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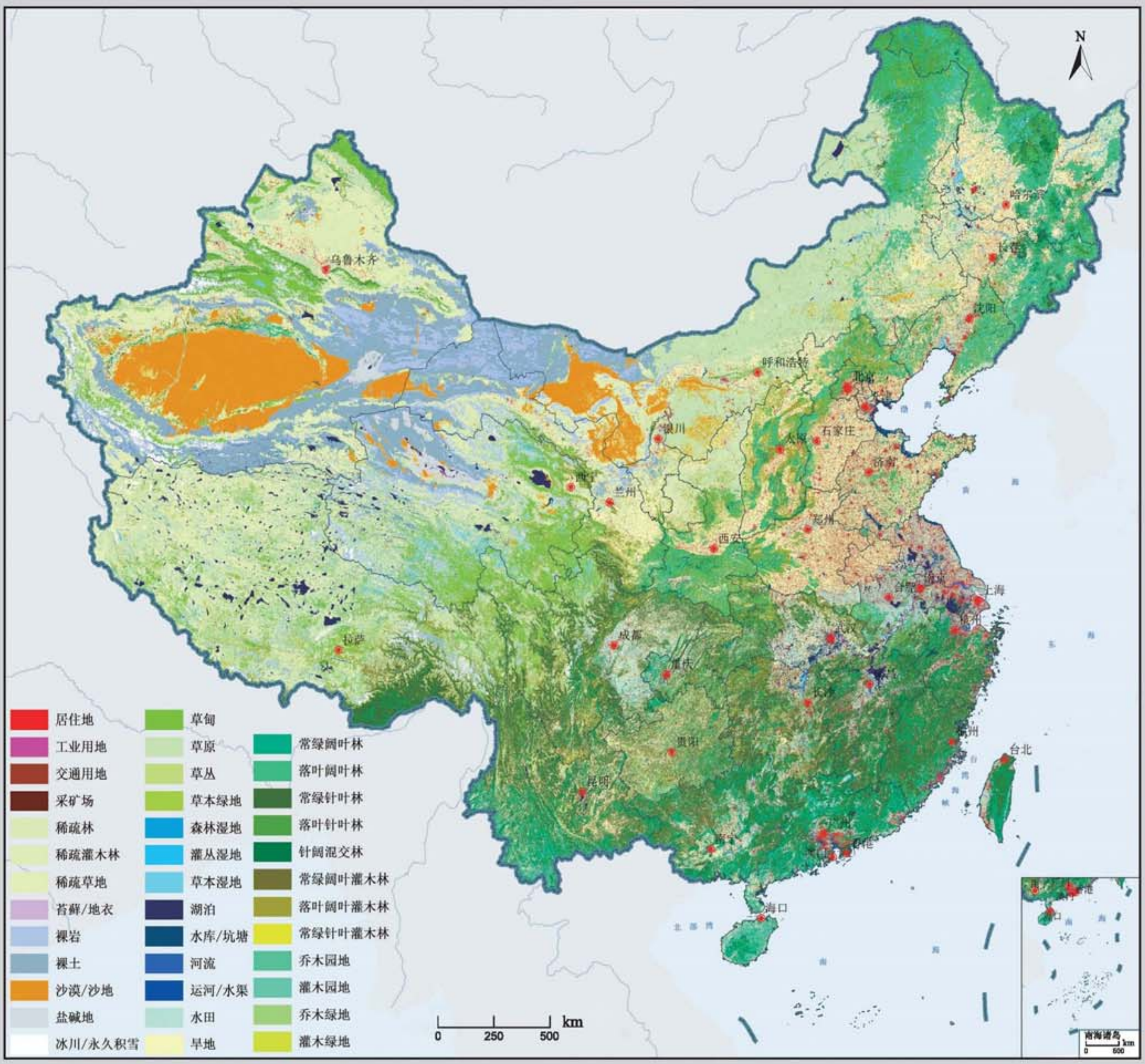

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Urban expansion simulation by coupling remote sensing observations and cellular automata

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Abstract: Traditional Cellular Automata (CA) requires parameter adjustments and results modification to improve performance especially in a long simulation period. This paper introduces the ensemble Kalman filter (EnKF) into the CA model and proposes a new geographical cellular automata model based on joint state matrix. The model will adjust model parameters and correct simulated results dynamically in the process of simulation by assimilating remote sensing observations. The change of model parameters can properly reflect temporal and spatial variations in the transition rules. Besides, the model can effectively release accumulated model errors. It was applied to the urban expansion simulation of Dongguan, Guangdong province, China. Experiments indicate that this model can modify the parameter value which can properly reveal the urban development pattern. It also can produce more reasonable results than logistics CA model and EnKF CA model in simulating this complex region.

Key words: cellular automata, urban expansion, data assimilation, ensemble Kalman filter, joint state matrix

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1 INTRODUCTION

The changes of urban land use affect not only the social economies of the local and surrounding areas, but also the regional or even global ecological environments. Studies have shown that the expansion of urban land use has an important contribution to the local economic growth. The intensification level of urban land use is closely related to economic growth, industrialization and urbanization (Nusrath & Shabeer, 2011). Urban land use changes have a profound impact on global climate change. They affect climate not only by changing the surface albedo, surface roughness, leaf area index, soil humidity, but also through the tropical island effect, carbon cycle, and so on (Charney, et al., 1977; Houghton, et al., 1983; Brovkin, et al., 1999).

Model simulation and remote sensing observations are two methods which can study and determine urban land use changes (Li & Huang, 2004). Model simulation can simulate the evolution process of urban area in time and space based on the inherent physical processes and dynamic mechanism of urban expansion. Cellular automata (CA) model is one of the most commonly used simulation tools (Li & Yeh, 2004). Remote sensing observation method can obtain true situation of urban land use at the observation time (Li, et al., 2007).

CA models are bottom-up approaches based on grid dynamic model controlled by local rules. They provide useful tools to simulate and predict complicated dynamic system behaviors. In CA model, the outcome at the previous iteration has deep impact on the outcome at the next iteration. Complex global patterns can be formed after many simulation iterations. Because of their strong modeling capabilities, CA models have been used for solving geographic problems (Wolfram, 1984; Couclelis, 1988). CA models are simple that the process of spatial evolution of land use change can be simulated conveniently by setting the simulation rules, model parameters, and initial value (Tobler, 1970; Batty & Xie, 1994; Chen, et al., 2004). They play important roles in studying the mechanism of urban land change and in understanding the process of spatial evolution of land use change (Clarke, et al., 1997; Li & Yeh, 2000; Wu, 2002). It is also significant in understanding and verifying the assumptions (theories) in urban geography (Couclelis, 1985; White & Engelen, 1993). Moreover, the global and local land surface models often require accurate land use information to achieve more objective results (Lawrence, et al., 2011). However, studies

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show that the CA model still suffers from uncertainties. (1) CA models always simplify complicated changing processes. For example, most CA models assume that the urban evolution rules remain unchanged, and they adopt static model parameters in the simulation process (Li & Liu, 2006). (2) Errors accumulate too fast during the simulation process. Urban evolution processes are complicated and non-linear. Thus, errors from data sources (e.g., field survey errors, digitization errors, and data conversion errors) are transferred and accumulated continuously during the simulation process (Li, et al., 2007).

Remote sensing is an alternative but effective approach to determine urban land use changes. It uses remote sensing interpretation and image recognition technology to extract urban change information from remote sensing images (Seto, 2002). It has greatly improved in terms of both accuracy and efficiency compared with early statistical or field survey. Remote sensing images have natural advantages, such as wide regional coverage, periodicity, continuity and economic efficiency. They can precisely determine the land use conditions in study area at a certain time. And researchers can easily study urban land use (i.e., space-time evolution, mechanism, and effect on social economy and local/global environment) to support national or regional sustainable development departments. By overlaying multi-phase image, some information, such as number and spatial location of land use changes, can be obtained. Such information is very important for land resources such as farmland, forest, and so on (He, et al., 2001). However, using only remote sensing data, it is difficult to achieve the spatial-temporal evolution of urban land use changes. The main reasons are listed as follows. (1) Remote sensing data record only the land use conditions of a study area at a certain time. Conversely, the evolution of urban expansion must be continuous in time and space. Therefore, it is necessary to use simulation model to extend remote sensing observations to temporal and spatial dimensions (Li, et al., 2007). (2) Remote sensing data have a series of uncertainties and errors, such as sensor error, atmospheric disturbance error, classification algorithm error, and so on (Li & Yeh, 1998).

