneous development patterns can be observed in large complex regions[15].

Understanding these parameter values can provide useful information for urban planning since they can control urban morphology in the simulation. Urban forms should be 'more compact and humane', instead of the increasingly spread-out of metropolitan development[16]. The morphology of a city is an important feature in the 'compact city theory'[17]. There is evidence indicating a strong link between urban form and sustainable development, although it is not simple and straightforward. Significant relationships have been found between energy use in transport and physical characteristics of cities, such as density, size, and amount of open space[18].

Rapid urban expansion in the fast growing cities of China has created a major concern for sustainable land use in these regions. Massive conversion of non-urban land into urban land has created a series of land use problems, such as decrease of food production, destruction of sensitive ecosystems, water and air pollution, and deprivation of future land supply[19]. Especially, fragmented use of land resources has further deteriorated land use problems. There is a need to promote compact development in China which has a low per-capita amount of land resources.

Modelling systems can be developed to provide the assistance in implementing the initiatives of sustainable land use[20]. These models are useful for carrying out scenario analysis which is a promising and interesting planning tool for investigating the future in a changing environment[21]. This analysis allows the generation of several alternative plans while being aware of uncertainties[22]. It can answer a series of "what will happen if" questions, and can also produce expected and desired scenarios to strengthen landscape planning.

This paper will use various sets of parameters of CA for simulating large regions instead of using a single set of parameters. A large complex region will be first segmented into a number of subregions according to administrative boundaries. This can improve the accuracies of simulation by using changeable transition rules. However, there are difficulties in defining these parameters because of using nonlinear equations. Genetic algorithms (GA) are used to determine these sets of parameters automatically. This paper will further explore the relationships between these parameters and urban morphology. These parameters are evaluated according to some spatial metrics. The modification of these parameters is carried out by using a heuristic swapping technique. The proposed method should be useful for simulating compact urban development under various assumptions for planning purposes.

2 Retrieving parameter values of CA using genetic algorithms (GA) and simulating planning scenarios

In an urban CA, transition rules are usually represented by using a probability function. The probability determines if land use conversion will take place according to a number of spatial variables that represent various forces in urban evolution[9]. The combined effects of these forces can be addressed by incorporating multicriteria evaluation (MCE) into cellular automata[9]. MCE can be used to capture the different blends of government and private developer preferences that govern different development regimes. The development probability is determined by a combined evaluation score r_{ij}, of which nonlinear transformation is used to discriminate the simulation patterns. The probability is expressed as follows[9]:

$$p_{ij}^t = \phi(r_{ij}^t) = \exp\left[\alpha\left(\frac{r_{ij}^t}{r^{\max}} - 1\right)\right], \tag{1}$$

where is a dispersion parameter ranging from 0 to 1; r_{ij}^t is the combined evaluation score at location ij; $r^{\max}$ is the maximum value of r_{ij}^t.

The composite evaluation score (r_{ij}^t) is calculated by using the following linear combination of various geographical variables:

$$r_{ij}^t = a + \beta_1 d_{\text{centre}} + \beta_2 d_{\text{industrial}} + \beta_3 d_{\text{railway}} + \beta_4 d_{\text{road}}, \tag{2}$$

where a is the constant; d_{centre}, $d_{\text{industrial}}$, d_{railway} and d_{road} represent the distances from the cell (ij) to the major urban centre, the industrial centre, railways and roads. $\beta_1,\cdots,\beta_4$ are the weights (parameters) for these variables.

These proximity variables are used to address the "action-at-distance". It is rather easy to understand the meanings of the weights in the MCE expression. A larger weight indicates that the associated variable has a more contribution to the development probability. However, this MCE-CA model cannot be calibrated for simulating realistic cities. A modification of this model is to transform it into a logistic form so that the calibration is possible[13]:

$$p_{ij}^t = \frac{\exp(-r_{ij}^t)}{1+\exp(-r_{ij}^t)} = \frac{1}{1+\exp(-r_{ij}^t)}. \tag{3}$$

Urban development is subject to a series of physical constraints and some uncertainties. By incorporating a series of constraints plus a stochastic factor, the above equation can be further revised as follows：

$$p_{ij}^t = (1+(-\ln\gamma)^{\alpha}) \times \frac{1}{1+\exp(-r_{ij}^t)} \times con(s_{ij}^t) \times \Omega_{ij}^t, \tag{4}$$

where γ is a stochastic factor ranging from 0 to 1, Ω_{ij}^t is the development intensity in the neighborhood, and $con(s_{ij}^t)$ is the total constraint score ranging from 0 to 1.

