Forecast of Dynamic Change of Land Use Based on Cellular Automata

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Abstract Land use change is a very complex process of evolution. On the basis of the principle of cellular automata, this article presents a kind of method that we can first mine state transition rule from historical map data, and then conduct forecast by virtue of Monte-Carlo method, achieving spatial dynamic forecast from map to map. We interpret TM remote sensing image in Ji'nan City in 2004 and 2006 to get present land use map for empirical research, and forecast land use map in 2012 and 2016, respectively. Studies show that this method of using spatial data to mine state transition rule, has advantages of simpleness, accuracy, strong real-time characteristic etc. in the simulation of dynamic change of land use, the results of which are roughly in line with the actual results, therefore, it can provide reference for land use planning.

Key words Cellular automata, Extraction of state transition rule, Spatial dynamic forecast, Land use

Land is the material base of human survival and development, and the change of land use structure will have a profound impact on mankind, but influenced by natural conditions, society, economy, technology, policy and many other natural and human factors, the process of land change is extremely complex and it is difficult to be forecasted and simulated accurately[1-3]. The traditional land use change model with strong subjectivity, is mainly to analyze the status quo of land use, optimize and improve land use, which cannot dynamically reflect the evolutionary process of land use, so it is difficult to meet the needs of land use planning[2]. Cellar Automata, as a general dynamic spatio-temporal model, has important application value in regional land planning, land use planning, overall urban planning and other fields. However, in the process of application, making the state transition rule is difficult. In order to avoid the impact of the subjective factors when defining the state transition rule, we propose the method of mining multistate transition rule of land use from historical map data, and forecast the unit state in the future according to Monte-Carlo method, to further simulate the uncertainties in the process of evolution.

1 Overview of cellular automata

Cellular automata produced in the 1940s, was first proposed by Von Neumann. A cellular automaton (pl. cellular automata, abbrev. CA) is a discrete model studied in computability theory, mathematics, physics, complexity science, theoretical biology and microstructure modeling. It has "bottom-up" modeling way and powerful spatial computing capacity, which is often used in research on evolutionary process of self-organizing system[3]. It consists of a regular grid of cells, each in one of a finite number of states, such as "On" and "Off" (in contrast to a coupled map lattice). The grid can be in any finite number of dimensions. The basic elements of cellular automata include cell, state, neighborhood, and state transition rules. Standard cellular automata only considers the role of neighborhood. The commonly used neighborhood includes Von Neumann neighborhood and Moore neighborhood. The first is composed of 4 surrounding cells connected with a central cell, while the second is composed of 8 cells adjacent to a central cell (Fig. 1). The core is the definition of state transition rule.

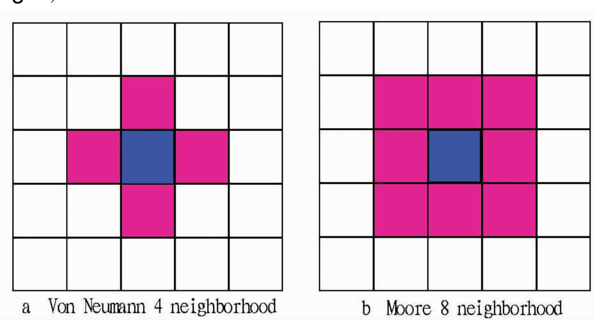

Fig. 1 Commonly used neighborhood of cellular automata

Cellular automata is fit to simulate and analyze complex behaviors of system, with more advantages in research on complex geographic systems with the spatial characteristics[2-3], which is widely used in geographic study in recent decades, and the relevant literatures are relatively common. However, most of the spatial state transition rules in cellular automata are made artificially[2-10], and the forecast process is often subjective. Besides, the automatic extraction issue of spatial state transition rule is still not well resolved[11], causing the dynamic law hidden in spatio-temporal data to be ineffectively utilized. Professor Li Xia has researched the cellular automata simulation method of urban evolution based on case reasoning earlier[12-13], and led the team to research the extraction method of state transition rule in conversion of non-urban land into urban

