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A Vector-based Cellular Automata Model for Simulating Urban Land Use Change

LU Yi[1], CAO Min[1], ZHANG Lei[1, 2]

(1. *School of Geographic Science*, *Nanjing Normal University*, *Nanjing* 210023, *China*; 2. *Jiangsu Administration of Surveying*, *Mapping and Geoinformation*, *Nanjing* 210013, *China*)

Abstract: Cellular Automata (CA) is widely used for the simulation of land use changes. This study applied a vector-based CA model to simulate land use change in order to minimize or eliminate the scale sensitivity in traditional raster-based CA model. The cells of vector-based CA model are presented according to the shapes and attributes of geographic entities, and the transition rules of vector-based CA model are improved by taking spatial variables of the study area into consideration. The vector-based CA model is applied to simulate land use changes in downtown of Qidong City, Jiangsu Province, China and its validation is confirmed by the methods of visual assessment and spatial accuracy. The simulation result of vector-based CA model reveals that nearly 75% of newly increased urban cells are located in the northwest and southwest parts of the study area from 2002 to 2007, which is in consistent with real land use map. In addition, the simulation results of the vector-based and raster-based CA models are compared to real land use data and their spatial accuracies are found to be 84.0% and 81.9%, respectively. In conclusion, results from this study indicate that the vector-based CA model is a practical and applicable method for the simulation of urbanization processes.

Keywords: vector-based Cellular Automata (CA); land use change; transition rule; spatial accuracy; Qidong City

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1 Introduction

The Land Use and Land Cover Change (LUCC) International Project, which explores interaction procedures between geo-environmental and production systems, was proposed by the International Geosphere-Biosphere Program and the International Human Dimension Program in 1995 (Turner *et al*., 1995). Land use change has since become one of the frontier research areas of geography.

Currently, there are several different varieties of land use change models, including the spatial statistical model, the System Dynamic (SD) model, the Cellular Automata (CA) model, and the multi-agent model (Tang *et al*., 2009). The CA model in particular has several positive characteristics, such as openness, flexibility, nonlinear and self-adaptive processes. In addition, its simplified operation procedure reflects the complexity of science, namely that 'a complex system is derived from the interaction of simple subsystems' (Li *et al*., 2007). Consequently, the CA model has been widely applied for the simulation of land use change process in recent years.

A raster-based CA model was introduced into geography research in the 1960s by Hägerstrand (1965) as a spatially diffuse process model now considered the

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Corresponding author: CAO Min. E-mail: caomin@njnu.edu.cn

foundation of these types of models. Bonfatti *et al.* (1994) predicted dynamic change in the area of Venice lagoon under the influence of periodic tides. In China, research on CA theory and application began in the 1990s and was mainly associated with land use changes and urbanization processes (Zhou *et al.*, 1999). The transition rule is the most important parameter in the CA model, and researchers have used various methods to obtain transition rules, including artificial neural network (Li and Ye, 2005; Xu *et al.*, 2009), Fisher discrimination (Liu and Li, 2007), case-based reasoning (Li and Liu, 2007), rough set theory (Yang and Li, 2006), genetic algorithms (Yang and Li, 2007a), Bayesian method (Yang and Li, 2007b), kernel functions (Liu *et al.*, 2008), and support vector machines (Yang *et al.*, 2008). However, the regular cell formation and the single and fixed neighborhood configuration of raster-based CA model limit their ability to accurately simulate real world processes.

In order to solve the shortcomings of raster-based CA model, some researchers began to approximate real world processes using irregular polygons (known as ′vector cells′ rather than traditional regular cells) (Semboloni, 2000; Shi and Pang, 2000). Furthermore, the topology judge method (Benenson *et al.*, 2002; Torrens and Benenson, 2005) and distance judge method (Stevens *et al.*, 2007; Wang *et al.*, 2009) have been used to better define neighborhood, more spatial calculation procedures were added to the transition rule (Moreno *et al.*, 2009). These modifications ensure that the dynamic simulation procedures of the geographic entities in the study area can be performed. More recently, a vector-based CA model has been applied in land use change simulations for several regions, including Yiwu, China (Yang and Xue, 2009), Dongtai, China (Wang *et al.*, 2009), Tel Aviv-Yaffo, Israel (Benenson *et al.*, 2002), Saskatoon, Canada (Stevens *et al.*, 2007), Quebec, Canada (Moreno *et al.*, 2009), and Albert, Canada (Wang and Marceau, 2013). These researches have demonstrated that vector-based CA model can obtain parameters from sample data and effectively simulate land use change processes, providing simulation results which are similar to real world processes in quantity and spatial distribution of land use. These studies have revealed that the vector-based CA simulation offers a reasonable, practical and operational approach to land use modeling.