The terms of r_{ij}^t, Ω_{ij}^t and $con(s_{ij}^t)$ are dynamically updated during CA simulation. At each iteration, p_{ij}^t is compared with a threshold value to determine if a non-urbanized cell will be converted into urbanized cell:

IF $p_{ij}^t >$ Threshold and cell ij is undeveloped,

THEN The state of the cell will be converted into urban land.

It is inappropriate to use a single set of parameters to simulate urban dynamics in a complex region. An aggregated region usually consists of many sub-regions, such as a number of cities and towns. It is preferable to partition this region into a number of sub-regions. The transition rules in equation (2) can be revised as follows:

$$\begin{aligned} r_{ij,k}^t = {} & a_{0,k} + \beta_{1,k} d_{\text{centre},k} + \beta_{2,k} d_{\text{industrial},k} \\ & + \beta_{3,k} d_{\text{railway},k} + \beta_{4,K} d_{\text{road},k} \quad (k = 1,2,\cdots,K), \end{aligned} \tag{5}$$

where K is the total number of subregions.

These various sets of parameters are crucial for producing realistic results for simulating urban dynamics. A genetic algorithm (GA) can be used to find the optimal set of parameters of CA for each subregion. GA is based on the concept of natural selection which controls the evolution process in biology[23]. It can effectively find an approximate global maximum or minimum value according to fitness functions. It is generally applicable to a variety of complex optimization problems. In this optimization, the chromosome is devised to represent the set of parameters for subregion k according to the following expression:

$$CM = [a_{0,k}, a_{1,k}, \ldots, a_{m,k}, p_{\text{threshold},k}]. \tag{6}$$

Fitness functions should be defined for finding the optimal parameters of the CA model. Fitness functions are used to indicate the performance of each solution or individual (chromosome) in solving an optimal problem. In this study, the fitness function is defined by calculating the difference between the actual state (e.g. urbanized or not) and the predicted state. The optimal set of parameters should produce the minimum value (the least error) of the fitness function. Therefore, the fitness function is represented as follows:

$$f(x) = \sum_{i=1}^{n} (\widehat{f_i} - f_i)^2, \tag{7}$$

$$\widehat{f_i} = \begin{cases} 1 & \text{if} \quad \widehat{f_i} \geqslant p_{\text{threshold}} \\ 0 & \text{if} \quad \widehat{f_i} < p_{\text{threshold},} \end{cases}$$

where

$$\widehat{f_i}(x_1, x_2, \cdots, x_m) = \frac{1}{1 + \exp(-(a_{0,k} + \beta_{1,k} d_{\text{centre},k} + \beta_{2,k} d_{\text{industrial},k} + \beta_{3,k} d_{\text{railway},k} + \beta_{4,K} d_{\text{road},k}))}.$$

f_i is the actual states (f_i = 1 for urbanized cells; f_i =0 for non-urbanized cells) obtained from the classified remote sensing images.

The actual states are obtained from the classification of remote sensing imagery. The predicted state is calculated by using the logistic model. The whole region is divided into a number of subregions (e.g. cities) based on the administrative boundaries. The GA program is used to find the optimal set of parameters for each subregion. After the calibration, CA can then be used to simulate realistic development.

The evaluation of urban morphology can help to identify suitable parameters for simulating 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 that applied also to forecasts of future development[24]. These spatial metrics include Mean Patch Shape Index (MPSI), Mean Patch Fractal Dimension (MPFD), Mean Euclidean Nearest-Neighbor Distance (MNN), and Aggregation Index (AI). They are obtained by using a landscape analysis package, FRAGSTATS 3.3.

Mean Patch Shape Index (MPSI) is given as

$$\text{MPSI} = \frac{0.25 \sum_{i=1}^{n} P_i}{\sqrt{\sum_{i=1}^{n} A_i}}, \tag{8}$$

where MPSI is mean patch shape index, P_i is the perimeter of patch i, A_i is the area of patch i in terms of number of cells, n is the total number of patches. MPSI increases as patch shape becomes more irregular.

Mean Patch Fractal Dimension (MPFD) is calculated as

$$\text{MPFD} = \frac{\sum_{i=1}^{n} \left[\dfrac{2 \ln(0.25 P_i)}{\ln(A_i)} \right]}{n}, \tag{9}$$

where MPFD is mean patch fractal dimension. MPFD approaches 1 for shapes with very simple perimeters such as squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters.