CA simulation and remote sensing observation have their limitations. They should be integrated to develop an urban expansion model which can generate more reliable simulation results. Only a minority of researchers tried to solve the problems. Based on the Monte Carlo method, Clarke, et al. (1997) adjusted model parameters dynamically by combining with historical observation data. Their method requires numerous computations and a high-performance workstation has to run for several hundreds of hours. Yang and Li (2007) obtained the model parameters by using the genetic algorithm. However, this method requires all the observations of study area which cannot always be obtained in reality. Li and Liu (2007) proposed a CA model using case-based reasoning. The transition rules of the model can be updated by introducing into new cases. The model can update the transition rules but cannot control error accumulation in the process of simulation. Zhang, et al. (2011) proposed a CA model based on data assimilation (EnKF CA), which can control the accumulation of model errors by introducing data assimilation into CA model. However, this model adopts the static transition rules (parameters). To some degree, existing studies can integrate CA simulation and remote sensing observations to adjust the model parameters or simulation results. However, studies on correcting model rules (parameters) and controlling error accumulation simultaneously have not been reported.

To overcome the weakness of traditional CA model based on static rules, this paper proposes a new CA model based on joint state matrix, which can update model parameters and simulation results simultaneously in simulation process. The best advantage of this Ensemble Kalman Filter (EnKF) assimilation method based on the joint state matrix is that it can update the model parameters and status at the same time. Thus, it not only can dynamically adjust the model parameters, but also can reduce model error accumulation effectively. It is especially adapted to simulate complicated nonlinear systems with long simulated times (Aksoy, et al., 2006). Some scholars have applied the joint state matrix method to the two-dimensional nonlinear sea wind model (Aksoy, et al., 2006), the three dimensional cloud model (Tong & Xue, 2008), the atmospheric dispersion model (Zheng, et al., 2009) and achieved satisfying results. This paper tries to introduce the joint state matrix into CA to simulate the urban expansion of Dongguan. In the simulation, multi-phase remote sensing observation data will be imported into CA model to update the parameters and results dynamically. It also will reflect the self-adaptation feature of this CA model.

2 GEOGRAPHICAL CA BASED ON JOINT STATE MATRIX

Evensen (1994) proposed EnKF which is based on the stochastic dynamic prediction theory of Epstein. First, the algorithm generates the initial set of states using Monte Carlo method and ensemble forecast. And then, the initial set of states is entered into the model to make a prediction and a predicted set is obtained. Follow that, the predicted set and the observation set are entered into the EnKF update equation to obtain the analysis set of states. Finally, the analysis set is used as initial set for prediction and assimilation. The cycle repeats itself until the observations are not available. (Evensen, 1994; Li & Bai, 2010). The best advantage of this algorithm is that it does not require a linear observation operator and the adjoint model. And it can avoid calculating the error covariance matrix with a large computation. To update the model parameters and states at the same time, Aksoy, et al.(2006) used the joint state matrix method. This method integrates the state set and the parameter set into the same matrix (joint state matrix). The joint state matrix, which consists of the states and parameters, will be updated in the assimilation process. The implementation steps are listed as below.

(1) Initial stage. The parameter set is initialized.

$$b_0^i = \hat{b}_0 + e_0^i \tag{1}$$

where b_0^i is the parameter value after disturbance. $\hat{b}_0$ is the initial parameter value. e_0^i is the Gaussian noise, and the subscript "0" refers to $t=0$.

(2) Prediction stage. Each group of parameters will be entered into the model. And the predicted state set can be obtained at the next observation time t. The simulation process can be expressed as

$$X_t^{i-} = f(X_{t-1}^{i+}, b_t^{i-}) \tag{2}$$

$$\hat{Y}_t^i = H(X_t^{i-}, b_t^{i-}) = H(X_{jt}^{i-}) \tag{3}$$

where the "−", "+" refer to before and after update, respectively. X_{t-1}^{i+} is the state variable after update at time $t-1$. X_t^{i-} is the state variable before update at time t. f is the predicted model (i.e., the CA model in this paper). $\hat{Y}_t^i$ is the simulation observation variable mapping to the observation space, X_{jt}^{i-} is the joint state matrix consisting of model states and parameters, and H is the observation operator.

(3) Analysis stage. The EnKF update equation integrates the joint state matrix and the observation set to obtain a new joint state matrix which includes the new parameters and states.

$$X_{jt}^{i+} = X_{jt}^{i-} + K_t[Y_t^i - \hat{Y}_t^i] \tag{4}$$

where X_{jt}^{i-} and X_{jt}^{i+} are the joint state matrix before and after update, respectively, Y_t^i is the observation matrix, and K_t is the Kalman gain for updating the joint state matrix, expressed as

$$K_t = P_t^- H^{\mathrm{T}}[HP_t^- H^{\mathrm{T}} + R_t]^{-1} \tag{5}$$

In the equation,

$$P_t^- = \frac{1}{N-1}\sum_{i=1}^{N}(X_{jt}^{i-} - \overline{X_{jt}^-})(X_{jt}^{i-} - \overline{X_{jt}^-})^{\mathrm{T}} \qquad \overline{X_{jt}^-} = \frac{1}{N}\sum_{i=1}^{N} X_{jt}^{i-} \tag{6}$$

where P_t^- is the predicted error covariance matrix. In practice, $P_t^- H^{\mathrm{T}}$ and $HP_t^- H^{\mathrm{T}}$ are always calculated directly to reduce computation. R_t is the observation error covariance matrix, $\overline{X_t^-}$ is the mean value of state variable, and N is the number of sets.

(4) End stage. If observations are still available, the new model parameters and the new states obtained during the previous analysis stage are entered into the model. Step(2) is repeated for the simulation at time t+1. Otherwise, the process is completed.

The process of urban development is always nonlinear. However, the traditional CA model will result in linear simulation situation because it cannot dynamically adjust the model parameters and the simulated results in the simulation process. Thus, its simulated results do not conform to actual conditions. EnKF that based on the joint state matrix can update the parameters and states of the model by assimilating observation data. The method is very popular in simulating complicated nonlinear systems. We have done initial studies in integrating EnKF with the CA model, and a CA model based on data assimilation was proposed to correct simulated results. Based on previous study, the joint state matrix is introduced into CA model to dynamically update the parameters of the transition rule in the simulation process and to correct the simulated results. The flow diagram of update model parameters and results are shown in Fig.1, which mainly includes the following steps.

Step 1 Generation of parameters sets. Gaussian perturbation is added to the model initial estimated parameters (model parameters are the coefficients of spatial variables and the number of model parameters is marked as n). Each parameter is disturbed by adding a set of Gaussian noise (where the number of Gaussian noise set is N, and N is the ensemble size of EnKF). The generated random parameter set can be expressed as:

$$b_0^{i,n} = b_0^n + e_0^{i,n} \tag{7}$$

where $b_0^{i,n}$ is the i^{th} value in n^{th} parameter set after perturbations. b_0^n is the initial estimated value of n^{th} parameter. $e_0^{i,n}$ is the Gaussian noise, its variance is the normal distribution of the predicted value, superscript i is the series number of the parameter set members (i=1,2,⋯,N), and subscript "0" refers to t=0.

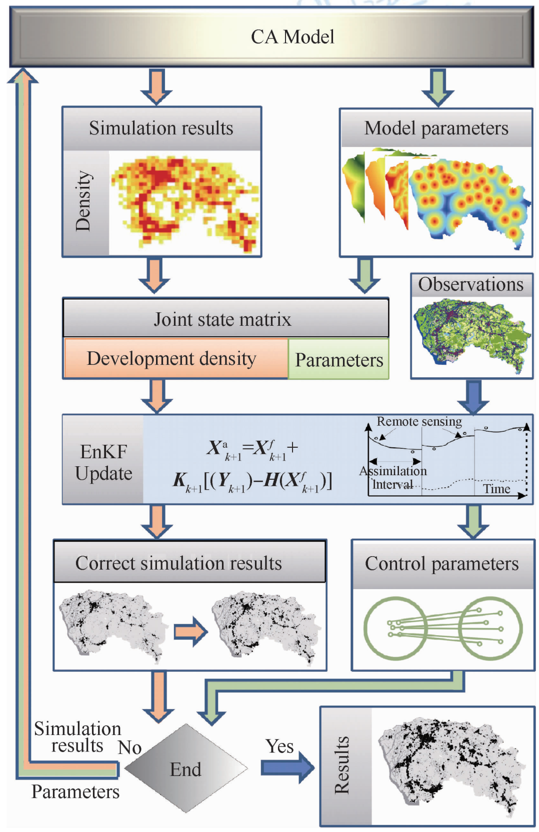

Fig.1 Updating the parameters and states of the CA model using the joint state matrix

