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Kiln Landscape Evolution Simulation Based on Particle Swarm Optimization and Cellular Automata Model

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Abstract

Due to the less accessibility to the data, relatively little literature has been found on how the ancient kiln site evolves. To understand how land has transformed kiln in ancient Jingdezhen DongHe River Basin from the Yuan Dynasty to the Ming Dynasty, we create virtual maps of ancient study area and present such concepts that unambiguously realize a combination model. In this model, Model parameters and neighborhood rules are obtained with the cellular automata model melt modified Particle Swarm Optimization algorithm. Meanwhile, model performance is evaluated using Moran's I index estimation for selected landscape pattern indices and make a comparative analysis of different evolution with different number of candidate site and different conversion threshold. In overall, the model that we propose is effective and feasible in simulating kiln landscape evolution in ancient when Geographic Information and System information are lacking.

Keywords: *Particle Swarm Optimization; Cellular Automata; Kiln; landscape evolution*

1. Introduction

Much of jingdezhen's ancient kiln research has taken place in NanHe river basin. However, JingDeZhen kiln landscape of the ChangJiang waters mainly focuses on the NanHe and DongHe river basin (Song-jie L, 2011). Thus, the transformation process of the kiln in DongHe river basin is very important to reveal the complicated phenomenon that kiln can evolve from farmland, shrub, wild land etc. Cellular automata (CA) are the typical simulate tool of geographical landscape evolution. Since Tobler first introduced CA model to geography field (Tobel, 1979), in recent decades, CA models have been widely used to simulate the land use transformation process (Batty and Xie, 1994; Berling-Wolff and Wu, 2004; Clarke et al., 1997; Wu and Webster, 1998). These studies suggest that the CA model for the evolution of the geographical landscape simulation is an effective and feasible.

The key to geographical landscape simulation by using CA is the definition of transformation rules, which describes the logical relationship of the simulation process, involves a large number of spatial variables and determines the results of the spatial variation (Liu X et al.2008). In recent years, many scholars have used artificial intelligence algorithms to optimize the CA transition rules parameters, and have obtained a good effect, such as Li Xia proposed to form the transformation rules by using ant intelligence algorithms to obtain the best parameters (Liu X et al, 2008), Li and Yeh

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proposed to obtain the CA transition values by using data mining (Li X and Yeh, 2004) and so on. We consider PSO algorithm has many advantages than genetic algorithm, such as use is simple speed - displacement model, to avoid the complex genetic operation, at the same time it's memory ability make it can track the current search and dynamic adjustment search strategy, has stronger global convergence ability and robustness, and don't need with the problem of feature information (Xiaoming ZHU, 2008). Therefore, the PSO - CA model proposed in this paper so as to automatic adjust parameters in CA conversion rules.

This paper makes use of PSO algorithm's advantage to search and optimize in the space quickly, programs the fitness function in Matlab7.0 software environment, determines the location of target grids from 60×78 grid space and makes a comparative analysis of different evolution with different value and conversion threshold value, getting the right value. With the right value, the simulated Moran's I index is close to the actual Moran's I index, proving that the model is also effective and feasible in simulating kiln landscape evolution in ancient times when Geographic Information System(GIS) information are lack.

2. The Virtual Map of Study Area

2.1. The Study Area Selection

Jingdezhen City (east longitude 116°57′--117°42′, north latitude 28°44′--29°56′) is located in Northeast JiangXi Province. From current archaeological excavations, JingDeZhen kiln landscape of the ChangJiang waters mainly focuses on the NanHe and DongHe river basin with the right amount of water. This paper has the representative kiln landscape evolvement of JingDeZhen DongHe river basin as the research object. The indicative region is shown in figure 1.

Figure 1. Study Area

2.2. Map Building

Because Jingdezhen GIS information has not been established at present, it may not have similar satellite maps of it in the Yuan era historical period, which results in the detailed terrain of the study area at that time having no direct access. In the actual drawing process, by comparison with the screenshot of the research area via Google Maps, located DongHe and the surrounding mountain land can be first identified and then the land information except mountain and river is randomly generated. Using the method, we can effectively explore the effect of the evolution of different geographical environment. This paper only shows one of them.