Mean Euclidean Nearest-Neighbor Distance (MNN) is represented by

$$\text{MNN} = \frac{\sum_{i=1}^{n} h_i}{n}, \tag{10}$$

where MNN is mean Euclidean nearest-neighbor distance, h_i is the distance from patch i to nearest neighboring patch of the same type (class) i, based on patch edge-to-edge distance, computed from cell center to cell center. MNN decreases as patches become more compact.

Aggregation Index (AI) is expressed by the following equation:

$$\text{AI} = \left[\frac{g_{ii}}{\max g_{ii}} \right] \times 100, \tag{11}$$

where AI is aggregation index, 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. max g_{ii} is expressed as

$$\max g_{ii} = \begin{cases} 2n(n-1), & m = 0 \\ 2n(n-1) + 2m - 1, & m \leqslant n \\ 2n(n-1) + 2m - 2, & m > n \end{cases} \quad (12)$$

where $m = a_i - n^2$, a_i is the area of class i (in terms of number of cells) and n is the side of a largest integer square smaller than a_i. AI equals 0 when the focal patch type is maximally disaggregated (i.e., when there are no like adjacencies); AI increases as the focal patch type is increasingly aggregated and equals 100 when the patch type is maximally aggregated into a single, compact patch.

These metrics can be combined to form a final utility function (U) by representing all these morphological effects. This utility function is defined as

$$U = \frac{1}{4}((1 - \text{NMPSI}) + (1 - \text{NMPFD}) + (1 - \text{NMNN}) + \text{NAI}), \quad (13)$$

where U is the combined utility function. The higher the utility value is, the better the urban morphology becomes in terms of compact development.

Since NMPSI, NMPFD, NMNN, NAI are measured at different scales. These metrics must be normalized before they are combined. The following equation is used for the normalization:

$$x_i' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}. \quad (14)$$

The spatial data are stored in ARCGIS GRID data format, which can be imported to FRAGSTATS 3.3 for the calculation of these metrics. The best set of parameters can be identified according to this utility function. This set of parameters can be cloned to other subregions for produce better urban forms.

3 Application and results

3.1 Retrieving the parameters for simulating urban dynamics in the Pearl River Delta

The study area is situated in the Pearl River Delta which has witnessed fast urban development since the economic reform in 1978. Because the study area is a large complex region with a hierarchy of cities, it can be segmented into a number of subregions for capturing the complexity of urban dynamics. In this research, the study area is divided into six major subregions based on the administrative boundaries of cities. They are the cities of Guangzhou city proper, Zengcheng, Conghua, Shenzhen, Dongguan and Zhongshan.

A genetic algorithm (GA) was used to determine the separate sets of parameters of CA for each subregion. The fitness function was calculated based on the empirical data from remote sensing and GIS. The dependent variable, land use conversion, was obtained by the classification of the Landsat TM images dated on 10 December, 1988 and 24 December, 1993 respectively.

It needs to determine some parameters before executing the programming. In this study, the population size was set to 100. The initial value of $a_{0,k}$ was 0.5, and all the initial values of $a_{1,k}, \dots a_{m,k}, \dots a_{M,K}$ were −0.01. The crossover rate and the mutation rate were 0.90 and 0.01 respectively. The strategies of elitist selection and diversity operation were also adopted to facilitate the search for the optimal parameters. It is found that GA has a very good convergence rate for searching the best set of parameters (Figure 1).

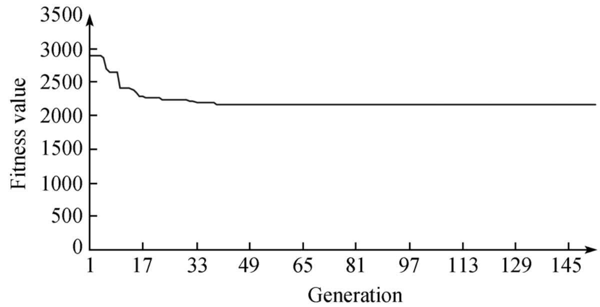

Figure 1 The convergence of GA in search for the best set of parameters.

Table 1 shows the retrieved parameters for simulating urban evolution in this region. Distinct sets of parameters are obtained for different cities in this region. Each set of parameters will control the unique evolution of urban morphology for a city. Traditional methods have difficulties in determining these parameters because of the complexities.