Step 2 Simulation using logistic regression CA model. Each group of parameter combinations are entered into the CA model for urban simulation, and different simulated results can be obtained. The CA simulation process can be expressed as

$$S_t^i = f(S_{t-1}^i, \Omega_t, b_t^{i,1}, b_t^{i,2}, \cdots, b_t^{i,n}) \tag{8}$$

where f is a transfer function that defines the state changes from time $t-1$ to the next time t. Ω_t is a neighborhood function. $b_t^{i,n}$ is the n^{th} parameter in the parameter combination of group i, and S_{t-1}^i and S_t^i are the descriptions of the status of all cells at times $t-1$ and t, respectively. The probability of cell (i,j) before transformation can be expressed as (Wu, 2002; Li, et al., 2008):

$$p_{d,ij}^{t-1} = \frac{RA \times \mathrm{con}(s_{i,j}^{t-1}) \times \Omega_{ij}^{t-1}}{1 + \exp[-1 \times (a + b_t^{i,1} \times x^1 + b_t^{i,2} \times x^2 + \cdots + b_t^{i,n} \times x^n)]} \tag{9}$$

where RA is a random item. Ω_{ij}^t is the development intensity in 3×3 neighborhood. con is the total constraint ranging from 0 to 1, which indicates the suitability for urban land development (Li, et al., 2008). a is a constant item. $b_t^{i,n}$ is coefficient of spatial variable, and x^n is the n^{th} spatial variable.

At each iteration, $p_{d,ij}^{t-1}$ is compared to determine if a non-urbanized cell will be converted into urbanized cell (Liu & Li, 2007). It is expressed as

$$S_t(i,j) = \begin{cases} \text{Developed}, & p_{d,ij}^{t-1} > rand_t(i,j) \\ \text{Undeveloped}, & p_{d,ij}^{t-1} \leqslant rand_t(i,j) \end{cases} \tag{10}$$

where $S_t(i,j)$ is the state of the cell (i,j) at time t, and $rand_t(i,j)$ is a random number from 0 to 1 that changes with time.

Step 3 Conversion of the simulated results. The use of N groups with different parameter combinations in CA model will yield different simulated results. And the results will be integrated into the state matrix to calculate the state error covariance. The state matrix requires the state value to be the real type. However, the simulated results of the CA model only have two states (i.e., urbanized or not). Thus, it is necessary to make some conversions. This paper divides the study area into regular grids with each grid contains $m\times m$ pixels (cells). Urban development density is used as state to be included in the data assimilation operation. The relationship between the state matrix from data assimilation $\boldsymbol{X}^i$(development density) and the simulated results of the model S^i can be expressed as

$$\boldsymbol{X}^i = \psi(S^i, m) \tag{11}$$

where m is the side length of the grid. The urban development density of each grid is given by

$$\boldsymbol{X}_{rc} = \frac{\sum\limits_{m\times m} \text{con}(s_{ij} = \text{urban})}{m \times m} \tag{12}$$

where the subscripts r, c are the row and column numbers of the grid. The relationship between the number of the grid (r,c) and the number of the simulated results (i,j) is given by $r=\text{int}(i/m)$ and $c=\text{int}(j/m)$ respectively. Development density can be used to calculate the error covariance. Similarly, the observation value is also represented by the development density.

Step 4 Establishing and updating the joint state matrix. The parameter values used in CA model will be integrated with the development density of the simulated result to a joint state matrix $\boldsymbol{X}_j$(i.e., parameters $b_t^{i,1}, b_t^{i,2}, \cdots, b_t^{i,n}$ are used as states to be added to the original state matrix $\boldsymbol{X}$ to create a joint state matrix$\boldsymbol{X}_j$ that contains parameters and states). The joint state matrix $\boldsymbol{X}_j$, instead of $\boldsymbol{X}$, is entered into the update equation of the EnKF. Therefore, the updated parameters and states can be obtained after assimilating observation data.

$$\boldsymbol{X}_{jt}^{i+} = \boldsymbol{X}_{jt}^{i-} + \boldsymbol{K}_t[\boldsymbol{Y}_t^i - \hat{\boldsymbol{Y}}_t^i] \tag{13}$$

Step 5 Correcting the simulated results and controlling the distribution of the model parameters. The correction of the simulated results based on updated states can be found in Zhang, et al. (2011). In filtering applications, when the prior distribution of a parameter is too narrow, the posterior distribution divergence will occur after data assimilation (Anderson & Anderson, 1999). One method that avoid filtering divergence is the minimum standard deviation method by using a threshold value. When the standard deviation of the parameter set is smaller than the threshold value, the standard deviation of the set is adjusted to the set threshold value. This method not only can ensure the narrowest distribution for a parameter, but also can avoid the continuous expansion of a set distribution caused by the expansion coefficient method (Aksoy, et al., 2006).

Step 6 Repeating Step 2 after entering the newly corrected simulated results and adjusted parameters into CA model. This cycle is performed continuously until all observation data are assimilated.

3 EXPERIMENTS AND ANALYSIS

3.1 Data and parameter settings

Dongguan was selected as the experimental area in this paper. The initial simulation data were the classification data from the remote sensing TM land use in 1993. The spatial variables of the logistic regression CA model (Fig.2) include distance to town center, distance to (common) road, distance to highway, and distance to railway. The initial weights of the distance and spatial variables in the logistic regression CA model are shown in Table 1. The weighted values were obtained by using logistic regression in SPSS software on the samples from 1993 to 1995.

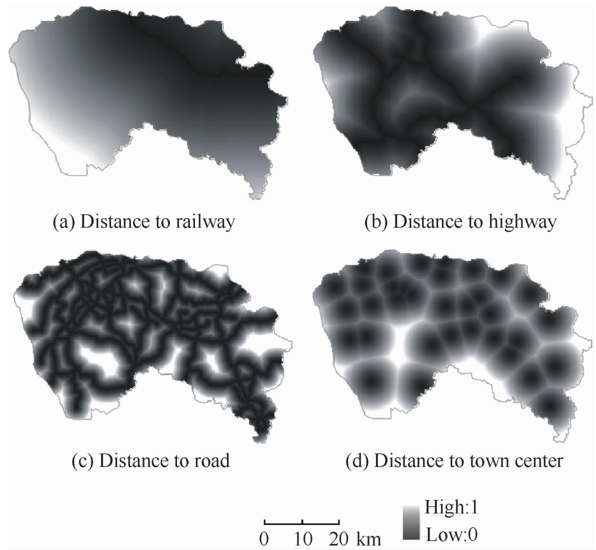

Fig.2 Space distance variable

Table 1 Initial value of model parameters in CA simulation

Space variable	Highway	Railway	Common road	Town center	Constant
Initial value	−0.738	0.601	−6.089	−5.423	−0.900

In this paper, the study area was divided into 257 (13×19) regular grids. Each grid has 40×40 pixels (cells). Thirty observation points (grids) were selected (Fig.3). The position and the number of observation points remained unchanged during the simulation process. The development intensity values of the observation points were obtained from the large-scale CAD data or QuickBird image in the corresponding area.

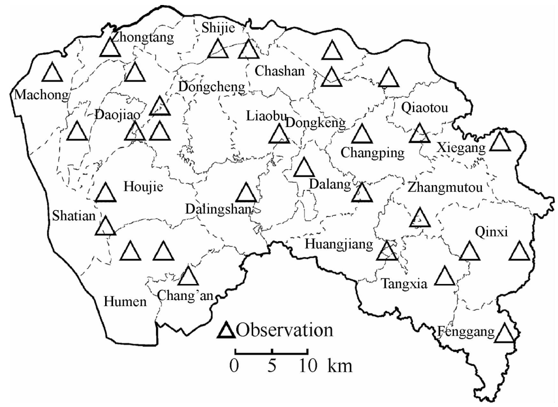

Fig.3 Location of observations

The parameter variance has great effect on the simulated results of the model. In the filtering process, minimum standard deviation method was used in this paper to ensure filtering convergence. The minimum standard deviation was one fourth of the initial standard deviation (Aksoy, et al., 2006). The simulation accuracy of the traditional CA model is about 80%, and the model error is 0.2. The observation error was mainly from resampling, and it was set to 0.05. The analysis error was set to 0.025. An ensemble size of 30 to 50 in general can meet the requirements. If the ensemble is oversized, the computations will be numerous, and the improvement in simulation results will not be obvious. If the ensemble is small, the statistical nature will not be reflected, and the error will be large (Crow & Wood, 2003). Thus, the ensemble size for this paper was 30.