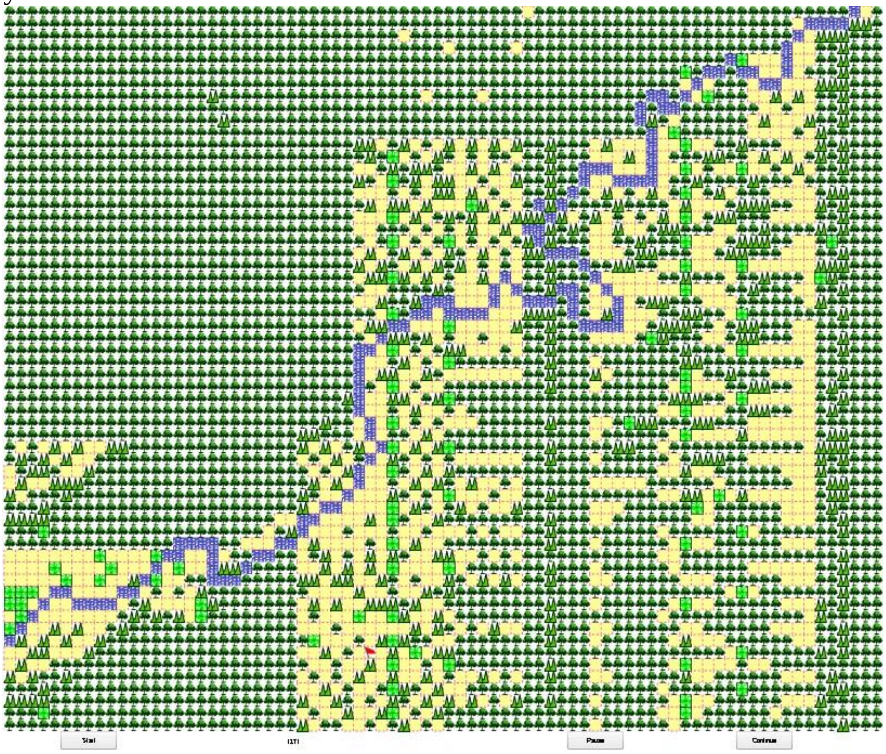

Figure 2. Grid Map of the Study Area

In FlashCS3.0 software environment, the indicated study area in figure 1 can be divided into 60 rows and 78 columns grid data by use of ActionScript3.0 language, and each grid land area is 20*20pixels. With the above method, we can get the two spatial dimensions grid map. The map is shown in figure 2, in this map, the idle land, the farmland, the clay mine, shrub, forest, the river, and kiln are indicated.

3. Particle Swarm Optimization and Cellular Automation Model

3.1. Improved Particle Swarm Optimization Algorithm

Particle Swarm Optimization Algorithm is an evolutionary computing technology based on swarm intelligence proposed by Kennedy and Eberhart in 1995 when simulating birds' migration and clustering behavior in the process of foraging, and when inspired by artificial life research results (Bo Xu, 2010). The algorithm principle is random particle searches for the optimal particle by constantly updating their position and speed through iteration. At each step of iteration, each particle updates its position and speed through the optimal values P_{best} and the global optimum G_{best} in weight control. This is the application of PSO algorithm to searching for the optimal target grid in the two-dimensional space, so the original particle swarm optimization algorithm must be improved as the following:

3.1.1. Integer of Particle Position: For randomly generated particle in the initial state, its location must be a unit in the two-dimensional grid space, namely, the values of the particle position are in the integer space. However, the original particle swarm optimization is based on real number space, so integer of particle position becomes necessary. In the initial randomly generated number of particles, the number of rows i is in the value [1, 60], the number of columns j is in the value [1, 78], so the starting position is an integer value. Then make integer modifications to the particle swarm optimization algorithm speed formula (Equation 1) to get the speed of the next moment, and at last get a new integer position by position formula (Equation 2).

$$V_{ij}^{t+1} = ceil\left(\omega \times V_{ij}^{t} + c_1 \times rand \times \left(Pbest_{ij}^{t} - X_{ij}^{t}\right) + c_2 \times rand \times \left(Gbest_{gj}^{t} - X_{ij}^{t}\right)\right) \tag{1}$$

$$X_{ij}^{t+1} = X_{ij}^{t} + V_{ij}^{t+1} \tag{2}$$

Where X and V respectively shows the i-th particle's position and velocity, w is inertia weight, c1,c2 is the acceleration factor, r1,r2 is two random number between [0,1], subscript j is particle's j-th dimension, t is iterations, i is i-th particle, ceil is integer function.