These retrieved parameters can be applied to generating realistic urban growth without any modifications (Figure 2(b)). They can be used to simulate urban development in the same period (1988—1993) from which the empirical data were obtained, and predict urban development in the "future" period (1993—2004) based on the growth trajectory. Very plausible results have been obtained by using these parameters to simulate urban development in 1988—2004, although these parameters are retrieved by using empirical data in 1988—1993. This is conformed by comparing the simulated patterns

Table 1 Retrieved parameters of CA for each city in the Pearl River Delta based on empirical data

	$a_{0,k}$	$a_{1,k}$	$a_{2,k}$	$a_{3,k}$	$a_{4,k}$	$a_{5,k}$	$P_{\text{threshold}}$
Guangzhou	1.476	–0.00079	–0.00794	–0.02519	–0.00245	–0.00402	0.445901
Zengcheng	1.500	–0.00089	–0.00010	–0.02048	–0.00010	–0.00032	0.512726
Conghua	1.500	–0.00088	–0.00872	–0.02832	–0.00010	–0.00010	0.542195
Shenzhen	1.500	–0.00010	–0.00480	–0.01656	–0.00794	–0.00010	0.512844
Dongguan	0.978	–0.00010	–0.00559	–0.01421	–0.00167	–0.00010	0.729893
Zhongshan	1.034	–0.00089	–0.00010	–0.02205	–0.00167	–0.00010	0.559767

(Figure 2(b)) with the actual patterns (Figure 2(a)) which is obtained by classifying remote sensing data. This indicates that CA have a strong capability of predicting urban development if they have been calibrated by using empirical data.

3.2 Simulating planning scenarios

A further step is to simulate planning scenarios based on the modification of these parameters. It is expected that some sets of parameters can have better performances in terms of compact development. The evaluation of urban morphology can help to identify these "good" parameters. The assessment is carried out by using some common landscape metrics.

Table 2 lists the results of assessing the actual urban forms of various cities in the study area. It is found that Guangzhou city proper has the largest value of the combined utility function. This provincial capital has the most compact form because of implementing strict development control. The whole region can have a better urban form if other cities can follow the behavior of the city proper. This can be realized by cloning these parameters from the city proper to other cities.

Figure 3(b) shows the results of simulating the development patterns of the whole region by using the parameters of the city proper. Cloning these parameters to the whole region has resulted in a significant increase of compactness for the whole region. This fact is supported by the significant increase of the combined utility value (Table 3). Therefore, this proposed method can produce not only a compact but also a practical form by cloning the realistic good parameters. It is possible to generate a complete compact form, but this form may not be practical. This proposed method is useful for creating a more acceptable urban form, assuming that the mechanism of urban development in the city proper is applicable to other cities.

The direct use of the parameters of the city proper may not be the best option since its land use problems can be propagated to other cities. A solution is to modify existing parameters based on the assessment of their performance. Different parts of parameters will play specific roles in controlling urban morphology. For example, some parameters will result in road-based development, but others will produce town-centre-based development. These parameters can be modified to produce more compact growth scenarios under various planning objectives.

Two options are available for modifying the existing best parameters (e.g. the parameters of the city proper) before they are used for the whole region. These two options of modification include: (1) "city centers-transport" concentrated development; (2) "city centers-town centers-transport" concentrated development. The first option is to address the trade-off between the attractions from city centres and transport networks. Most of the land development is attracted by city centres, but some by transport networks, such as roads, railways, and expressways. The second option is to address the trade-off between the attractions from city centres, town centres and transport networks. Most of the land development is attracted by city and town centres, but some by transport networks.

The parameters from the most compact city (e.g. the city proper) are used as the start point for the modification. A heuristic swapping technique is proposed for the search of better parameters compared to the existing ones. The search is constrained by the total amount of land use conversion, which is obtained from the classification of remote sensing images. It is to ensure that the total amount of land use conversion is the same between the simulated and the actual (expected). The new parameters are obtained by interactive modification of the weights between city centres, town centres and roads. The detailed procedure of modification for "city centers-transport" concentrated development is as follows:

(1) The initial weights ($a_{M,K}$) are set to the minimum absolute value (–0.0001) for all the variables, such as city centres, roads, railways, and expressways (Figure 4(a)). This is to guarantee the minimum attraction to these factors.