Current methods for neighborhood definition are entirely based on topology relationships and distance between vector cells. The former method neglects the influence of non-adjacent cells, while the latter method makes it difficult to determine the optimal distance threshold used for neighborhood definition. There is a need for improvement of conventional neighborhood definition methods. In order to address the current research gap, this paper tries to arrange cells according to their spatial locations and land use types, and consider both macro influences of spatial variables and micro influences of other cells in the transition rules of a CA model. The downtown of Qidong City, Jiangsu Province, East China is used as the study area, and a vector-based CA model is built for simulating land use change processes. Finally, a simulation of urban development process of the study area is performed and spatial accuracy is used as the method to evaluate the performance of vector-based CA model, which can aid land use planners with decision-making.

2 Materials and Methods

2.1 Study area

Qidong City, a county-level city in Jiangsu Province, China (31°41′06″–32°16′19″N, 121°25′40″–121°54′30″E) is located on the north side of the Changjiang (Yangtze) River Estuary (Fig. 1). It receives 1037.1 mm in precipitation and 2073 hours of sunshine, annually. In addition, the annual mean temperature is 15℃ and average humidity is 81%, consistent with a typical humid subtropical marine monsoon climate. The dominant wind direction is from the southeast all year around and the annual mean wind speed is 3.5 m/s.

This study considers the downtown of Qidong City as the study area. As of late 2007, the downtown of Qidong City occupied an area of 26.98 km^2. The main land use types are construction land and farm land, accounting for 64% and 24% of the total area, respectively. The area is also comprised of 8% transportation land and 2% water area. The remaining 2% of the study area belongs to wood land.

2.2 Data and processing

Pre-processed Systeme Probatoire d'Observation dela Tarre (SPOT) images in 2002 and Advanced Land

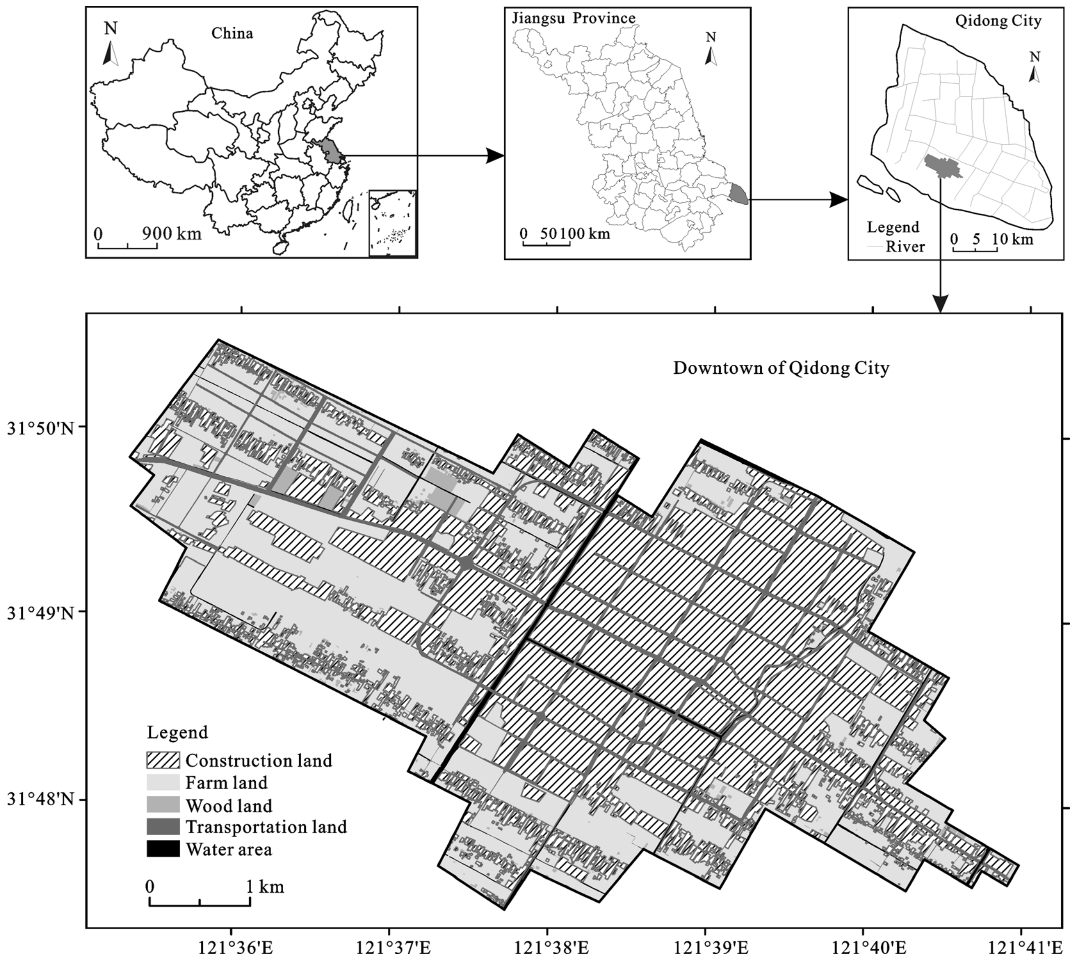

Fig. 1 Location of study area and its land use distribution

Observing Satellite (ALOS) images in 2007 both with 2.5 m resolution of the Qidong City were the principal spatial data source of the paper, which were acquired from the spatial database of the School of Geographic Science, Nanjing Normal University. The images had already been corrected and registered to the WGS84 space coordinates system. Therefore, they were directly interpreted by visual interpretation method and supplemented with land use map of the study area in 1996.