3.1.2. Fitness Function: In ancient times, Jingdezhen Ceramic production used clay as raw material and wood as fuel, and finished products were transported through rivers, so the development of a plot into a kiln to a large extent was affected by the distance from the river, the distance from the mountain and the distance from the clay mine. According to this characteristic, the fitness function of particle swarm optimization algorithm is defined as Equation 3.

$$f(x, y) = \frac{1}{N}\sum_{i=1}^{3}\left((x - x_i)^2 + (y - y_i)^2\right) \tag{3}$$

Among them, (x_1, y_1) is the nearest river coordinates away from the current grid, (x_2, y_2) is nearest mountain coordinates away from the current grid, (x_3, y_3) is the nearest clay mine coordinates from the current grid, (x, y) is current grid coordinates. N value of is 2 or 3, when none of the river distance, mountain distance and clay mine distance is zero, N is 3; when one of them is zero, N is 2.

3.2. Particle Swarm Intelligence and Cellular Automata Model

Cellular Automata general includes four elements of the unit, state, close range and conversion rules(Liu et al 2008). The four-tuple formula is $A = (L_d, S, N, F)$, among which, L represents the grid space divided by a rule, namely a cellular, d is the dimension of L, usually equal to 1 or 2, S means the state of each cell and is a discrete finite set, N is neighbors cellular, F is the conversion rules, and is the core part of CA. The state transition of each cell from the time T to T+1 is determined by the conversion rules.

To facilitate research, this article looks on the study area as an island, the division of the CA of the square grid space as an experimental basis, using the Moore neighborhood, fixed value boundary. Suppose map _maps is a 60×78 grid map, each grid cell is 20*20 pixels, cellular space $L = \{\_maps_{i,j} \mid 1 \le i \le 60, 1 \le j \le 78\}$, dimension $d = 2$, and state sets $s = \{0,1,2,3,4,5,6\}$, number 0-6 respectively stands for idle land, river, mountain, shrub, farmland, porcelain corresponding productive land(kiln), clay mine. Center Cellular _maps[i][j] has eight neighbors cell. The conversion rules f melting the improved particle swarm algorithm, described as follows:

1. Through improved particle swarm optimization algorithm to determine the location of target grids from 60×78 grid space, making the average distance from target distance grid to the clay mine, DongHe and the surrounding mountain is the minimum K. The K regions will be developed into candidate land of the kiln.

2. To analyze the suitable conditions of the candidate land, if the suitable conditions are satisfactory, it can evolve into the kiln, or it can not. The adaptation function (Equation 4) will return [0,1], such as if the plot itself is river, the return value is 0; if it’s mountain, the return value is 0.7; if it’s shrub, the return value is 0.8; if it’s farmland, the return value is 0.3; and if it’s idle land, the return value is 0.5.

$$Con(S_{ij}^{t} = suitable) \tag{4}$$

Among them, S_{ij}^{t} represents the state of (i,j) block at t moment.

3. Whether a block can be developed into a kiln is affected by its own conditions as well as by the surrounding neighbor’s cell, represented by the neighborhood function (Equation 5). Because the ancient ceramic production needed a large number of kiln men and the traffic was not convenient at that time, kiln men could only perch on the local village. If village is in the neighbourhood, the function value is 1; if mountain and river is in the neighbourhood, the function value is 1; if mountain is in the neighbourhood but river is not in, the function value is 0.6; if river is in the neighbourhood but mountain is not in, the function value is 0.8; if mountain and river is not in the neighbourhood, the function value is 0.

$$\Omega_{ij}^{t} = \frac{\sum_{3\times3} Con(S_{ij} = suitable)}{3\times3-1} \tag{5}$$

4. Whether a region can be developed into a kiln can be obtained by the formula 6, and then set the probability threshold, if the result is greater than the probability threshold, it can evolve into the kiln; otherwise, it can’t.

$$P_{ij}^{t} = Con(S_{ij}^{t} = suitable) \times \Omega_{ij}^{t} \tag{6}$$

4. Experimental Simulation and Analysis

Improved particle swarm optimization in Matlab7.0 software programming can quickly search the candidate target block, then put the location of the candidate block into FlashCS3.0 software and use ActionScript3.0 language programming to realize cellular automata model. After experimental simulation model is built, the evolution of the jingdezhen DongHe River kiln landscape from the Yuan Dynasty to the Ming Dynasty is simulated experimentally.