3.2 Model application

The model proposed in this paper was applied in Dongguan, Guangdong province. The urban land use in 1993 was used as the initial simulation data. Fig.4 shows the simulated results of the model during the three stages, 1993—1997, 1997—2001, and 2001—2005. The urban development of Dongguan in 1993—2005 went from slow to fast, particularly from 2001—2005. Urban expansion speed was accelerated, and urban land use obviously increased. Based on the urban landscape morphology, the urban expansion in Dongguan was slow in 1993—1997, and urban land was focused in the town center. In 1997—2001, the urban expansion was fast. The pattern of urban expansion also changed from expansion in the town center to expansion in the town center and along the roads. In 2001—2005, the speed of urban expansion was faster than that in previous stages. And the area of urban land use increased even more. It also can be found that the simulated results of the joint CA were similar to in real situations. Table 2 shows that the urban expansion pattern change over time (i.e., the parameter values of common roads and high ways became large, and the parameter values of town centers became small). In Table 3, the accuracy of the joint CA

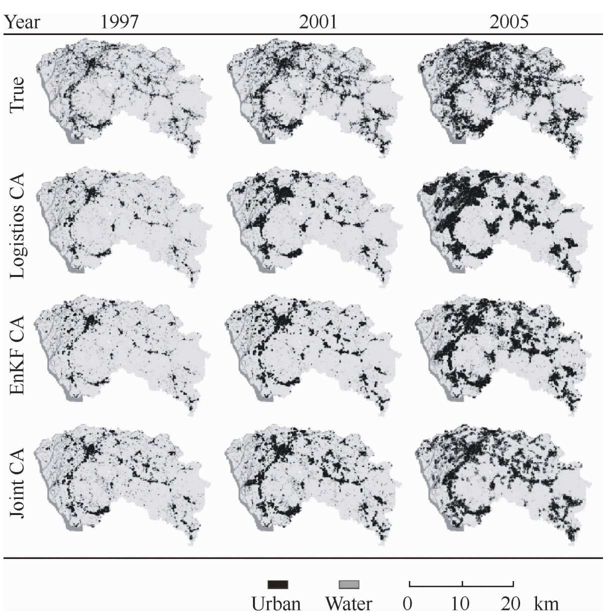

Fig.4 Comparison of the simulated results among different methods

model in 1997, 2001, and 2003 are 88.4%, 79.8% and 69.2%. And the Kappa coefficients in 1997, 2001, and 2003 are 0.587, 0.486 and 0.368, respectively. Clearly, the simulated results of the joint CA had better effects, whether in spatial form or point-to-point simulation accuracy. These results also showed that the joint CA can not only couple remote sensing observation data during the simulation process, but also adjust the model parameter to depict the actual urban development mode.

Table 2 Changes in the model parameters

	Highway	Railway	Common road	Town center	Constant term
1997	−0.530	0.161	−3.454	−1.728	0.472
2001	−0.386	1.111	−2.298	−2.646	0.027
2005	−0.454	1.071	−2.579	−2.491	0.706

Table 3 Simulation accuracy and Kappa coefficient

Year	Accuracy/%			Kappa coefficient		
	Logistic CA	EnKF CA	Joint CA	Logistic CA	EnKF CA	Joint CA
1997	87.7	87.9	88.4	0.550	0.568	0.587
2001	76.9	79.0	79.8	0.428	0.475	0.486
2005	64.0	68.4	69.2	0.279	0.364	0.368

3.3 Model comparison

To verify the effectiveness of the proposed model, we used three different models and compared their results. The three models were the traditional logistic regression CA model, the EnKF CA (Zhang, et al., 2001) model and the joint CA model. The simulation results were used to compare with the actual situation. The actual situation can be obtained after atmosphere, geometric corrections and object-oriented classification of the remote-sensing image TM. Fig.4 shows the comparison of urban land simulated using all models and practical urban land.

In general, the simulated results of all the models are similar to the actual situations in 1997. Up until 2001, the results of logistic regression CA model were different from actual situations. In 2005, the simulated results are non-ideal with lowest accurate results. Conversely, the simulated results of the EnKF CA model are better than those of the traditional CA model. In 2005, the simulated results of EnKF CA also have evident errors in the northwest and southwest of the study area. However, the joint CA model can well reflect the reality.

Most new urban lands were around the original urban lands in 1997. All models can change the rural cells of high suitability into urban cells. Therefore, the three models showed few differences in term of variance or simulated results (Fig.4 and Table 3). And the results are similar to actual situations.

The actual scene shows that the urban development style from 1997 to 2001 is expansion along the roads and in the town centers, different from the simple expansion in the town centers at previous stage. However, the new urban lands in logistic regression CA model are mostly focused on the city center different from actual scene. And there are some errors in the western, Humen in the southwest and Dalingshan, which is south of the study area. The error of logistic regression CA model is larger than others, mainly because the model parameters and the simulated results cannot change in the simulation process. The

EnKF CA model can better control the expansion in the city center, Humen, and Dalingshan. The simulated results were corrected and better than those of the traditional logistic regression CA models. The joint CA model can obtain even better results, particularly in the eastern of the study area. The expansion along the roads is obvious, which agrees with the actual situation. The model can adjust parameters correctly, reflecting the mode of urban development properly. In Table 2, the parameter values of the "highway" and the "common road" in 1997—2001 increase, and the parameter value of the "town center" decreases. This information indicates that the expansion of the model simulation along the roads is increasingly obvious. However, it does not imply that the expansion of the town center is becoming less. The main reason is that the "road" (including highways and common roads) has a certain correlation with the "town center" (the related coefficient of the town center to the common road is 0.514). The situation reflected by the parameter changes of the joint CA model is consistent with the expansion pattern of the study area. The simulation results also indicate that the model is effective and consistent with the actual situation.

In 2005, urban expansion in Dongguan is obvious. The simulated results of logistic regression CA showed that many new urban lands are focusing in Machong (northwest of the study area), Shijie (north of the study area), Shatian (southwest of the study area), and Dalingshan (South of the study area). Only a few new urban lands emerged in Fenggang (southeast of the study area). The reason for these results is that the logistic regression CA model still used the previous expansion pattern, expanding in the town center, so that large errors were incorporated into the simulated results. Although EnKF CA can better reflect the urban expansion than Logistic CA model, it also has simulation errors. The simulation results, containing Shatian in the southwest, Dalingshan in the south, Qingxi in the southeast, and Shijie in the north, greatly differed from actual situations. In these areas, the joint CA can achieve better performance. The model can reduce the error to a large degree. It can also reasonably reflect the actual situation of urban development by integrating the simulated results with observation data, adjusting the parameter values of the CA model and correcting the simulated results.

Aside from comparing the simulated results, we also compared the simulation accuracy and the kappa coefficient of each model (Table 3). The table shows that the logistic regression accuracies and the Kappa coefficients in 1997, 2001, and 2005 are 87.7% and 0.550, 76.9% and 0.428, 64.0% and 0.279, respectively. Logistic regression CA cannot adjust the model state and parameter. Therefore, its accuracy and coefficients is the lowest. Compared with the logistic regression CA model, EnKF CA can adjust the simulated results in the simulation process. It released the accumulation of the model error to a certain degree. Therefore, its accuracy has improved. In 1997, 2001, and 2005, the accuracies and the Kappa coefficients of EnKF CA are 87.9% and 0.568, 76.9% and 0.475, 68.4% and 0.364, respectively. The EnKF CA model considers the accumulation of errors in the simulated results but neglects the dynamic changes in the model parameters. The joint CA model considers the changes of model parameter and the accumulation of model error. Therefore, it is more reliable than the logistic regression CA and EnKF CA models, as indicated by the improved accuracy by 0.5%, 0.8%, and 0.8% in 1997, 2001, and 2005, respectively, compared with that of the EnKF CA model.

4 CONCLUSION

In this paper, EnKF were introduced, and a new CA model based on the joint state matrix was proposed. In this model, data assimilation method was used to integrate the CA model with the remote sensing observation data, correcting the model parameters and the simulated results automatically. The experiments in Dongguan showed that the model can precisely correct the model parameters which are consistent with urban expansion pattern. Besides, the model can adjust the simulated results to better represent the actual situations. Based on the simulation accuracy and Kappa coefficient results, the simulation proposed in this paper is better than the traditional logistic regression CA model. Compared with the EnKF CA model, the proposed model is more suitable to the situations as the model parameters (transition rules) can change with time. It has a strong adaptive capacity for simulating complicated nonlinear geographies. However, if the number of model parameters are too many (e.g., more than 10), the simulation results of joint CA model will have poor performance. In future, we will try to improve the simulation performance for conditions of many model parameters.