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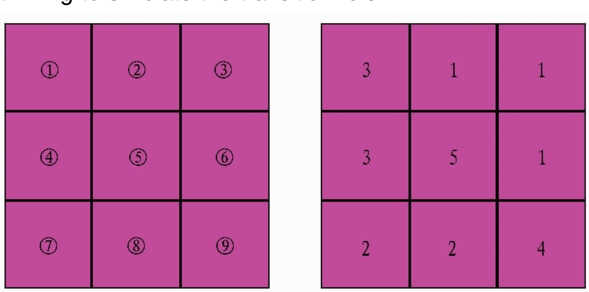
construction land on the basis of the logistic regression model[3], ant colony algorithm[14], Fisher discriminant method[15]. The conditions in transition rule are spatial distance variable and neighborhood. He calculates the probability of non-urban land transforming into urban construction land. In research, the number of states has two values, that is, what studied is one-way conversion problem of " change or not change". Multi-state transition rule of land use (Three states and more) is used broadly, but there are few researches on the extraction method of transition rule in academic world at present. Part of another researches adopt Markov Chain Method, but the spatial relationship is difficult to enter the state transition probability matrix. It can only conduct extraction and forecast of conversion rules between the area of various types of areas[17-18], so it is not the real dynamic spatial forecast.

1.1 Extraction of state transition rule The definition of state transition rule is the core of cellular automata model, and the state transition rule completely consistent with the actual situation is still difficult to be extracted at present. The state transition rule can only be simulated approximately to the extreme. The method of mining state transition rule from (t_1, t_2) historical map data is as follows: according to data, we set the size of cell space as $m \times n$ and the state number of cell as d, and adopt Moore neighborhood. We establish the local combination state on the basis of Moore 8 neighborhood (Fig.2). At time t_1, the number of all spatial combination states of neighboring cell and cell c_{ij} is d^9; at time t_2, the number of possible states of cell c_{ij} is d. So, when developing from time t_1 to time t_2, the number of corresponding spatial combination states is d^{10}. When the value of d is big, the number of all combination states is very large, not conducive to using computer simulation. In practical application, the number of cell states is generally a relatively small number, and the spatial combination states have apparent regularity. Some combination states will not appear definitely. This greatly reduces memory and storage of combination states, and we can easily use computer programming to simulate the transition rule.



a The central cell b Moore neighborhood code of the central cell

Fig.2 The central cell and Moore neighborhood code

The mining algorithm of state transition rule is as follows. First, conduct superposition operation of the cell space and the study area established; label the cells overlapping with the study area as 1; label the cells not overlapping with the study area as 0; clear in advance in later calculation. Second, extract the combination state codes of cells at time t_1 and the neighboring cells; scan the cells line by line to obtain the corresponding attribute, and write it into the corresponding attribute table of cell. Third, extract the combination state codes of cells at time t_2 and the neighboring cells; scan the cells line by line to obtain the corresponding attribute, and write it into the corresponding attribute table of cell. Fourth, write the combination state codes of cells at time t_1 and t_2 into the database. Fifth, establish state transition frequency table. Scan each cell in entire cell space at time t_1 and t_2; test the combination state code of cell c_{ij} at time t_1, and look up code value table to obtain the sequence number of code value (Array subscript); check and measure the status code v of this cell at time t_2. Conduct calculation: $s(u, v) = s(u, v) + 1$. Then establish two-dimensional state frequency table s. Sixth, establish the state transition probability table. The state transition frequency table is normalized as follows: $p(u,v) = s(u, v) / \sum_{w=1}^{t} s(u, w)$, $\forall u, v = 1, 2, \cdots, d$, where d is the number of spatial states. At this point, $\sum_{v=1}^{t} p(u, v) = 1$, $\forall u$. Thus we get local state transition rule of cellular automata.

1.2 Monte-Carlo forecast method The rules of dynamic evolution of land use are not constant, having strong uncertainty at certain moments[19], so some scholars prefer to use probability transition rule to replace certainty transition rule. This will make taking the state with the largest probability as a rule to define possible. For one conditional combination state at time t_1, there may be d kinds of resulting state of the central cells at time t_2, and if we forecast object in accordance with the maximum probability, we will lose considerable information. In order to fully reflect the complexity and uncertainty of land use change, we introduce Monte-Carlo method to describe. Monte-Carlo method is also called statistical test simulation method, which is a simulation method of using a series of random numbers to express the probability distribution, to solve complex phenomenon through random sampling of relevant random variables or random processes. Let P (The probability vector of d resulting states at time t_2 corresponding to cell c_{ij} at time t_1) = $[p_1, p_2, \cdots, p_d]$, $\sum_{k=1}^{a} p_k = 1$.