After the interpretation of images, land use data for downtown of Qidong City in 2002 and 2007 are derived in shapefile format, one of the widely applied spatial data formats being used to describe the spatial characteristics and attributes of a geographic vector entity. The shapefile is composed of a series of land patches, each of which contains three attributes: land use type, perimeter, and patch area. Land use types of the study area were determined by the ′Code for classification of urban land use and planning standards of development land′. Consequently, land patches of the study area were classified into five categories: farm land, wood land, construction land, transportation land and water area, and all of the land use areas were polygons.

The five types of land in the study area were used to generate two types of vector cells according to their original attributes (Fig. 2). This study combines farm land and wood land together, and defines them as nonurban cells. Similarly, construction land is defined as urban cells. Since the areas of water and transportation land changed very little from 2002 to 2007, they are taken as the spatial variables of land use change in the study area and are not converted into vector cells. In 2002, there are 1056.6 ha nonurban cells and 1353.5 ha urban cells in the study area. When it comes to 2007, the areas of nonurban and urban cells are 689.1 ha and 1721.0 ha, respectively.

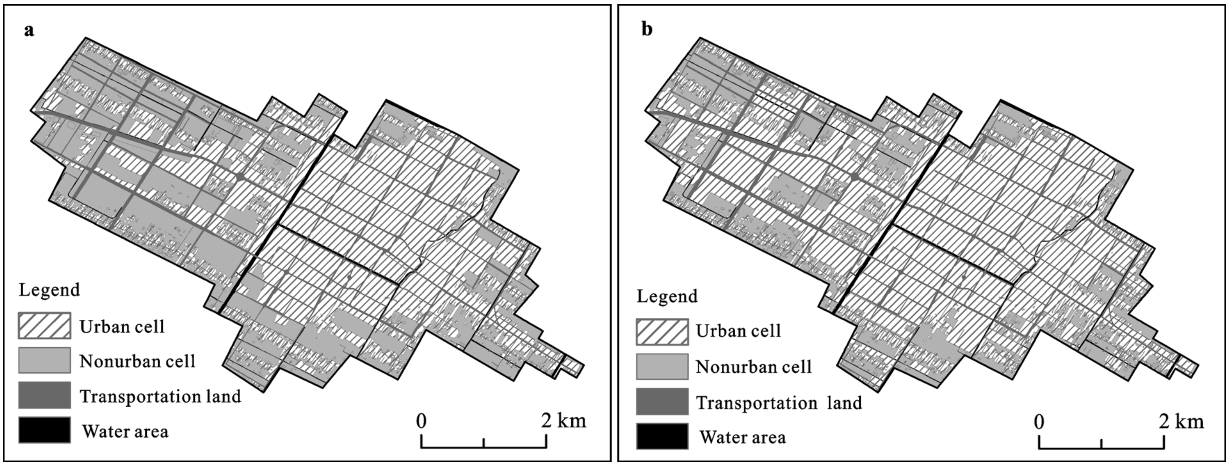

Fig. 2 Vector cells and spatial variables of study area in 2002 (a) and 2007 (b)

2.3 Methods

2.3.1 Neighborhood definition of vector-based CA model

There are two primary types of vector cells: center cell and neighbor cell. The form and state of center cell will change under appropriate conditions, while the neighbor cell has an influence on the transformation of the center cell. If the influence is larger than a transformation threshold value, a portion of the center cell will change. The essence of neighborhood definition is to find cells that have an influence on center cell.

In traditional raster-based CA model, neighbor cells are usually defined according to a single and fixed configuration, such as Moore or Von Neumann neighbor cells. However, for vector-based CA, this method is not applicable and researchers have instead used the topology adjacent judge method (Benenson *et al*., 2002; Torrens and Benenson, 2005) or the distance judge method (Stevens *et al*., 2007; Wang *et al*., 2009) to determine which cells are defined as the neighbor of each center cell.

In this paper, we introduce the concept of a 'dynamic neighborhood' (Moreno *et al*., 2009) as a supplement to the conventional neighborhood definition methods of defining neighbor cells. The dynamic neighborhood can be described by the following methodology: if vector cell *A* and vector cell *C* are spatially separated by vector cell *B*, and the state of cell *B* is favorable for cell *A* to be transformed into cell *C*, then cell *C* can be defined as the neighbor of cell *A*, even though they are not topologically adjacent.

The three-step procedure for the neighborhood definition is as follows. 1) Evaluate the topology of the center cell and other vector cells. If a vector cell is spatially adjacent to the center cell and their states are not the same, it is defined as the neighbor of the current center cell. 2) If a vector cell and the center cell are separated by another vector cell, but their states coincide with the dynamic neighborhood relationship, this cell is defined as a neighbor as well. 3) When the neighborhood definition of a center cell is finished, another cell is defined as the center cell. Loop through steps 1 and 2 until all of the vector cells in the study area have been evaluated.