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耦合遥感观测和元胞自动机的城市扩张模拟

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摘　要：在传统元胞自动机(CA)模型中，静态的模型参数和模型误差不能释放是影响城市扩张模拟效果的两个重要原因。文中引入集合卡尔曼滤波方法到 CA 模型中，提出了基于联合状态矩阵的地理元胞自动机。该模型在模拟过程中可以通过同化遥感观测数据，动态地调整模型参数和纠正模拟结果，使模型参数能够反映转换规则的时空变化，同时也能较好地释放积累的模型误差。将模型应用于东莞市的城市扩张模拟中，实验结果表明，模型能够准确地调整模型参数使之符合城市发展模式，同时也能有效地控制模型误差，其模拟的空间格局与真实情况吻合。

关键词：元胞自动机，城市扩张，数据同化，集合卡尔曼滤波，联合状态矩阵

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1 引　言

城市土地利用变化不仅影响着当地及周边地区的社会经济，也影响着区域甚至全球的生态环境。研究表明，城市用地的扩张对当地的经济增长有着重要的贡献，城市用地的集约化程度与经济增长、工业化和城市化水平有着密切的关系(Nusrath 和 Shabeer，2011)。城市变化也深刻影响着全球的气候变化。它不仅通过改变地表反照率、地面粗糙度、叶面积指数和土壤湿度等影响气候，还通过热岛效应、碳循环等方式影响气候(Charney 等，1977；Houghton 等，1983；Brovkin 等，1999)。

研究并获取城市用地的扩张变化需要用到模型模拟和观测这两种基本方法，它们均有着各自的特点(李新和黄春林，2004)。模型模拟方法可以根据城市扩张的内在物理过程、动力学机制模拟出城市在时间和空间上的连续演变过程，其中 CA 模型是常用模拟工具(Li 和 Yeh，2004)。而观测则可以获取到城市用地在观测时刻的真实情况(李新 等，2007)。

CA 模型是一个能够有效模拟和预测复杂动态系统行为的工具。它是一种由局部规则控制、“自下而上”的格网动力模型。CA 的研究思路充分体现了复杂系统局部个体行为产生全局、有秩序模式的理念，非常适用于复杂地理过程的模拟和预测(Wolfram，1984；Couclelis，1988)。它包含空间演化过程和一系列的模型参数。通过设置模拟规则、模型参数和初始值，可以方便地模拟出土地利用类型变化的空间演变过程(Tobler，1970；Batty 和 Xie，1994；陈建平 等，2004)，对于研究城市土地变化的机理、把握土地变化的演变规律有举足轻重的作用(Clarke 等，1997；Li 和 Yeh，2000；Wu，2002)。对于理解和验证城市地理学中的假设和理论也有相当重要的意义(Couclelis，1985；White 和 Engelen，1993)。在全球、区域的陆面过程模型中也常常需要输入城市发展空间格局或者土地利用的相关信息，

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准确的土地利用信息有助于得出客观结果(Lawrence 等,2011)。但是,CA 模型还存在一些不确定性:(1)模型往往对复杂的变化过程进行简化。如在模拟过程中假设城市演化规律不变而采用静态的模型参数(Li 和 Liu, 2006)。(2)模拟过程时误差积累过快。由于城市演化过程常常是复杂、非线性的,来自数据源的误差(如野外调查误差、数字化误差和数据转换误差)会在模拟过程中不断传递且积累(黎夏等,2007)。

观测是另一种获取城市用地变化的有效手段。它往往是使用遥感影像数据并利用遥感解译与图像识别技术,从遥感影像中提取城市变化信息(Seto 等,2002)。与早期的统计或实地调查相比,在精度和效率方面有了极大提高。遥感影像具有天然的优势,如广域性、周期性、连续性和经济性等特点。它能够迅速准确地获取研究区在某一时刻的土地利用状况,也能够方便地研究城市用地的时空演变过程、机理与其对社会经济、局部/全球环境所产生的效应,为国家或地区的可持续发展战略提供决策支持。通过叠置多期影像还能获取土地变化的类型、数量和空间位置等信息,还能对重要的土地资源(如农田、森林等)进行及时预警(何春阳 等,2001)。但是,仅仅采用遥感数据很难完整、连续地反映城市用地的时空演变过程,主要原因有:(1)遥感数据记录是研究区某一具体时刻的土地利用状况,是瞬时的,然而城市用地的时空演变过程在时间和空间上都应该是连续的。因此,需要运用模拟模型,把遥感瞬时观测扩展到时间维和空间维上(李新 等,2007)。(2)运用遥感方法得到的资料会有一系列的不确定和误差,如感应器的误差、大气扰动误差和分类算法误差等(Li 和 Yeh, 1998)

CA 模拟和遥感观测都具有一定局限性,整合两种方法可以得到更符合实际情况的城市扩张过程。目前为止,仅有少数学者尝试相关研究。Clarke 等人(1997)根据蒙特卡罗方法并结合历史观测数据来动态调整模型参数。他们的方法运算量巨大,需要高性能工作站运算几百小时。杨青生和黎夏(2007)利用遗传算法获取模型参数,但该方法需要获得全区观测数据,在实际中常常难以获取。黎夏和刘小平(2007)提出案例推理(CBR)的 CA 模型,根据新的案例动态更新转换规则。以上模型能够更新转换规则,但不能控制模拟过程中的误差积累。张亦汉等人(2011)提出了基于数据同化的 CA 模型(EnKF CA)。模型通过引入数据同化方法整合遥感观测,较好地控制了模型误差的积累,但采用了静态的转换规则(参数)。已有研究能够在一定程度上整合 CA 模拟和遥感观测,可以调整模型参数或者模拟结果,但是目前尚未实现同时动态修正模型规则和控制误差积累。

因此,本文提出了基于联合状态矩阵动态更新模型和状态的 CA 模型以代替基于静态规则的 CA 模型。基于联合状态矩阵的集合卡尔曼滤波同化方法的优势是能够在同化时刻同时更新模型参数与状态,即在动态调整模型参数时也能有效地减少模型误差积累。它特别适用于模拟时间较长的复杂非线性系统中(Aksoy,2005)。已有学者将联合状态矩阵方法应用在 2 维非线性海风模型(Aksoy,2005)、3 维的云模型(Tong 和 Xue,2008)和大气扩散模型(Zheng 等,2009)中,并取得良好的效果。本文把联合状态矩阵引入元胞自动机中,并以东莞市的城市扩张为例,通过加入多个年份的遥感观测资料对 CA 模型进行校正,使得模型能够动态更新参数和状态,实现 CA 模型的自适应。

2 基于联合状态矩阵的地理元胞自动机

集合卡尔曼滤波 EnKF 是 Evensen(1994)根据 Epstein 的随机动力预报理论而提出的算法。该算法首先用 Monte Carlo 方法与集合预报的思想生成初始状态集合并输入到模型中进行预测得出预测集合。然后把预测集合和观测集合输入到集合卡尔曼滤波更新方程中,得到更新后状态集合,即分析集合。最后用分析集合作初始集合预测到下一个观测,如此循环(Evensen,1994;李新和摆玉龙,2010)。算法最大的优势是不需要模型的切线性算子和伴随模式等,而且它也不需要计算维度很大的误差协方差矩阵。为了能够同时更新模型参数和状态,Aksoy(2005)提出联合状态矩阵方法。该方法将状态集合和参数集合整合到同一矩阵(即联合状态矩阵)中,并在同化时刻同时更新由状态和参数组成的联合状态矩阵。实现步骤如下:

(1)初始阶段:参数集合初始化。

$$b_0^i = \hat{b}_0 + e_0^i \tag{1}$$

式中,b_0^i 为扰动后的参数值;$\hat{b}_0$ 为参数初始值;e_0^i 为扰动噪声;下标‘0’为 $t=0$ 时刻。

(2)预测阶段,将每组参数输入到模型中,分别预测至下一个观测时刻 t 得到预测状态集合,其模

拟过程可表示为：

$$\boldsymbol{X}_t^{i-}=f(\boldsymbol{X}_{t-1}^{i+},b_t^{i-}) \tag{2}$$

$$\hat{\boldsymbol{Y}}_t^i=\boldsymbol{H}(\boldsymbol{X}_t^{i-},b_t^{i-})=\boldsymbol{H}(\boldsymbol{X}_{jt}^{i-}) \tag{3}$$