We conduct cumulative summation of elements of probability vector, and get the cumulative vector of probability $P^{(s)}$ = $[p_1^{(s)}, p_2^{(s)}, \cdots, p_d^{(s)}]$, where $p_k^{(s)} = \sum_{q=1}^{k}$, $k = 1, 2, \cdots, d$.

d elements in $P^{(s)}$ form the segmentation of (0,1), and d subintervals $(0, p_1^s]$, $(p_1^s, p_2^s]$, $\cdots$, p_{t-1}^s, $p_t^s]$ are the resulting states of cell transformation. As for the resulting state of cell c_{ij} at time t_2, we can use uniform random number to produce function in order to conduct random forecast, that is, for one specific conditional combination of states at time t_2, it produces one random number r distributed evenly in (0, 1). If $r \in (p_{k-1}^{(s)}, p_k^{(s)}]$, we can judge that the state of cell at time t_3 is k.

When conducting forecast, the starting point of forecast is the moment closer to now. The forecast interval is the interval of time between two maps, and we can determine how many periods of the future map data we want to forecast according to the actual needs.

2 Forecast example of dynamic change of land use based on cellular automata

We take some regions of Ji'nan City located in the south bank of the Yellow River as the study regions, including Lixia District, Shizhong District, Huaiyin District, and Tianqiao District in the transition zone of mountainous areas in central Shandong and the northern plain of Shandong. The study regions, south to the Yellow River, north to Taishan Mount, are in 36°14′20″ – 36°53′45″N, 116°30′39″ – 117°22′06″E, with a total area of approximately 1 251 km^2 and rich geographic information. The TM images in 2004 and 2006 are taken as basic data. In accordance with the state land classification scheme, the study regions are divided into six types: cultivated land, woodland, grassland, water area, urban-rural industry, mining and residential land and unused land (The corresponding code is 1, 2, 3, 4, 5, 6). And the interpretation signs for each land type are established. We use Erdas and Mapinfo software to conduct remote sensing interpretation and get land use map. The initial state set of cell $s_i = \{1, 2, 3, 4, 5, 6\}$.

First, we rasterize the land use maps in two phases, to obtain cellular space. Here the grid size is set as 250 m × 250 m; the number of lines and columns of grids constructed is set as 190 × 187; the number of grids in the study area is set as 20 021. In Mapinfo, we scan the raster layer created overlapping with land use map in 2004 and 2006, respectively, so as to assign grids to the attribute of the land type with the largest overlapping area, and construct the database of combination states. According to the extraction method of state transition rule and random probability forecast method, we use Mapbasic and VFP software to write code in advance, and finally forecast the map data in 2012 and 2016 using random probability forecast method, which can be shown in Fig. 3 and Fig. 4.

We compare the predicted map data in two periods and the grid data according to overlapping of land use map in 2004 and 2006. The results can be shown in Table 1.