2.3.2 Transition rule of vector-based CA model

The transition rule of the vector-based CA model is made up of three sub rules: the influence of spatial variables calculation, the neighbor cell influence calculation, and the center cell transformation. The first sub rule determines the sequence in which the cells are evaluated, the second rule decides whether a center cell will be transformed, and the third rule specifies which portion of a current center cell will be transformed and then quantifies the area.

(1) Sub rule of spatial variable influence calculation

The vector-based model uses the water area, transportation land, and urban center as spatial variables of the study area, and then calculates the weighted sum of their influences on center cells in order to evaluate each center cell. In the paper, natural variable, transportation variable, and urban structure variable are specified as the water area, transportation land and urban center. A principal component analysis is also used to quantify the weights of each spatial variable. Four steps are used to determine the weights (Song and Gao, 2002): 1) Compute the mean X and the covariance matrix S of the sample. 2) Solve the characteristic equation $|S–\lambda_i| = 0$ and determine the eigenvalues of S (λ_1, λ_2 and λ_3). i is the unit matrix. 3) Calculate the characteristic vector of eigenvalues. 4) Determine the variances contribution values for each eigenvalue according to the vector of eigenvalues. The contribution values are equal to the weights of three spatial variables.

As a result, the influence of spatial variables on nonurban cells can be described as:

$$I = w_1 \times I_{\mathrm{U}} + w_2 \times I_{\mathrm{T}} + w_3 \times I_{\mathrm{W}} \tag{1}$$

where I is the total influence of the variables to a nonurban cell; I_{U}, I_{T} and I_{W} are the influences of urban center, transportation land, and water area; and w_1, w_2 and w_3 are the weights of I_{U}, I_{T} and I_{W}, respectively.

In this analysis, the more a center cell is affected by the spatial variables, the higher probability it is to be transformed and the earlier it will be judged by other sub transition rules.

(2) Sub rule of neighbor cell influence calculation

When a center cell is transformed, the segment that changes is determined not only by its own area and form, but also by those of its neighbor cells. The distance between the center and neighbor cells, as well as the transformation probability are also considered.

In this analysis, there is only one type of transformation, namely from a nonurban cell to an urban cell. For example, cell N_1 is a nonurban cell (the center cell at present) and cell U_1 is an urban cell. The influence from transforming N_1 into U_1 (F) can be described as:

$$F = P_{\mathrm{NU}} \times A / d \tag{2}$$

where P_{NU} is the probability that the cells are transformed from nonurban to urban, and is computed using historical land use data (Equation (3)); A is the area of center cell N_1 within the neighborhood of neighbor cell U_1; d is the distance between the centroids of cells N_1 and U_1.

$$P_{\mathrm{NU}} = A_{\mathrm{NU}} / A_{\mathrm{N}} \tag{3}$$

where A_{NU} and A_{N} represent the changed and total area of nonurban cells in 2002.

(3) Sub rule of center cell transformation

Whether a nonurban cell is transformed depends on both the influence of neighbor cells and the transformation threshold T, the judgment of transformation from nonurban to urban cell is represented as follows:

$$\text{if} \begin{cases} F > \mathrm{T}, \text{then } G^{t+1}(C_{ij}) = G^{t+1}(C_{ij}) - \Delta G, S^{t+1}(C_{ij}) = \mathrm{U} \\ F < \mathrm{T}, \text{then } G^{t+1}(C_{ij}) = G^{t+1}(C_{ij}), S^{t+1}(C_{ij}) = \mathrm{N} \end{cases} \tag{4}$$

where $G^{t+1}(C_{ij})$ is the form of the center cell C_{ij} at time $t + 1$; ΔG is the area that center cell transformed from nonurban to urban, and $S^{t+1}(C_{ij})$ is the state of center cell C_{ij} at time $t + 1$. Equation (4) indicates that if the influence on center cell N_1 from neighbor cell U_1 (F) is larger than transformation threshold T, then a proportion of center cell N_1's state will be changed from N (nonurban) to U (urban). If the influence F from neighbor cell U_1 on center cell N_1 is smaller than threshold T, then the center cell N_1 will not be transformed. Threshold T is a constant that is obtained from sample data of the study area.

For instance, the transformation from nonurban cell N_1 (center cell) to urban cell U_1 (neighbor cell) can be divided into five steps. 1) Calculate the influence F of neighbor cell U_1 on center cell N_1 (Fig. 3a). 2) If influence F is larger than transformation threshold T, buffer analysis will be executed on neighbor cell U_1 with preset buffer radius. If area of intersect part of U_1's buffer zone and N_1 is less than ΔG, buffer radius should be increased properly and buffer analysis will executed once more (Fig. 3b). 3) Execute step 2) repeatedly until area of intersect part is larger than ΔG and their difference is in tolerance (according to experimental result, area of intersect part equals to ΔG exactly is impossible) (Fig. 3c). 4) The intersect part will be transformed from center cell N_1 to neighbor cell U_1 (Fig. 3d); 5) Finally, the intersect part should be erased from center cell N_1 and then emerged with neighbor cell U_1 (Fig. 3e).