Simulation of the existing objective facts is the basic condition of judging a model is reasonable or not, however, the more important purpose of the model lies in predicting or deducing unknown facts. K value and conversion threshold in the evolution rules are the most main factors affecting the process of the evolution. So, this paper adjusts one of the two factors to experimental investigation when the other related factor is unchanged. Table 1 shows the contrast results by compared with different period.

Table1. The Simulation Results under Different Values

K value	Probability threshold value P				Simulation results			
45	Yuan Dynasty	0.8	Ming Dynasty	0.6	Yuan Dynasty	Figure 3	Ming Dynasty	Figure 4
45	Yuan Dynasty	0.6	Ming Dynasty	0.4	Yuan Dynasty	Figure 5	Ming Dynasty	Figure 6
39	Yuan Dynasty	0.8	Ming Dynasty	0.6	Yuan Dynasty	Figure 7	Ming Dynasty	Figure 8
39	Yuan Dynasty	0.6	Ming Dynasty	0.4	Yuan Dynasty	Figure 9	Ming Dynasty	Figure 10
17	Yuan Dynasty	0.8	Ming Dynasty	0.6	Yuan Dynasty	Figure 11	Ming Dynasty	Figure 12
17	Yuan Dynasty	0.6	Ming Dynasty	0.4	Yuan Dynasty	Figure 13	Ming Dynasty	Figure 14