式中，上标“−”，“+”表示更新前与更新后，$\boldsymbol{X}_{t-1}^{i+}$ 为时刻 $t-1$ 更新后的状态变量，$\boldsymbol{X}_t^{i-}$ 为时刻 t 更新前的状态变量，f 为用于预测的模型(本文指 CA 模型)，$\hat{\boldsymbol{Y}}_t^i$ 为映射到观测空间的模拟观测变量，$\boldsymbol{X}_{jt}^{i-}$ 为由模型状态和参数构成的联合状态矩阵，$\boldsymbol{H}$ 为观测算子。

(3)分析阶段，融合联合状态矩阵和观测集合，并根据集合卡尔曼滤波方法，得出新的联合状态矩阵，其中包括新的参数和状态：

$$\boldsymbol{X}_{jt}^{i+}=\boldsymbol{X}_{jt}^{i-}+\boldsymbol{K}_t[\boldsymbol{Y}_t^i-\hat{\boldsymbol{Y}}_t^i] \tag{4}$$

式中，$\boldsymbol{X}_{jt}^{i-}$ 与 $\boldsymbol{X}_{jt}^{i+}$ 分别为更新前后的联合状态矩阵，$\boldsymbol{Y}_t^i$ 为观测矩阵，$\boldsymbol{K}_t$ 是用于更新联合状态矩阵的卡尔曼增益，其计算方法如下：

$$\boldsymbol{K}_t=\boldsymbol{P}_t^-\boldsymbol{H}^{\mathrm{T}}[\boldsymbol{H}\boldsymbol{P}_t^-\boldsymbol{H}^{\mathrm{T}}+\boldsymbol{R}_t]^{-1} \tag{5}$$

式中，

$$\boldsymbol{P}_t^-=\frac{1}{N-1}\sum_{i=1}^{N}(\boldsymbol{X}_{jt}^{i-}-\overline{\boldsymbol{X}_{jt}^-})(\boldsymbol{X}_{jt}^{i-}-\overline{\boldsymbol{X}_{jt}^-})^{\mathrm{T}}\quad \overline{\boldsymbol{X}_{jt}^-}=\frac{1}{N}\sum_{i=1}^{N}\boldsymbol{X}_{jt}^{i-} \tag{6}$$

式中，$\boldsymbol{P}_t^-$ 为预测误差协方差矩阵，常常直接计算 $\boldsymbol{P}_t^-\boldsymbol{H}^{\mathrm{T}}$ 与 $\boldsymbol{H}\boldsymbol{P}_t^-\boldsymbol{H}^{\mathrm{T}}$ 以减少计算量，$\boldsymbol{R}_t$ 是观测误差协方差矩阵，$\overline{\boldsymbol{X}_t^-}$ 是 t 状态变量平均值，N 为集合个数。

(4)判断是否到结束时刻(即判断是否有同化完所有的遥感观测)，若未到，将分析阶段中得出的新模型参数和新状态输入到模型中，返回步骤(2)进行模拟预测，否则结束。

城市发展往往是非线性的，然而传统的 CA 模型由于不能实时调整模型参数和模拟结果而呈线性式发展，故其模拟结果往往有较大的误差。基于联合状态矩阵的 EnKF 能够方便地通过同化观测数据更新模型的参数和状态，特别适合于复杂非线性系统的模拟。在引入 EnKF 到 CA 模型方面，我们进行了初步探索并提出了基于数据同化的 CA 模型，实现了对模拟结果的纠正。在该模型基础上，考虑到参数组合对模拟结果的影响是显著的，因此，通过构建联合状态矩阵，实现在模拟过程中动态更新转换规则中的参数以及修正模拟结果，从而提高模拟效果(图 1)。主要包括如下步骤：

步骤 1　生成初始参数集合。对模型参数(即各个空间变量的系数，共 n 个)进行高斯扰动，每个参数均扰动成有 N(N 为集合卡尔曼滤波中的集合

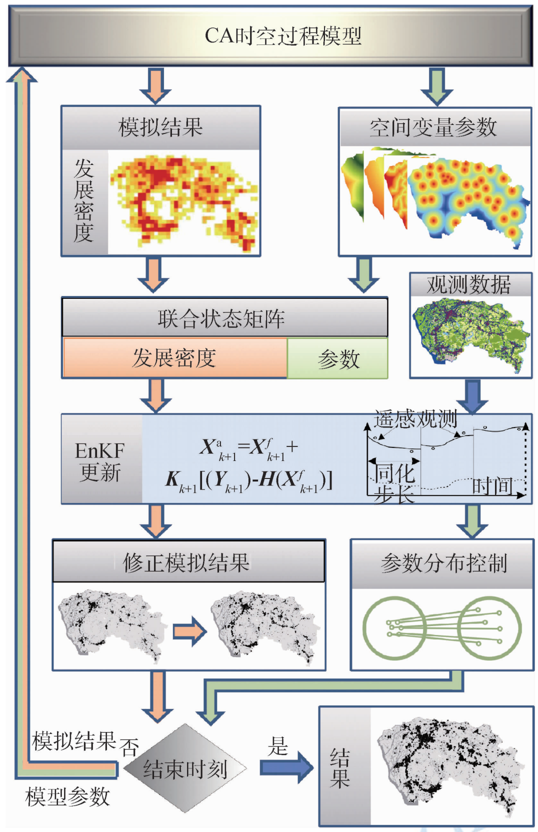

图 1　利用联合状态矩阵更新 CA 模型参数和状态

个数)个不同的参数值的集合。生成随机参数集合可表示为：

$$b_0^{i,n}=b_0^n+e_0^{i,n} \tag{7}$$

式中，$b_0^{i,n}$ 为第 n 个参数扰动后的集合成员值，b_0^n 为第 n 个参数初始估计值，$e_0^{i,n}$ 为扰动噪声，其分布符合均值为 0，方差为预测值的正态分布，上标 i 是集合成员序号，$i=1,2,\cdots,N$，下标‘0’表示 $t=0$ 时刻。

步骤 2　逻辑回归 CA 模型的模拟。把 $\boldsymbol{N}$ 组不同的参数组合输入到 CA 模型中分别进行城市模拟，可得出 N 组不尽相同的模拟结果。CA 模拟过程可表示为：

$$S_t^i=f(S_{t-1}^i,\varOmega_t,b_t^{i,1},b_t^{i,2},\cdots,b_t^{i,n}) \tag{8}$$

式中，f 为定义元胞从时刻 $t-1$ 到下一时刻 t 时刻状态的转换函数，$\varOmega_t$ 是邻域函数，$b_t^{i,n}$ 是第 i 组参数组合中第 n 个参数，S_{t-1}^i 和 S_t^i 分别是 $t-1$ 和 t 时刻的所有元胞状态的总体描述。式中任意元胞(i,j)转换前的概率可表示为(Wu，2002；Li 等，2008)：

$$p_{d,ij}^{t-1}=\frac{RA\times\mathrm{con}(s_{i,j}^{t-1})\times\varOmega_{ij}^{t-1}}{1+\exp[-1\times(a+b_t^{i,1}\times x^1+b_t^{i,2}\times x^2+\cdots+b_t^{i,n}\times x^n)]} \tag{9}$$

式中，RA 是随机项；$\varOmega_{ij}^{t}$是邻域函数，一般是通过计

算 3×3 的核来计算元胞在空间上的相互影响;con 是元胞自然属性,常用介于 0—1 的值表达土地城市发展的适宜性(Li 等,2008);a 为常数项,$b_t^{i,n}$ 为空间变量的系数,x^n 为第 n 个空间变量。

元胞(i,j)的状态是否变化常常使用软分法进行判断(刘小平和黎夏,2007),表达式为:

$$S_t(i,j)=\begin{cases}\text{发展},p_{d,ij}^{t-1}>rand_t(i,j)\\ \text{不发展},p_{d,ij}^{t-1}\leqslant rand_t(i,j)\end{cases} \tag{10}$$

式中,$S_t(i,j)$是元胞(i,j)在 t 时刻的状态;$rand_t(i,j)$是 0—1 间随时间变化的随机数。

步骤 3 模拟结果转换。采用 N 组不同的参数组合会得出不同的模拟结果,然后把结果整合到状态矩阵中,以计算状态误差协方差。状态误差协方差的运算要求状态值是连续型。但是,CA 模型的模拟结果只有两种形式(发展与不发展),故不能直接参与计算。本文把研究区分成若干个规则的方格,每个方格包含 $m×m$ 个像元(元胞),用城市发展密度作为状态参与数据同化运算。数据同化中的状态矩阵 $\boldsymbol{X}^i$(发展密度)与模型的模拟结果 S^i 的关系可表示为:

$$\boldsymbol{X}^i=\psi(S^i,m) \tag{11}$$

式中,m 为方格边长,每个方格的城市发展密度为:

$$\boldsymbol{X}_{rc}=\frac{\sum\limits_{m\times m}\text{con}(s_{ij}=\text{urban})}{m\times m} \tag{12}$$