3 Results and Analyses

3.1 Influence of spatial variables on transformation from nonurban to urban

Studies have shown that transportation accessibility depends on the ease of transportation which can be defined as the distance to road or urban center. Distance to water is also an important variable for environment evaluation (Liu *et al.*, 2006). Both of the above-mentioned spatial variables play an important role in land use change in the study area. Variable influence is reduced as the distance between spatial variable and vector cell is increased (Cao *et al.*, 2012). In order to determine the impact of each spatial variable

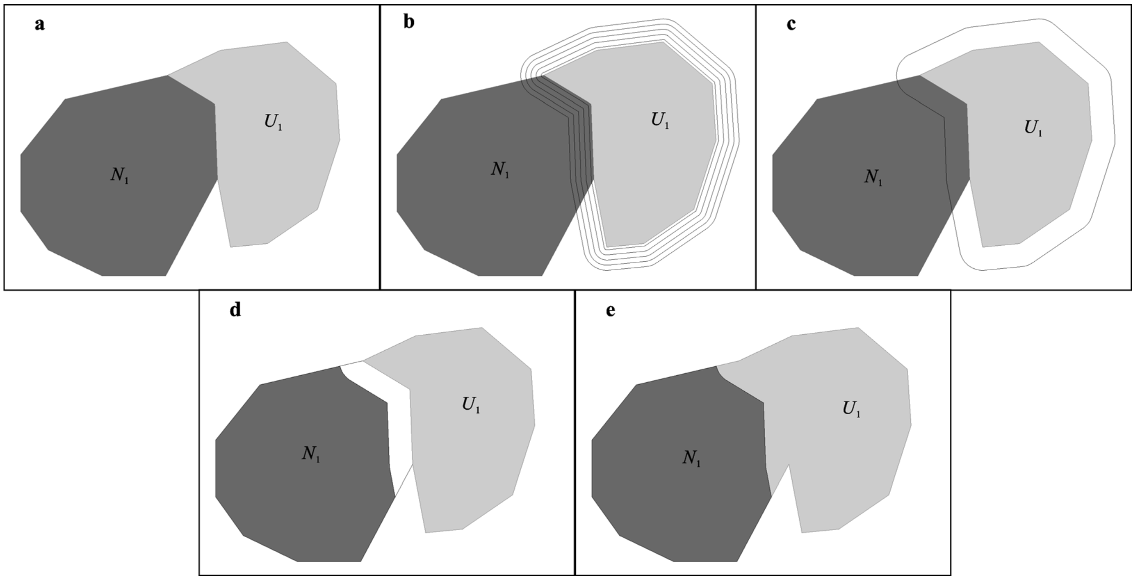

Fig. 3 Transformation procedure of center cell N_1 under influence of neighbor cell U_1. N_1 is nonurban cell, and U_1 is urban cell

on vector cells quantitatively, the influence of spatial variables is analyzed.

3.1.1 Influence of water area and transportation land

It was assumed that two buffer zones shared the same center object with different radii. The proportion of the larger buffer zone falling outside their intersection was defined as the buffer ring. Six buffer rings with buffer radii of 0–50, 50–100, 100–150, 150–200, 200–250 m and 250–300 m were constructed by taking the water area as the center object. The areas of newly increased urban cells within the six buffer zones were calculated in years 2002 and 2007. When the buffer radius is 300 m, there are very few vector cells located outside of the buffer zone. As a result, the buffer radius does not increase any further. The areas of newly increased urban cells contained in the six buffer rings of water area and four buffer rings of transportation land in 2002 and 2007 are shown in Table 1.

According to the upper statistics, we can conclude the relationship between transformation probability of nonurban cells and their distances to water area and transportation land respectively. The influence of water area and transportation land on transformation of nonurban cells was found to decrease with an increase in distance to nonurban cells, with the influence of water area on nonurban cells decreasing linearly when the radius of buffer ring is larger than 50 m. On the other hand, when the radius of buffer ring is less than 50 m, the transportation land has the maximum influence on nonurban cells. When the distance between transportation land and nonurban cells is larger than 50 m, the decline rate of the influence of transportation land on nonurban cells considerably reduced. The influence of spatial variable on nonurban cells will decline when the distance between them increased is in accordance with the theory of Li *et al*. (2007).