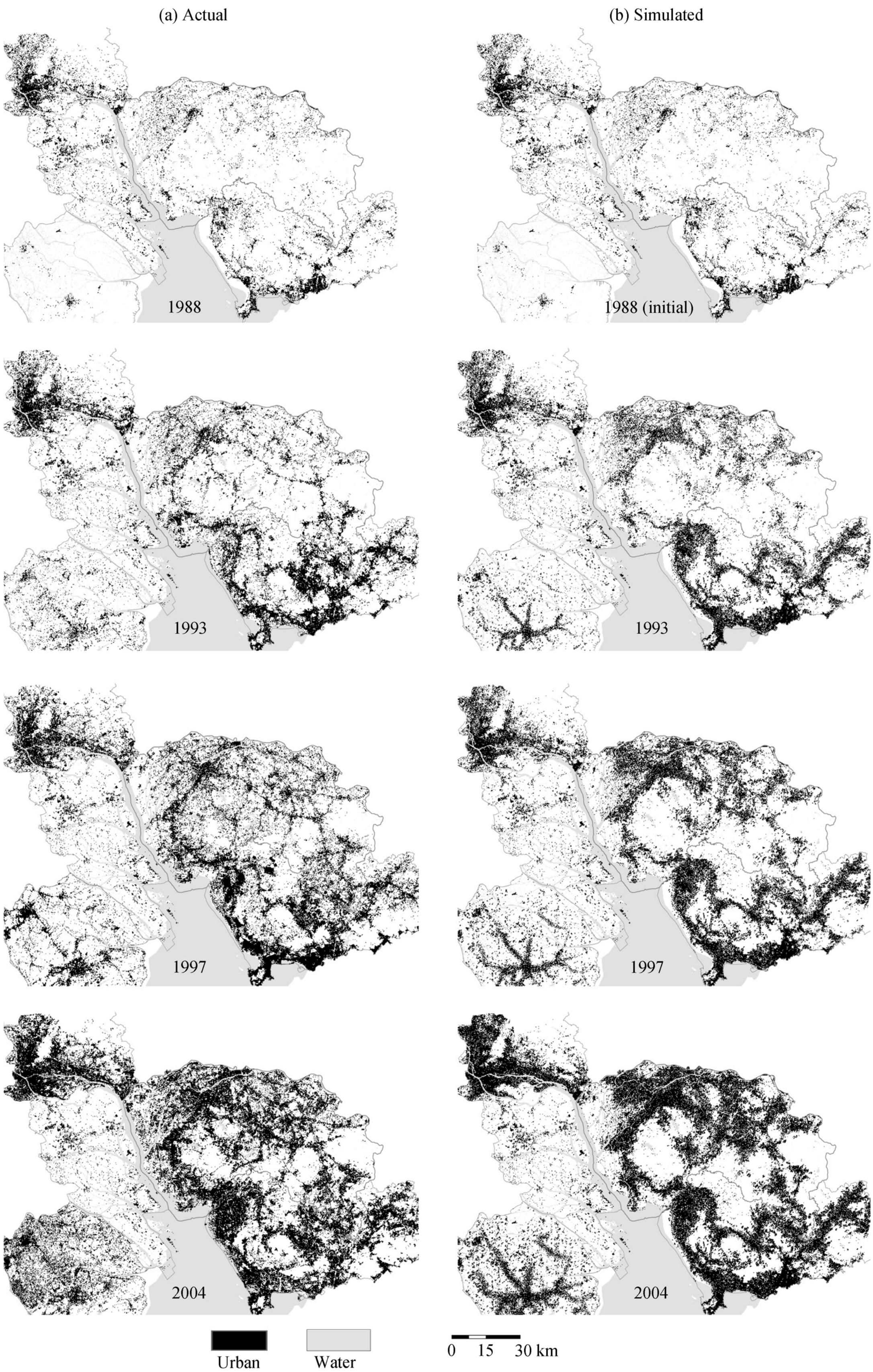

Figure 2 Realistic simulation of urban growth for the cities in the Pearl River Delta in 1988－2004.

Table 2 Assessment of the urban forms for the cities in the Pearl River Delta using spatial metrics

	MPSI	MPFD	MNN	AI	U
Guangzhou	1.3789	1.0507	143.2747	69.7479	1.0000
Zengcheng	1.4712	1.0712	171.8017	58.2507	0.4349
Conghua	1.4224	1.0748	197.2318	39.6987	0.2444
Shenzhen	1.4983	1.0559	161.6018	68.7973	0.6676
Dongguan	1.5213	1.0603	172.5922	55.7620	0.4367
Zhongshan	1.4920	1.0647	218.5303	55.1756	0.2850

Table 3 Comparison of the simulated urban forms between using the original parameters and using the cloning parameters