式中,r,c 为方格的行列号,与模拟结果的行列号的关系是,$r=\text{int}(i/m)$,$c=\text{int}(j/m)$。获得每个方格的城市发展密度后,便可用发展密度来计算误差协方差。同理,观测值也是用发展密度来表示。

步骤 4 构建并更新联合状态矩阵。整合 N 组 CA 模型的参数值和其模拟结果的发展密度到同一个联合状态矩阵 $\boldsymbol{X}_j$ 里,即把参数 $b_t^{i,1},b_t^{i,2},\cdots,b_t^{i,n}$ 作为状态增加到状态矩阵 $\boldsymbol{X}$ 中,构成一个包含参数和状态的联合状态矩阵 $\boldsymbol{X}_j$。再将此联合状态矩阵 $\boldsymbol{X}_j$ 代替 $\boldsymbol{X}$ 并输入到集合卡尔曼滤波方法的更新方程公式,通过同化观测数据可得到更新后的参数和状态:

$$\boldsymbol{X}_{jt}^{i+}=\boldsymbol{X}_{jt}^{i-}+\boldsymbol{K}_t[\boldsymbol{Y}_t^i-\hat{\boldsymbol{Y}}_t^i] \tag{13}$$

步骤 5 修正模拟结果及控制模型参数分布。根据更新后的状态对模拟结果修正(张亦汉 等,2011)。在滤波应用中,当参数的先验分布过窄时,数据同化后,后验分布发散就会常常发生(Anderson 和 Anderson,1999)。一种避免滤波发散的方法是最小标准差法(阈值)。当参数集合的标准差小于阈值时,重新调整集合的标准差为设定的阈值。这种方法能够保证参数的最窄分布,也能够避免膨胀系数法使得集合分布不断扩大的情况(Aksoy,2005)。

步骤 6 把修正后的模拟结果和调整分布后的参数重新输入到 CA 模型后,返回步骤 2,便可进行下一时刻的模拟迭代,如此循环,直到同化完所有观测数据。

3 实验及分析

3.1 数据与参数设置

模型选用东莞市作为试验区,模拟初始数据是 1993 年遥感 TM 土地利用分类数据。逻辑回归 CA 模型的距离空间变量(图 2)包括离镇中心距离,离(普通)道路距离,离高速公路距离,离铁路距离。逻辑回归 CA 模型中距离空间变量的初始权重如表 1 所示,其权重值的确定是由 SPSS 软件对 1993—1995 年影像随机采样的样本得进行逻辑回归得到的。

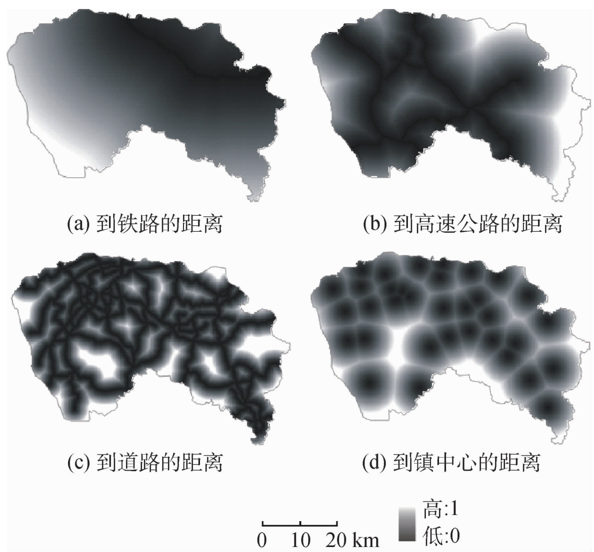

图 2 空间距离变量

表 1 CA 模型参数初始值

距离空间变量	高速公路	铁路	普通公路	镇中心	常数项
初始值	−0.738	0.601	−6.089	−5.423	−0.900

本文将研究区划分为 257(13×19)个规则方格,每个方格有 40×40 像元(元胞),从中选择出 30 个观测点(图 3),观测点的位置及数量在模型运行的过程中保持不变。观测点的发展强度值是从对应区域的大比例尺 CAD 数据或遥感快鸟影像数据中获得的。

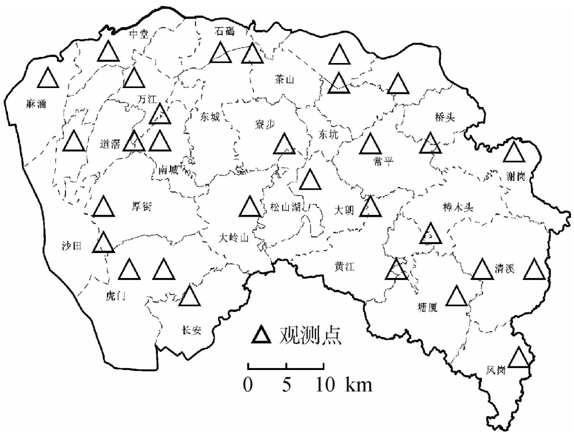

图 3　观察点位置图

参数组合方差的大小对模型模拟结果的误差统计有较大影响。本文认为各个参数的服从标准正态分布。在滤波过程中，常常由于参数先验分布太窄而导致滤波发散。因此这里采用设置最小标准差方法来保证滤波收敛，最小标准差为初始标准差的1/4(Aksoy,2005)。由于传统CA模型的模拟精度约为80%，选定模型误差0.2；观测误差主要来源于重采样，设定观测误差为0.05; 而分析误差则取0.025。通常集合大小为30—50能够满足要求。集合过大，运算量会非常大且对结果改善不明显；集合过小，体现不出统计特征并且误差较大(Crow 和 Wood,2003)。故本文选择集合大小为30。

3.2　模型应用

将本文提出的Joint CA模型应用到广东省东莞市，并以1993年东莞城市用地作为模拟起始数据，对1993年—1997年、1997年—2001年和2001年—2005年期间的东莞城市用地变化进行模拟。图4给出了模型在3个阶段的模拟效果。可以发现，东莞市在1993年—2005年的城市发展是一个由慢到快的阶段，特别是在2001年—2005年，城市扩张速度加快，城市用地增长明显。在城市景观形态上看，东莞市在1993年—1997年，城市扩张较慢且基本上沿城镇中心发展；在1997年—2001年，城市扩张速度加快，同时城市扩张的方式也由沿城镇中心转变为沿中心和沿道路发展并存的扩张方式。在2001年—2005年，城市扩张速度比上一阶段更快，城市用地的面积也变得更多。同时，也可以发现Joint CA的模拟结果在整个过程中，其空间布局上与实际情况非常接近。从表2中也能明确表明城市扩张方式在变化，即，普通公路和高速公路的参数值变大，城镇中心的参数值变小。从表3中，Joint CA模型在1997年、2001年及2003年的精度及Kappa系数分别为88.4%和0.587，79.8%和0.486与69.2%和0.368，精度和Kappa系数均较高。可以看出，Joint CA模型的模拟结果不论在整体的空间形态上还是点对点的模拟精度上均有很好的效果。也说明Joint CA模型在模拟过程中可以有效地同化遥感观测数据，能够准确地调整模型参数使之与真实的城市发展模式一致，也能够较好地释放积累的模型误差，使得模拟结果的空间格局与真实情况更吻合。

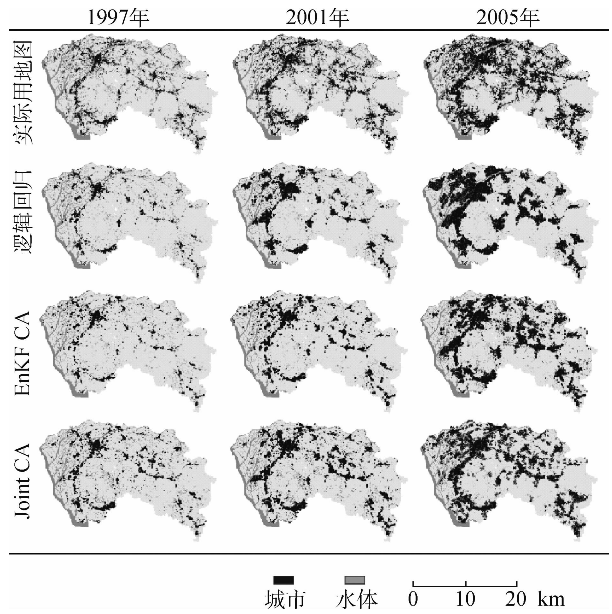

图 4　模拟结果对比

表 2　参数值变化

	高速公路	铁路	普通公路	镇中心	常数项
1997 年	−0.530	0.161	−3.454	−1.728	0.472
2001 年	−0.386	1.111	−2.298	−2.646	0.027
2005 年	−0.454	1.071	−2.579	−2.491	0.706