Table 1 Areas of newly increased urban cells in two groups of buffer rings from 2002 to 2007

Radius of buffer ring (m)	Area of newly increased urban cells within buffer rings of water area (ha)	Area of newly increased urban cells within buffer rings of transportation land (ha)
0–50	46.1	135.5
50–100	50.5	107.7
100–150	42.6	62.1
150–200	38.8	32.5
200–250	32.0	–
250–300	26.4	–

Note: '–' means that when the buffer radius is greater than 200 m, there is hardly any vector cells located outside the buffer zone of transportation land

3.1.2 Influence of urban center

Using the same statistical method, the influence of urban center on transformation of nonurban cells was found to be relatively more complex. When the distance between a nonurban cell and urban center is less than 1500 m, the transformation probability of nonurban cells was observed to increase with an increase in distance. The closer a nonurban cell is to the urban center, the more likely the cell is to be located in an urban surrounding, resulting in a relatively lower transformation probability. When the distance between nonurban cell and urban center reaches 1500 m, the area belongs to the suburb in the study area, which consequently gives the highest transformation probability. As distance further increases from 1500 m to 2000 m, the influence of urban center begins to decrease, and becomes very low between 2000–3000 m. When the distance between nonurban cell and urban center is greater than 3000 m, the transformation probability of nonurban cells is less than 6%, and the transformation probability of nonurban cells at the edges of the study area is only 2% (distances between these nonurban cells and urban center are close to 3500 m) (Fig. 4).

3.2 Land use simulation based on vector-based Cellular Automata model

In the current study, the total area of nonurban cells in 2002 is 1056.6 ha, with 689.0 ha remaining as nonurban cells in 2007. According to Equation (3), the value of P_{NU} is 35%, which means that 35% of nonurban cells in 2002 were transformed into urban cells. Analysis of the sample data showed that when the value of the transformation threshold T is set to 0.52, the simulated area change corresponds to real observations during 2002 and 2007. In the final model, the values of P_{NU} and T are set to 0.35 and 0.52, respectively, and the number of iterations is set to 100. After parameter setting, the prototype system programmed in Visual Studio 2008 is used to simulate changes in land use from 2002 to 2007.

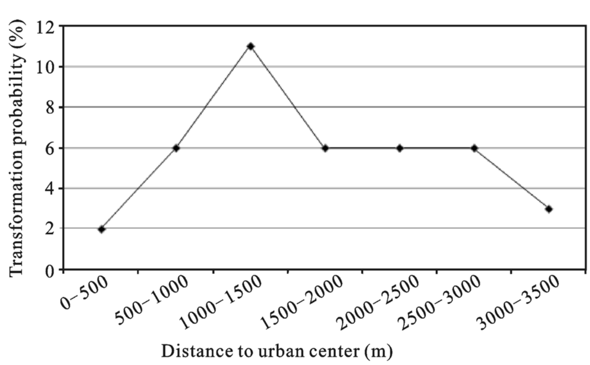

Fig. 4 Change trend of transformation probability of nonurban cells under influence of urban center from 2002 to 2007

The simulated LUCC process by vector-based CA model is shown in Fig. 5. The difference between the distributions of nonurban cells in 2002 and 2007 illustrates rapid urban expansion in the study area, particularly in the northwest and southwest parts. Initially, there were still a variety of fragmented nonurban cells spread all over the downtown of Qidong City when the iteration number is 20 (Fig. 5a). After 40 iterations, nearly all nonurban cells in the northern part and some nonurban cells adjacent to arterial road in the western part were transformed into urban cells (Fig. 5b). When the iteration number came to 60, nearly the entire northeastern part of the study area was occupied by urban cells (Fig. 5c). After 80 iterations, nonurban cells located near the urban center, especially those in the east-west direction were transformed into urban cells due to their proximity to the center of the study area (Fig. 5d). The majority of the eastern part of the study area was transformed into urban area at the fifth stage (from 80 to 100 iterations) of the simulation process (Fig. 5e).

On the basis of the simulation result, we can conclude that 185.5 ha newly increased urban cells were located in the northwest part of the study area, which has the most obvious land use change from 2002 to 2007. Secondly, 90.7 ha cells in the southwest part of the study area were transformed from nonurban to urban during the same time period. The area of newly increased urban cells in above-mentioned two parts accounts three-quarters of increased area of urban cells in the study area. What′s more, the simulation result also shows that in the northeast and southeast parts of Qidong City, 76.8 ha and 14.5 ha nonurban cells in 2002 were transformed to urban cells in 2007 respectively.

3.3 Model verification

The simulation results of raster-based and vector-based CA models were compared with actual land use data in 2007 (Fig. 6). The ′correct urban cells′ are the simulated urban cells which correspond to the real observations in 2007, and the ′incorrect urban cells′ are the cells which conflict with the observations. The ′urban land′ refers to the area of urban land in 2007 which is not covered with simulated urban cells and