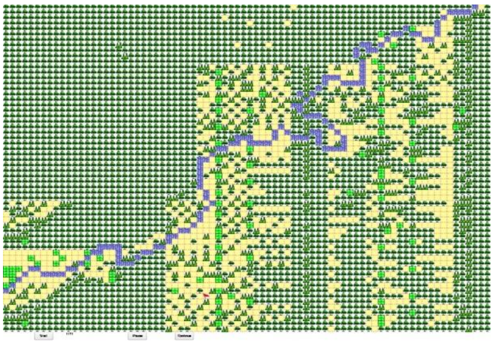

Figure 3.(k=45,p=0.8)Yuan Dynasty

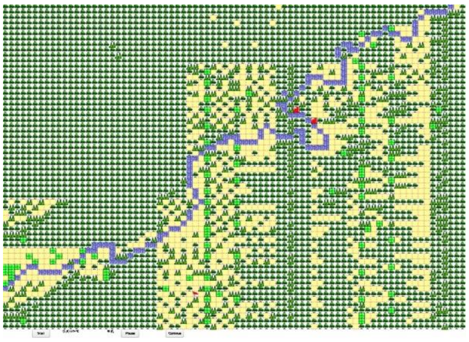

Figure 4.(k=45,p=0.6)Ming Dynasty

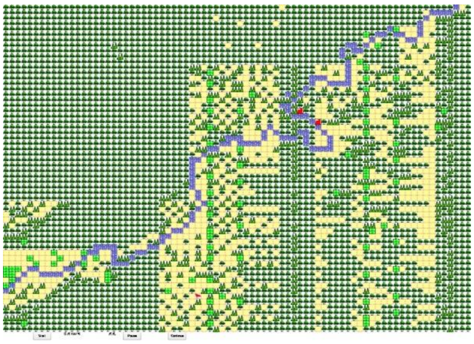

Figure 5.(k=45,p=0.6)Yuan Dynasty

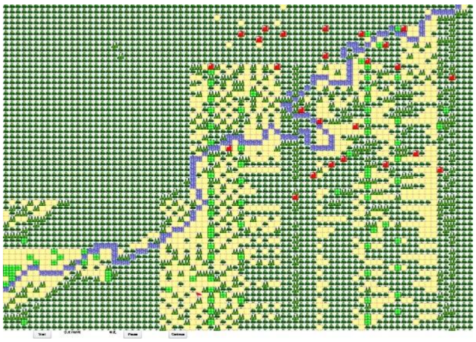

Figure 6.(k=45,p=0.4)Ming Dynasty

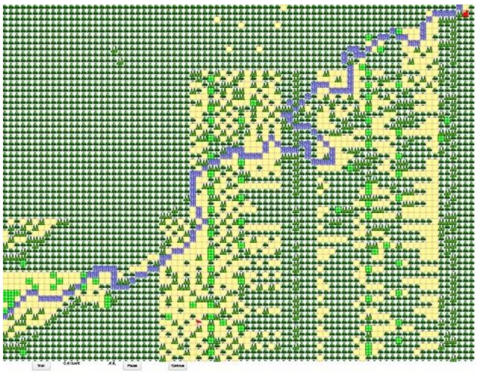

Figure 7.(k=39,p=0.8)Yuan Dynasty

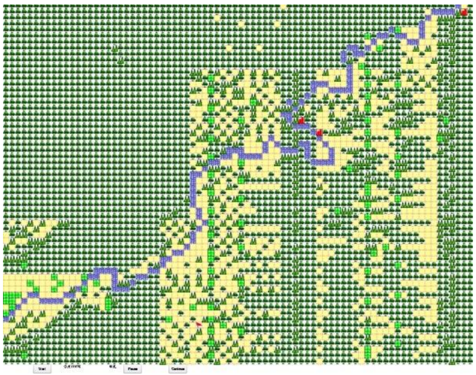

Figure 8.(k=39,p=0.6)Ming Dynasty

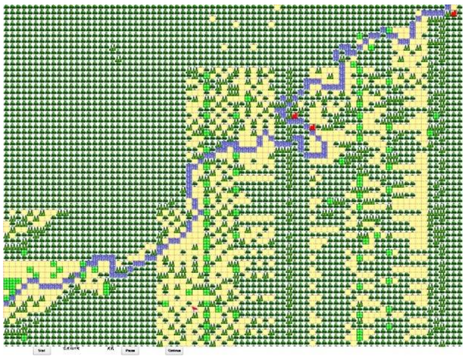

Figure 9.(k=39,p=0.6)Yuan Dynasty

Figure 10.(k=39,p=0.4)Ming Dynasty

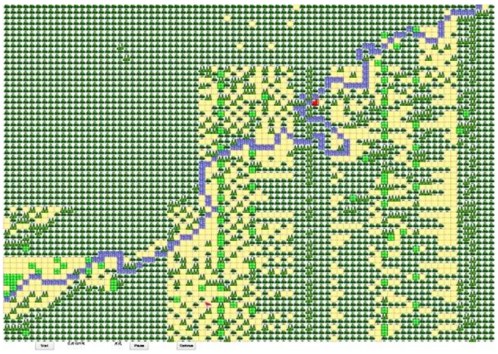

Figure 11.(k=17,p=0.8)Yuan Dynasty

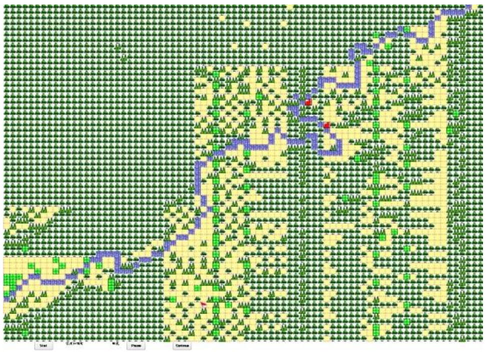

Figure 12.(k=17,p=0.6)Ming Dynasty

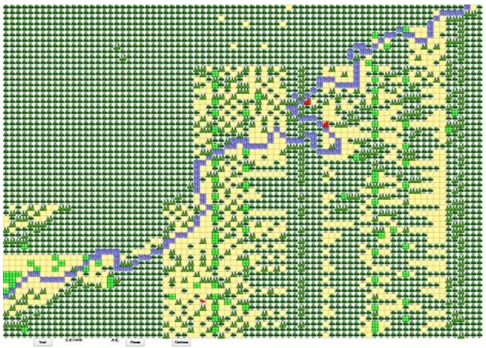

Figure 13.(k=17,p=0.6)Yuan Dynasty

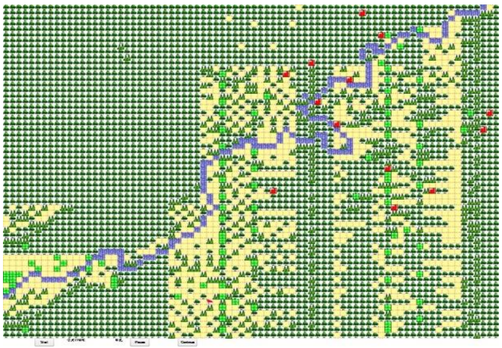

Figure 14.(k=17,p=0.4)Ming Dynasty

At present, the model test methods are generally the point-by-point comparison and the overall comparison (Liu X, 2007). Point-by-point comparison is to congruent the simulation results and the actual situation, then compare and calculate its accuracy point by point; the overall comparison is concerned with the similarity between the simulated spatial pattern and the actual spatial pattern, often using Moran's I index contrast. Moran's I index is calculated based on the covariance relation of statistical correlation coefficient. Moran's I index is commonly used to describe the spatial autocorrelation, and its formula is:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ji}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{7}$$

In the formula, n is the number of spatial units involved in the analysis, x_i and x_j respectively stands for observations of an attribute feature in the spatial units i and spatial unit j, W_{ij} is the neighboring weight matrix of spatial units i and j. If adjacent, W_{ij} is 1, if not adjacent W_{ij} is 0. In this paper, Moran's I index is used for model checking, and the compared results of the table 1 are programmed in Matlab7.0, as shown in Table 2.

Table 2. Moran's I Index Contrast

Moran's I index	Time		Major Parameter				
	Yuan Dynasty	Ming Dynasty					
Actual Value	0.1395	0.1358	K Value	Probability Threshold Value P			
Simulative Value	0.1394 (figure 3)	0.1398 (figure 4)	45	Yuan Dynasty	0.8	Ming Dynasty	0.6
	0.1398 (figure 5)	0.1366 (figure 6)	45	Yuan Dynasty	0.6	Ming Dynasty	0.4