表 3　模拟精度与 Kappa 系数

年份	精度/%			Kappa 系数		
	逻辑回归	EnKF CA	Joint CA	逻辑回归	EnKF CA	Joint CA
1997	87.7	87.9	88.4	0.550	0.568	0.587
2001	76.9	79.0	79.8	0.428	0.475	0.486
2005	64.0	68.4	69.2	0.279	0.364	0.368

3.3　模型对比

为了验证模型的有效性，分别用3个不同的模型对研究区进行模拟，并对模拟结果进行了对比。所用的3个模型是传统逻辑回归CA模型、EnKF

CA 模型和 Joint CA 模型。其中 EnKF CA 模型是张亦汉等人(2011)提出的模型。用 CA 模拟真实的城市时,需要检验其与实际情况的吻合程度。图 4 是各个模型模拟的城市用地和实际城市用地的对比图。其中,实际城市用地图是先对遥感影像 TM 进行大气纠正和几何纠正,然后再用面向对象方法对影像进行分类得出的。

总体而言,在 1997 年,各个模型的模拟结果在整体空间布局上均与实际情况非常接近;模拟到 2001 年,逻辑回归 CA 模型在部分镇中心模拟出与实际情况不符合的过度发展;在 2005 年模拟结果更不理想,与实际情况有较大的误差。同时也可以发现 EnKF CA 模型的模拟结果优于传统 CA 模型的模拟结果。2005 年 EnKF CA 模型的模拟结果在研究区的西北及西南部分仍有过度模拟的情景,而 Joint CA 模型能够较好地反映出真实情况。

从图 4 中可以发现,在模拟初期,由于转换量较少,而且很多城市用地都是在原有的城市用地的周边进行扩张,对于元胞区位优势明显的地方,各个模型都能够将其转变为城市用地元胞,故它们在精度等的比较和模拟结果上的差别都较小,且均接近真实情况。

真实情景表明,1997 年—2001 年阶段,东莞市的城市扩张方式是沿道路扩张与镇中心扩张并存,与模拟初期单纯的镇中心扩张有所区别。然而逻辑回归 CA 的模拟结果中的新增城市用地大部分集中在中西部发展较成熟的市中心、西南部的虎门等地,故模拟结果在这些地区存在新增城市用地过多情况。而且在研究区南部的大岭山等地也存在一定的误差。逻辑回归 CA 由于不能在模拟过程中改变模型参数及模拟结果,故其模拟的城市情况,仍然是镇中心扩张,故产生了较大的模拟误差。EnKF CA 模型能够较好地控制市中心,虎门与大岭山等地区过度扩张的情况,通过修正模拟结果,达到了一定的缓和作用,其结果优于传统的逻辑回归 CA 模型。Joint CA 模型能够得到更好的模拟结果,特别是研究区东部地区,沿道路扩张的情景已显示得非常明显,与真实情况很接近。模型能够正确地调整参数,从而正确反映出城市发展模式。在表 2 中,1997 年—2001 年,“高速公路”与“普通公路”的参数值增大,而“镇中心”的参数值减小。这说明模型模拟沿道路扩张的趋势越来越明显,但并不能说明镇中心扩张作用越来越小,主要因为“道路”(包括高速与普通公路)与“镇中心”变量有一定的相关(镇中心与普通公路相关系数为 0.514)。Joint CA 模型的参数值变化反映情况与此阶段研究区的扩张方式是一致的,也可以说明模型有效并且能够反映真实情景。

在后期(2005 年),东莞市城市扩张更加明显。逻辑回归 CA 模型模拟结果在研究区的西北部麻涌、北部石碣、西南部沙田与南部大岭山均出现新增城市用地过多的情况,而东南部凤岗等却出现新增城市用地过少的情况。主要由于逻辑回归 CA 模型仍然按初期的单纯镇中心扩张为主的扩张方式,故模拟结果有较大的误差。EnKF CA 模型虽然能够较好的反映东莞的城市扩张,但是仍然出现的一定的误差。在西南部沙田,南部大岭山,东南部清溪以及北部石碣均与真实情景相差较大。在这些地区,Joint CA 模型却能够获得较好地模拟结果。模型通过整合模拟结果与观测资料、调整 CA 模型参数值并修正模拟结果,并能够较大程度地减少模型误差,更合理地反映东莞市的城市发展真实情景。

除了对比模拟结果外,我们也对比了各个模型的模拟精度及 Kappa 系数(表 3)。从表中可知,逻辑回归精度及 Kappa 系数在 1997 年、2001 年及 2005 年分别为 87.7% 和 0.550,76.9% 和 0.428 与 64.0% 和 0.279。由于逻辑回归不能调整模型状态和参数,故其模型精度最低。逻辑回归 CA 模型,EnKF CA 在模拟过程中能够调整模拟结果,在一定程度上控制了模型误差的积累,精度也有了一定提高。在 1997 年、2001 年及 2005 年其精度及 Kappa 系数分别为 87.9% 和 0.568,76.9% 和 0.475 与 68.4% 和 0.364。EnKF CA 模型考虑了模拟结果的误差积累,但忽略了模型参数的动态变化。Joint CA 模型考虑了模型参数和模型误差,并作了修正措施,相比逻辑回归模型和 EnKF CA 效果更为理想。因而,相比 EnKF CA 模型,其精度在 1997 年、2001 年及 2005 年分别提高了 0.5%、0.8% 和 0.8%。

4 结 论

引入集合卡尔曼滤波到 CA 模型中,提出了基于联合状态矩阵的 CA 模型。通过应用数据同化方法有效地耦合了模拟模型和遥感观测数据,自动地在模拟过程中修正模型参数和模拟结果。以广东省东莞市为研究区,模拟其城市演化过程。实验表明,模型能够正确地调整模型参数使之符合城市发展规律,同时也能调整模型的模拟结果使其更接近

真实情况,较好地平衡模拟发展过度的区域和发展过少的区域。对比模拟精度及 Kappa 系数可以发现,本文提出的模型明显好于传统逻辑回归 CA 模型。与 EnKF CA 模型相比,本模型更适用于模型参数随时间变化的情景,很好地体现了在复杂系统模拟中的自适应特点,在模拟复杂非线性地理过程时具有较强的适应能力。如果模型参数较多(大于 10 个),Joint CA 的效率会受到一定影响,拟在后续研究中着重讨论模型参数个数对模拟结果的影响。

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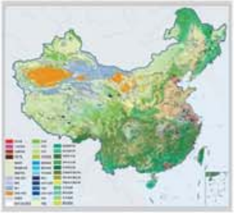

封面说明

About the Cover

2010年中国土地覆被遥感监测数据集（ChinaCover2010）

The China National Land Cover Data for 2010 (ChinaCover2010)

2010 年中国土地覆被遥感监测数据集（ChinaCover2010）由中国科学院遥感与数字地球研究所联合其他 9 个单位历时两年完成，应用 30 m 空间分辨率的环境星（HJ-1A/1B）数据，利用联合国粮农组织（FAO）的 LCCS 分类工具，构建了适用于中国生态特征的 38 类土地覆被分类系统，采用基于超算平台的数据预处理、面向对象的自动分类、地面调查获得的 10 万个野外样本以及雷达数据辅助分类相结合的方法，数据精度达到 85%。ChinaCover2010 主要基于国产卫星影像，将遥感与生态紧密结合，充足的野外样点以及严格的产品质量控制在最大程度上保证了数据的精度，可为中国生态环境变化评估以及生态系统碳估算提供基础数据支撑。（网址：http://www.chinacover.org.cn）

The China National Land Cover Data for 2010 (ChinaCover2010) has been completed after two years of team effort by the Institute of Remote Sensing and Digital Earth (RADI), Chinese Academy of Sciences (CAS), together with nine other institutions' participation. The HJ-1A/1B satellite at 30 m resolution is main data source. Based on the landscape features in China, 38 land cover classes have been defined using UN FAO Land Cover Classification System (LCCS). Super computers were used in the data preprocessing. An object-oriented method and a thorough field survey (about 100000 field samples) were used in the land cover classification, with radar imagery as auxiliary data. The overall accuracy of ChinaCover2010 is around 85%. Mainly based on domestic imagery, the products take advantage of various in situ data and strict quality control. ChinaCover2010 is a good dataset for ecological environment change assessment and terrestrial carbon budget studies. (Website: http://www.chinacover.org.cn)

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