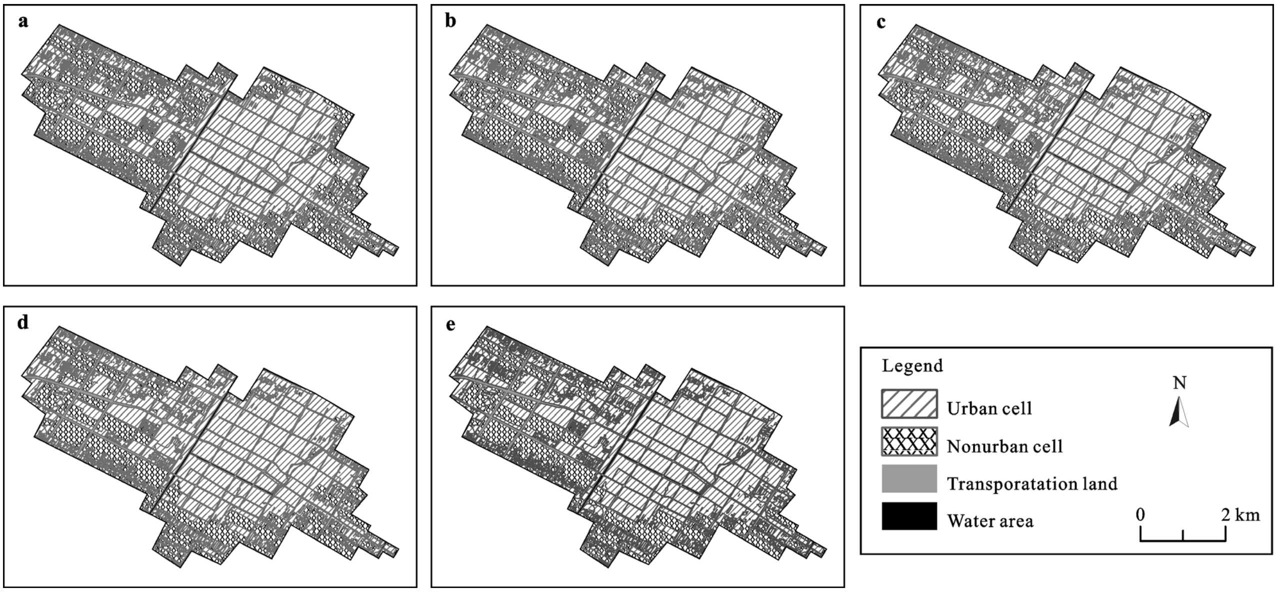

Fig. 5 Land use simulation results after 20 (a), 40 (b), 60 (c), 80 (d) and 100 (e) iterations in study area

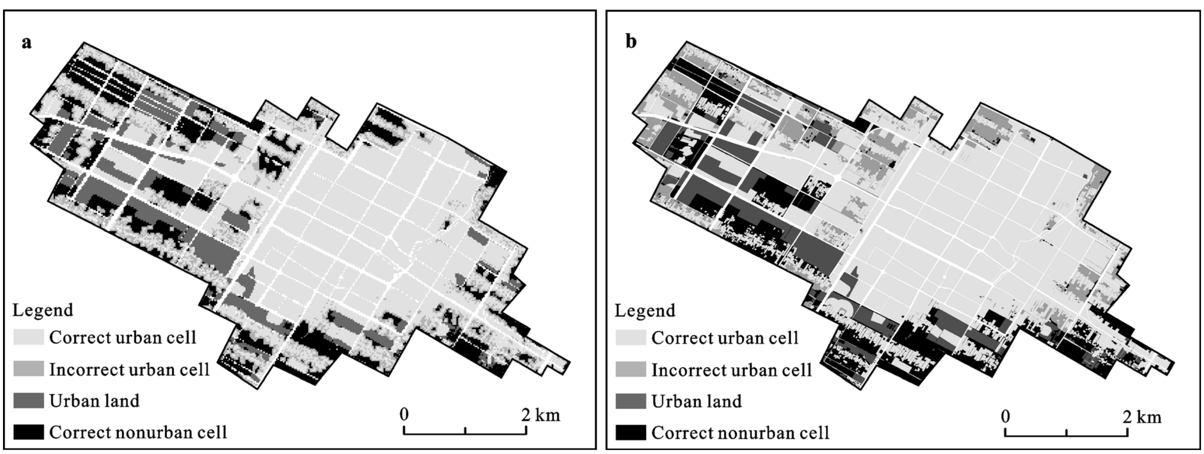

Fig. 6 Overlap of simulated raster (a), vector (b) urban cells and reality ones in 2007

the 'correct nonurban cells' are the simulated nonurban cells which correspond to the real observations in 2007. The spatial accuracies were calculated from simulation results in order to evaluate the effect of raster-based CA and vector-based CA model.

The overlap number (to raster-based CA) or area (to vector-based CA) of the simulated and the real urban cells in 2007 are used as the numerator, total number (to raster-based CA) or area (to vector-based CA) of the real urban cells in 2007 as the denominator and their quotients as the spatial accuracy of them. From spatial statistics, the overlap area of simulated and real distributions of urban cells in 2007 is 1453.5 ha and the total area of real urban cells is 1721.0 ha. Consequently, the spatial accuracy of vector-based CA model is 84.0%. Additionally, spatial accuracy of raster-based CA is as much as 81.9%, which is a little bit lower than vector-based CA model. In conclusion, the vector-based CA model, which is proposed in the paper, has a relative higher spatial accuracy than that of traditional raster-based CA model.

4 Discussion

Results presented by Zhou *et al*. (1999) showed that the cell size of a raster-based CA model impacts the accuracy of simulation results. However, by representing vector cells as irregular polygons, vector-based CA decreases the loss of accuracy when geographical entities are defined as cells. From these considerations, it is clear that the current vector-based CA model is less sensitive to cell size than raster-based CA model. Experimental results confirm that vector-based CA is more accurate in the land use change simulation when compared with traditional raster-based CA for the same study area. Thus, a vector-based CA model can be considered as a practical method to supplement traditional CA in the LUCC research field.