	MPSI	MPFD	MNN	AI	U
Original parameters	1.4988	1.0657	258.7611	78.5389	0.0000
Cloning parameters of the city proper	1.4409	1.0586	249.6434	79.4347	0.4350

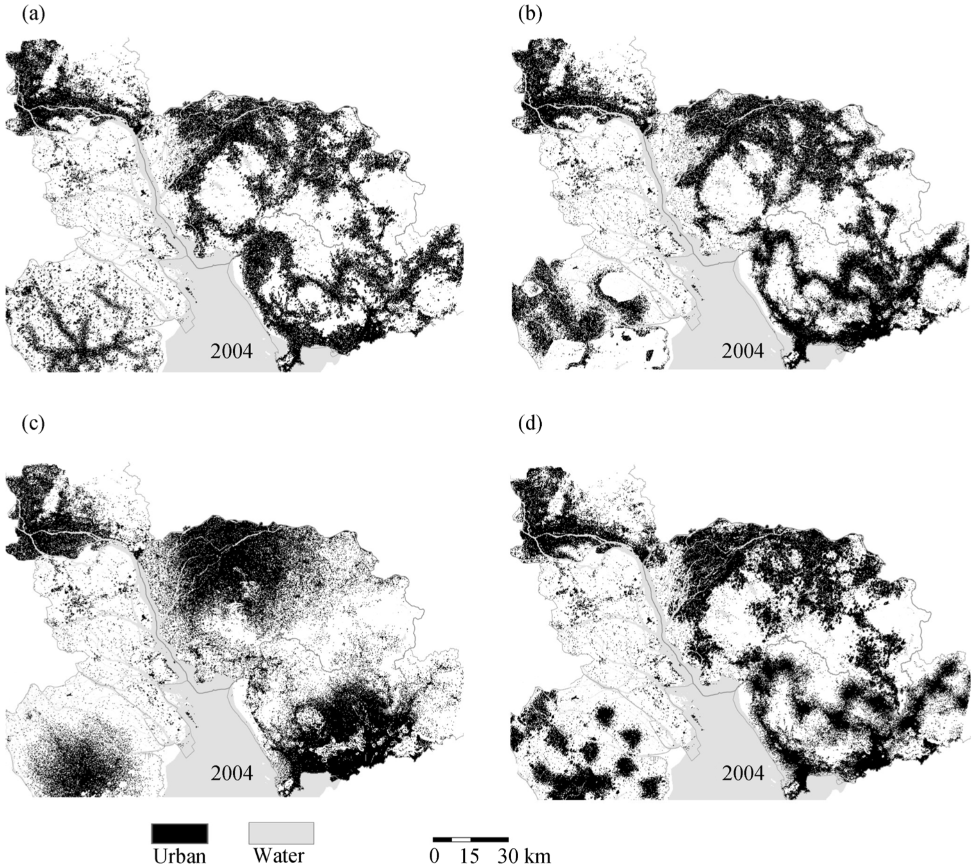

Figure 3 Simulation of compact cities in the Pearl River Delta in 2004. (a) Realistic simulation; (b) using Guangzhou's parameters; (c) modified parameters for "urban centre-road" development; (d) modified parameters for "urban centre-town centre-road" development.

(2) Then the absolute weight for the variable of urban centres will be increased, constrained by the total amount of land conversion. The constraint is to guarantee that the amount of the simulated land conversion is equal to that of the actual (expected). This increase will result in a more amount of land development around urban centres, and a less amount of land development around transport networks. It will thus create a polarized effect of land development around urban centres (Figure 4(b)).

(3) The modification is also applied to the absolute weight for transport networks. This change will result in a more amount of land development around transport networks, and a less amount of land development around urban centres. It will thus create a polarized effect of land development around transport networks (Figure 4(c)).

(4) Repeat step (2) and (3) again until the urban form cannot be further improved significantly in terms of compact development (Figure 4(d)).

The swapping technique was used to modify the parameters for producing the scenario of “city centers-transport” concentrated development. The modified parameters are shown in Table 4. Figure 3(c) is the simulation results based on this set of modified parameters.

Table 4 Modified parameters for “city centres-transport” concentrated development

$a_{0,k}$	$a_{1,k}$	$a_{2,k}$	$a_{3,k}$	$a_{4,k}$	$a_{5,k}$
1.2	−0.00183	−0.0001	−0.018	−0.0001	−0.0001

The same procedure was applied to the derivation of the parameters for “city centres-town centers-transport” concentrated development. Table 5 shows the retrieved parameters according to this modification. The simulation outcome based on this set of modified parameters is shown in Figure 3(d).