	0.1392 (figure 7)	0.1395 (figure 8)	39	Yuan Dynasty	0.8	Ming Dynasty	0.6

	0.1395 (figure 9)	0.1349 (figure 10)	39	Yuan Dynasty	0.6	Ming Dynasty	0.4
	0.1413 (figure 11)	0.1398 (figure 12)	17	Yuan Dynasty	0.8	Ming Dynasty	0.6
	0.1398 (figure 13)	0.1349 (figure 14)	17	Yuan Dynasty	0.6	Ming Dynasty	0.4

From table 2, we can find:

1. If k values are the same, the simulation results when Yuan and Ming dynasty's probability threshold value P is respectively 0.6 and 0.4 are better than those when probability threshold P is respectively 0.8 and 0.6, because their Moran's I index is closer to actual value. This shows probability threshold value shouldn't be set too high, and being too high means being too harsh on the candidate plots' geography conditions, which causes most candidate plots unable to convert to kilns, far from the actual circumstances.
2. Because of the chronological order in the evolution process, the setting that Yuan dynasty's probability threshold value is higher than that of Ming dynasty meets gradient location's actual circumstances. First the most geographically convenient location (Transition probability threshold maximum) is chosen to be kiln, then the relatively convenient location does in the next dynasty because the best location has been chosen.
3. Evolution process is continuous, so the two dynasties' simulation results should be linked and analyzed. It's found that when K value is 39 and when probability threshold value P of Yuan Dynasty and Ming Dynasty is respectively 0.6 and 0.4, the simulation result is closest to the actual circumstances, realizing many kilns' evolution, such as Raonan, Neiyao, Yaoli and Shiqian, etc.

5. Conclusion

Making use of PSO algorithm's advantage to search and optimize in the space quickly, based on the cellular automata model, this paper simulates the evolution of JingDeZhen DongHe river basin kiln landscape from the Yuan Dynasty to the Ming Dynasty. It compares and analyzes simulations with different K value and probability threshold value, finally determining appropriate values. With the value, Moran's I index from the simulated result is close to that under the actual circumstances, proving that the simulated spatial pattern is close to actual circumstances and that the model can solve the problem of landscape evolution caused by GIS spatial data deletion.

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