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A Novel Integration Model for the Simulation of Kiln Landscape in Ancient Fu Liang Area

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Abstract

Re-creation of the land use transformation at different periods in time is valuable for revealing how policy change influence ancient Fu Liang kiln. To date, there has been little focused on the model of historical Fu Liang kiln change. On the contrary, current research has emphasized that the transformation process of kiln has been described by literal presentation. However, Dynamical and visual model can provide insights into kiln change processes and are valuable for land use transformation. For this reason, we create virtual maps of ancient Fu Liang area and propose such constructs to unambiguously denote a novel integration model. In this model, ancient virtual maps are created by ARCGIS10.0 software and PCI9.0 software, land use changes are performed through cellular automata, decision processes are controlled beyond the multi-agent, spatial optimization is represented by particle swarm optimization. We use the simulation approach to recreate the kiln transformation of Fu Liang, Jiang Xi, annually from 1271 to 1554. The simulation of the model is of richer changing hierarchy and can better reflect the whole process from the first to the last firing, and can be used to preferable create dynamic model and theory. Additionally, the model can better reflect the interaction of the political situation, institutions and the natural environment.

Keywords: *ARCGIS; Multi-agent; Particle Swarm Optimization; Cellular Automata; Kiln*

1. Introduction

Forecasting land use change is complicated and challenging, because it involves in dynamic and complex activities, including the interactions between multiple land use attributes (*e.g.*, physical suitability, accessibility) and decision-makers (*e.g.*, court) (Zhao et al 2012).In addition, due to far away from today and lack some data leads the research of ancient land use change to became more harder. Many land use change have been researched and reported in the literature with various approaches and varying performance during the past. Some scholars have been studied the ecological and sociological effects of land conversion for agricultural uses (Riebsame *et al*. 1994), the effects of land transformation to urbanization (Jenerette & Wu 2001), and the effects of land conversion into grassland (Conant *et al*. 2001), But utilize model to illustrate the effects of land change into ancient kiln is little understood. In recent years, certain scholars have reported in the literature the forming process of ancient kilns. For example, some researchers have studied the figure’s evolutionary development of Jing

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De Zhen kilns (Lin *et al.* 2008), some scholars explored the developmental process of Jingdezhen porcelain making activities from geographical environment(Conant et al 2001), however, these methods are purely static and inscrutable. For deducing the process of land uses change into kilns, I proposed the dynamical visual model utilized computer technology with geography in 2012 year.

In land use change studies, scholars have developed different kinds of modeling. Among, cellular automata (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). CA models are usually implemented in a two-dimension grid space through a set of transition rules that govern the state of each cell based on the configuration and characteristics of its adjacent cells (Li and Yeh, 2002; Wu,2002). The discrete cells in the CA model represent the state of spatial and temporal characteristics of complex urban processes and enable the integration of raster-based geospatial datasets into GIS (Zhao and Peng, 2010). Although CA models, to a certain extent, have been successful to simulate land use change, there are problems that restrict their further application. In practice, the land use change process is very complex, because it involves the influences of social and human factors explicitly(Benenson *et al.* 2002). Also, CA models have rather limited capacities for incorporating decision processes of individuals and organizations (Torrens and Benenson, 2005).Thus, the multi-agent system (MAS) for land-use change model is proposed to fill this gap.

Under certain social interactions, adaptation, and decision-making choices, agent-based models capture the behavior and decision-making processes of each individual decision-maker (agent) and their interactions (Matthews *et al.* 2007).For example, Deadman and Gimblett carried out research on people-environment interaction using agent-based models in which they simulated people deciding on taking a route during recreational trips in a forest area (Deadman and Gimblett 1994). Batty used agents to simulate the movement of large number of people in carnival and street parades at small scale spatial scales (Batty *et al.* 2003). In the UrbanSim model, agents are used to reflect key choices of households, businesses, developers, and government bodies and their interactions in the real estate market (Felsenstein *et al.* 2010).

In this study, we developed a integrate model consists of CA and MAS to simulate the kiln dynamics of the ancient Fu Liang area. In this model, land use changes are performed through cellular automata, decision processes are controlled beyond the multi-agent. Additionally, agents are divided into two categories, they are the political agent and the artificial agent, respectively represents the political information and the position of kilns in the real-world. These agents will interact with each other by a series of actions, such as communications, cooperation and competitions(Liu *et al.* 2006). Actually, to solve the position of kilns is a spatial optimization problem. For solving the special optimization problem, we use the particle in particle swarm optimization (PSO) to denote the candidate position of kilns. PSO, which simulates the social behavior of bird flocks, is a population-base stochastic optimization algorithm for finding optimal regions of complex search spaces through the interaction of particles (Xiaoping Liu *et al.* 2013). Many studies have demonstrated that PSO is highly robust and can offer different routes through the problem hyperspace than other evolution algorithms (Boeringer and Werner, 2004). However, very few studies of PSO focused on discrete combinatorial optimization because the original PSO is customized to continuous function value optimization (Yin, 2006). Land use allocation belongs to a typical discrete combinatorial optimization problem, which cannot be solved by the original

PSO directly. Hence, this paper uses modified PSO to solve above problem under a dynamic environment with cooperative agents.