Table 5 Modified parameters for “city centers-town centers-transport” concentrated development

$a_{0,k}$	$a_{1,k}$	$a_{2,k}$	$a_{3,k}$	$a_{4,k}$	$a_{5,k}$
1.2	−0.0023	−0.0023	−0.0023	−0.0001	−0.0001

The performances of the above development options were assessed in terms of compact development. Table 6 lists the improvement of the combined utility value for these options, compared to the realistic development. There is an improvement of the utility by directly using the parameters of the city proper. More improvement of the utility is obtained by modifying these existing parameters according to this heuristic method.

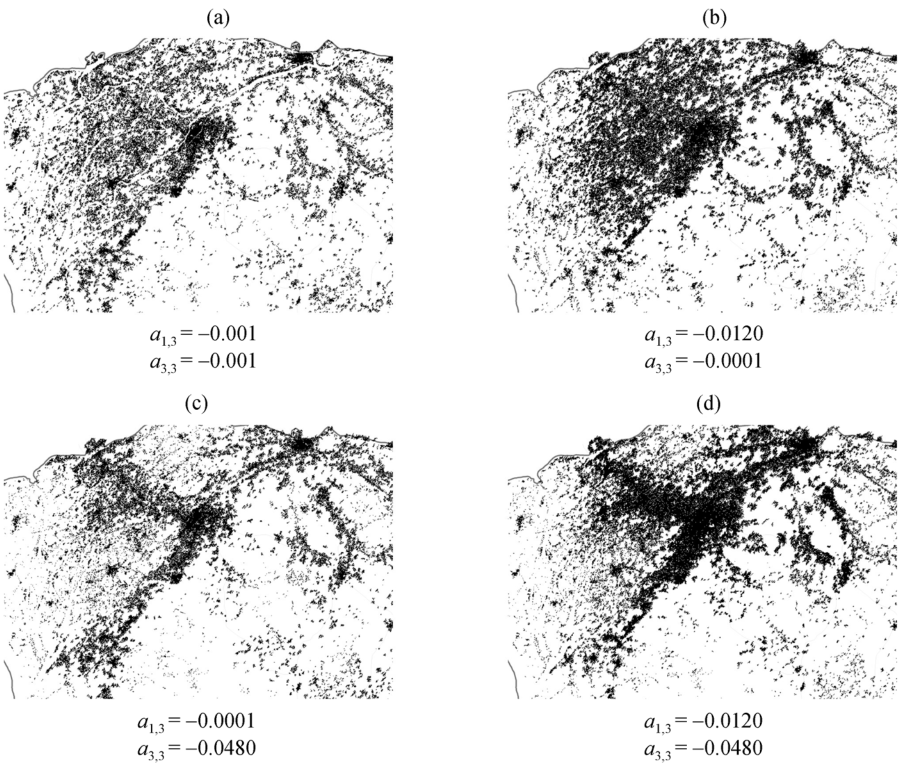

Figure 4 Obtaining new parameters by interactive modification of the attractions between city centers and roads.

Table 6 Improvement of the combined utility value for various development alternatives

	MPSI	MPFD	MNN	AI	U
Original parameters	1.4988	1.0657	258.7611	78.5389	0.0000
Using the parameters of the city proper	1.4409	1.0586	249.6434	79.4347	0.4350
“City centers-transport” concentrated	1.3529	1.0521	249.2032	84.2656	0.9242
“City centers-town centers-transport” concentrated	1.3965	1.0566	245.0450	81.4199	0.7183

4 Conclusion

Rapid urban development has resulted in intensive land use conflicts in many fast growing countries. Compact development can be formulated to alleviate land use problems in these regions. The simulation, prediction, and optimization of urban development are essential for promoting compact cities. CA can be used to simulate the evolution of cites by using local rules. These models can be also used to assist land use planning by incorporating planning objectives in the simulation.

Genetic algorithms (GA) can be used to determine the parameters of CA in a more robust way. The sets of parameters for various subregions can be found by using empirical data from remote sensing and GIS. Better simulation results can be obtained by using separate transition rules instead of unified ones. There are spatial variations of urban dynamics in a large complex region due to localized land use policies. It is better to divide a complex region into subregions for producing more consistent simulation results.