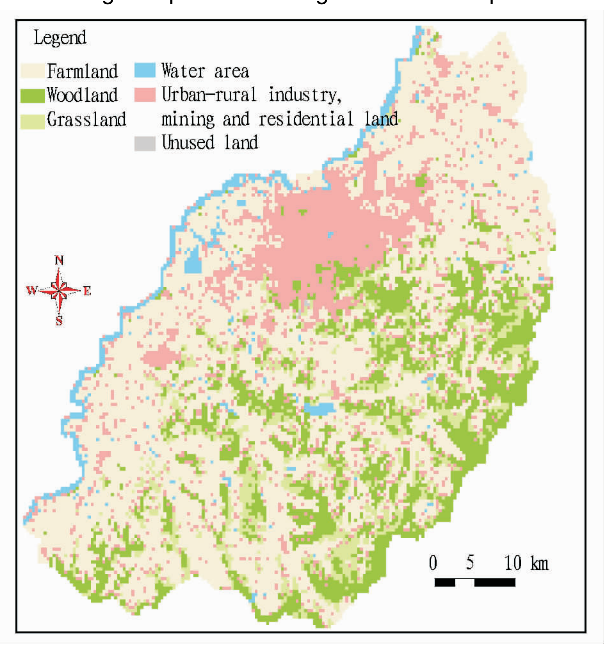


Fig. 3 Land use forecast in 2012

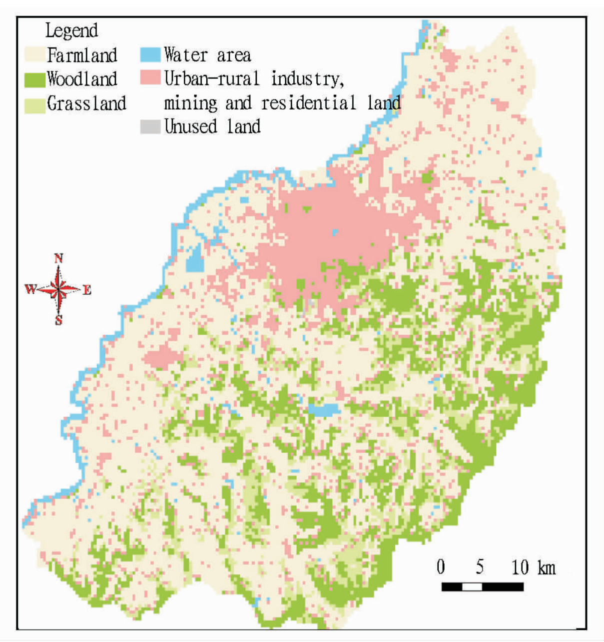


Fig. 4 Land use forecast in 2016

Table 1 Cell number of 6 land use types in Ji'nan City

Year	Farmland	Woodland	Grassland	Water area	Urban-rural industry, mining and residential land	Unused land	Total
2004	10 528	3 937	2 160	686	2 700	10	20 021
2006	10 492	3 760	2 026	686	3 049	8	20 021
2012	10 443	3 551	1 862	683	3 476	6	20 021
2016	10 119	3 535	1 856	674	3 831	6	20 021

Table 1 shows that in six land types, the cultivated land and urban-rural industry, mining and residential land undergo the most prominent changes over time. The area of cultivated land declined from 676.81 km^2 in 2004 to 632.44 km^2 in 2006, and the proportion of cultivated land area also declined from 54.09% to 50.54%; the area of urban-rural industry, mining and residential land shows upward trend, increasing from 168.75 km^2 in 2004 to 239.44 km^2 in 2006, and the proportion of the area of urban-rural industry, mining and residential land also rises from 11.96% to 19.13%, an increase of 7 percentage points. The area of woodland, grassland and water area decreases slightly, and the area of unused land will not change after 2012. It can be found that in a future period of time, impacted by economic growth, the concentration of population and other factors, in the study area, the urban scale tends to distend ceaselessly, and a part of cultivated land, grassland, woodland and water area will be transformed into urban-rural industry and mining land.

From the forecast results, we can find that the main city zone of Ji'nan City experiences obvious east-west extension, small and medium-sized settlements tend to expand. The main reason is as follows. On the one hand, the economic development leads to increase in the area of industrial land, the land resources in the city zone are limited, and exorbitant land prices force some enterprises to move to the areas around the city, so the surrounding towns near the city center with convenient transportation, become the first choice. On the other hand, in the future, Ji'nan City is still in the stage of rapid urbanization, and there is a sharp increase in urban population, especially the population from outside, so it is bound to generate greater demand for housing in urban areas. Under the weight of high housing prices in the city, the cultivated land, woodland and other types of land in suburb that can be easily transformed into residential land, forming outward expansion. Under this situation, the current amount of cultivated land will be subject to more severe challenges.

3 Conclusion

Cellar automata has a great advantage in simulating land use change, the evolution of urban spatial structure, and other complex processes. The simulation results can be regarded as the reference basis for formulating land use planning in the future period. In the study, it adopts the method of mining transition rule from two historical maps in different periods, thus we can try to mine transition rule from more historical serial maps. In the study, the state transition rule is mined from maps, with strong objectivity, avoiding forecast deviation arising from the traditional method of making transition rule by people. However, the land use change is also affected by human factors, to some extent reflecting the subjective views of policy makers, therefore, in addition to mining rules, correcting the rules in accordance with relevant policies and regulations so that the subjective influencing factors and objective influencing factors are both reflected reasonably, is the focus of future research.

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