The simulation result of vector-based CA model depends on the accuracy of vector-format spatial data. Large-scale spatial data can represent the study area and predict land use change result more accurately. Unfortunately, the difficult to obtain spatial data with high accuracy limits the application of vector-based CA. The novel concept of 'dynamic neighborhood' (Moreno *et al*., 2009) considers both the topological relationship and the states of cells, which improves the accuracy of simulation result.

The difference between the average distances of incorrect and correct urban cells to water area is 26% (Table 2), which is the greatest difference among the differences of two kinds of vector cells' average distances to different variables. The difference between average distances of incorrect and correct cells to transportation land is 16%, and the difference between average distances of incorrect and correct cells to urban center is the smallest one, as much as 2%. What's more, 60.5% of the southwest part and 53.9% of the northwest part in the study area were nonurban area in 2002. It means that there are more nonurban cells to be chosen as newly increased urban cells in these two parts. The simulation results of above-mentioned two parts of incorrect and correct cells are more deviate from reality compared with the southeast and the northeast parts of study area. It indicates that the larger nonurban area a part owns, the lower simulation accuracy it will have.

According to Table 2, since the average distance of correct cells to transportation land is shorter than the average distance of incorrect cells, the influence of transportation land on nonurban cells is higher than we expect. On the contrary, we can also conclude that the influence of water area on nonurban cells is not as much as we originally assume according to the average distances of incorrect and correct cells to water area. Consequently, if the proper improvement on the weight of transportation land (w_2) and reduction on the weight of water area (w_3) are executed, those nonurban cells that are closer to transportation land are expected to be transformed in priority. As a result, the above-mentioned adjustment is likely to improve the spatial accuracy of vector-based CA in a further step.

Table 2 Distance from incorrect and correct cells to spatial variables

Cell	Average distance to transportation land (m)	Average distance to water area (m)	Average distance to urban center (m)
Incorrect cells	63.3	171.0	2444.3
Correct cells	54.7	230.3	2483.8

The vector-based CA model was shown to more accurately simulate the land distribution pattern of the study area compared with traditional raster-based CA model. In the vector-based CA model, the land patches of study area are represented by vector cells, where each cell corresponds to the irregular shape and size of a land patch. The transition rules consist of different sub rules to calculate micro influences of spatial variables and micro influences of current urban cells. The shape and attribute of the vector cells changed simultaneously in the transformation procedure of a nonurban vector cell, generates a more realistic representation of the evolution of the landscape. We can conclude from model verification part that the accuracy of vector-based CA's output is 2.1% higher than the output of traditional raster-based CA. These above mentioned findings of are in agreement with previous research (Moreno *et al*., 2009).

5 Conclusions

A vector-based CA model was applied to simulate the land use change in the downtown of Qidong City, a region in the Jiangsu Province of eastern China from 2002 to 2007. The cell definition, spatial variables, neighborhood configuration and transition rules of the vector-based CA model were discussed.

1) In the vector-based CA model, the sequence of evaluating the nonurban cells is affected by the spatial variables. The nonurban cell which obtains the greater influence from spatial variables has a higher probability to be transformed and will be judged by other sub transition rules earlier. The spatial variables were found to significantly influence the simulation results of the vector-based CA model. In addition, whether the evaluated nonurban cell will transform or not depends on the influence of neighbor urban cell on it, which is directly proportional to the areas of both cells and inversely

proportional to their centroid distance. 2) Northwest and southwest were the two main parts of urbanization process of the study area from year 2002 to 2007. According to the simulation result of vector-based CA model, 185.5 ha of nonurban cells in the northwest part of Qidong City were transformed to urban cells, which equals to half of the total transformed area of nonurban cells during the same time period. What's more, another 25% of transformed nonurban cells were located in the southwest part of the study area, with a 90.7 ha area. The simulation result of newly increased urban cells corresponds to real land use map in 2007. 3) In this study, the overlap ratio of simulated urban cells and real ones are taken as the spatial accuracy of CA models. The simulation results of the vector-based CA and raster-based CA models indicate that their spatial accuracies were found to be 84% and 81.9%, respectively in 2007. Consequently, the performance of vector-based CA model confirms that it has a higher accuracy in land use change simulation than traditional raster-based CA model.

In conclusion, this study showed that the vector-based CA model is an appropriate method for exploring the regularity of LUCC processes in single center study areas with water area and transportation land in it. Some spatial variables were not considered due to shortfalls in the available data, including the terrain and elevation of the study area. Consequently, a variable system is required to be built in order to describe the macro influences of spatial variables change in the study area more completely, as they can affect the direction, type, and strength of the urbanization process of a study area in a further step. The use of variable system in combination with the current transition rules of vector-based CA model faces great challenges, but it has the potential to provide a better prediction of land use change and increase the ability to understand the LUCC process more comprehensively and accurately.

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