A number of spatial metrics can be defined to assess urban morphology in terms of compact development. The morphological utility can be conveniently calculated after the classification of remote sensing images. It is possible to produce better urban forms by replacing existing parameters with better parameters based on the assessment. The parameters of good performance can be cloned from a city to other cities to improve urban morphology. The existing parameters can be further modified according to a heuristic swapping method. This provides an operation method to create more compact patterns around urban centres, town centres, and transport networks. The modification is accomplished by the interactive increase of the polarized effect of land development around urban centres, town centres and transport networks. Experiments indicate that much more improvement of the utility in terms of urban morphology is obtained by modifying existing parameters.

1 Goles E. Cellular automata, dynamics and complexity. In: Manneville P, Boccara N, Vichniac G Y, et al. eds. Cellular Automata and Modeling of Complex Physical Systems. Berlin: Springer, 1989. 10—20
2 Batty M, Xie Y. From cells to cities. Environ Plan B, 1994, 21: 531—548
3 White R, Engelen G. Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns. Environ Plan A, 1993, 25: 1175—1199[DOI]
4 Wolfram S. Cellular automata as models of complexity. Nature, 1984, 31(4): 419—424[DOI]
5 Itami R M. Simulating spatial dynamics: cellular automata theory. Landscape Urban Plan, 1994, 30: 24—47
6 Deadman P D, Brown R D, Gimblett H R. Modelling rural residential settlement patterns with cellular automata. J Environ Manage, 1993, 37: 147—160[DOI]
7 Couclelis H. From cellular automata to urban models: new principles for model development and implementation. Environ Plan B, 1997, 24: 165—174[DOI]
8 White R, Engelen G. Cellular automata as the basis of integrated dynamic regional analysis. Environ Plan B, 1997, 24: 235—246[DOI]
9 Wu F, Webster C J. Simulation of land development through the integration of cellular automata and multicriteria evaluation. Environ Plan B, 1998, 5: 103—126[DOI]
10 Li X, Yeh A G O. Modelling sustainable urban development by the integration of constrained cellular automata and GIS. Int J Geogr Inform Sci, 2000, 14(2): 131—152[DOI]
11 Li X, Yeh A G O. Neural-network-based cellular automata for realistic and idealized urban simulation. Acta Geogra Sinica, 2002, 57(2): 159—166
12 Li X, Yeh A G O. Data mining of cellular automata's transition rules. Int J Geogra Inform Sci, 2004, 18(8): 723—744[DOI]
13 Wu F. Calibration of stochastic cellular automata: the application to rural-urban land conversions. Int J Geogra Inform Sci, 2002, 16(8): 795—818[DOI]
14 Clarke K C, Hoppen S. Gaydos L A. Self-modifying cellular automaton of historical urbanization in the San Francisco Bay area. Environ Plan B, 1997, 24: 247—261[DOI]
15 Li X, Yeh A G O. Analyzing spatial restructuring of land use patterns in a fast growing region using remote sensing and GIS. Landscape Urban Plan, 2004, 69(4): 335—354[DOI]
16 Bourne L S. Self-fulfilling prophecies? decentralization, inner city decline, and the quality of urban life. J Am Planning Assoc, 1992, 58(4): 509—13
17 Jenks M, Burton E, Williams K. Compact cities and sustainability: An introduction. In: Jenks M, Burton E, Williams K, eds. In The Compact City: A Sustainable Urban Form? London: SPON Press, 1996. 11—12
18 Banister D, Watson S, Wood C. Sustainable cities: transport, energy, urban form. Environ Plan B, 1997, 24: 125—143[DOI]
19 Yeh A G O, Li X. Economic development and agricultural land loss in the Pearl River Delta, China. Habitat International, 1999, 23(3), 373—390[DOI]
20 Zandera P, Kächele H. Modelling multiple objectives of land use for sustainable development. Agr Syst, 1999, 59: 311—325[DOI]
21 Nijkamp P, Ouwersloot H, Rienstra S A. Sustainable urban transport systems: an expert-based strategic scenario approach. Urban Studies, 1997, 34(4): 693—712[DOI]
22 Tress B, Tress G. Scenario visualisation for participatory landscape planning—a study from Denmark. Landscape Urban Plan, 2003, 64: 161—178[DOI]
23 Goldberg D E. Genetic Algorithms in Search, Optimisation and Machine Learning (Reading, MA: Addison-Wesley), 1989
24 Herold M, Goldstein N C, Clarke K C. The spatiotemporal form of urban growth: measurement, analysis and modeling. Remote Sens Environ, 2003, 86: 286—302[DOI]