The overall goal of our research reported in this article is to explore how to create ancient maps of study area and propose such constructs to unambiguously denote an integration model by fusing CA, MAS, PSO together. We also compare simulated results with excavation results and conduct scenario analysis to illuminate multiple alternative possible pasts and to examine their impacts on government and environment.

2. Study Area and Virtual Map

2.1. Study Area

Fu Liang (east longitude 117°25’, north latitude 29°37′) is located in Northeast Jiang Xi Province. Current archaeological excavations show the position of kilns in Fu Liang area mainly focuses on the Dong He river basin. The research region is shown in Figure 1.

Figure 1. Study Area

2.2. Virtual Map

Since Fu Liang GIS information has not been established in ancient, which results in the detailed terrain of the study area at that time having no direct access. I ever use Flash software to build the similar region map (Tao, L., *et al.* 2013), but the method is not suitable in this paper due to the amplification of the study area. By consulting relevant literature, we know the nature environment of Fu Liang almost no change over the years. So in the actual drawing process, we assume the land use of Fu Liang in the Ming Dynasty is extremely similar to 1980. Following, in PCI Geomatica V9.0 software environment, by means of the TM data of the study area in 1980 from the U.S. Geological Survey, the rivers, the surrounding mountains, the farmlands, the shrubs, the residents in the region can be recognized by Visual interpretation. The diverse lands in the region are represented various colors, detail as Figure 2. Figure 3 shows the land use types of study area in 1980. In the case of CA model, the data were converted into grid cells (30m*30m) in Arcgis10.0.

Value	Name	Color
1	Mountain	
2	Shrub	
3	Resident	
4	River	
5	background	
6	farmland	

Figure 2. Land Type

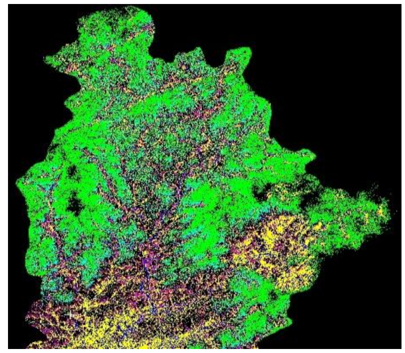

Figure 3. Virtual Map

3. The Integration Model

The integration model in this paper is developed to forecast land use change. It will mainly consider the following two aspects: (1) the decision-making behavior of government; (2) the spatial suitability of land use change, such as slope and neighborhoods attribute. The overcall model framework is composed of two main components: a multi-agent model, a CA model. The multi-agent model represents the individual's decision-making behavior, including political agent and artificial agent. A transitional rule with agent predict that the probability of change of land use state of each cell in the CA model. The overall model workflow is shown in Figure 4.

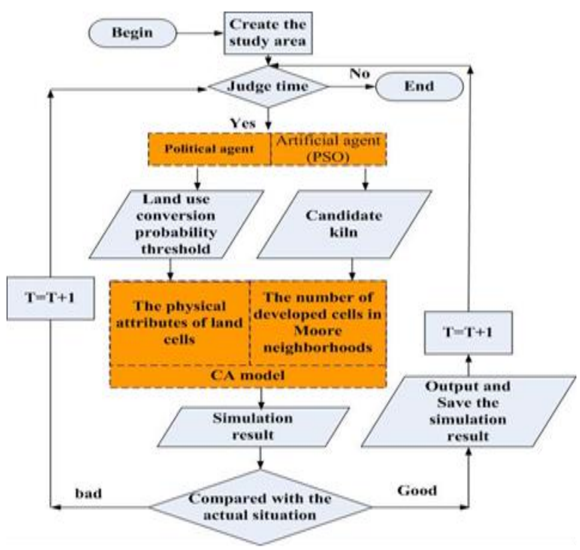

Figure 4. The Workflow of Integrate Model

3.1. A Multi-agent Model

In general, many factors may influence land use change in some way, but it is impossible and unnecessary to explicitly consider every factor given the purpose of our model. In addition, constrained by relevant research data, the agents in our model are classified into two groups: political agents and artificial agents.

3.1.1. Political Agents: Decision-making is implemented at two layers: the individual and joint decision among all agents. The hierarchical structure of social organization indicates that the lower-level processes are constrained by higher-level dynamics (Wu 1999; Wu and David 2002; Verburg 2006). In our study, imperial court usually has more power than local official in decision making in ancient peacetime, furthermore, political situation has the highest prerogative in decision making. Based above the view, the political agents in this paper mainly consider political situation and political institution. The research is divided into four stages in term of the feature of political situation and political institution:

1) A.D.1*271*-A.D.1349

In this period, Yuan dynasty was established and gradually became stable, so its political situation is defined stable. Moreover, the rulers of Yuan dynasty attached great importance to handicraft industry embodies the political institution, which not only improved the status of ceramic craftsmen, but also set up Fu Liang Ceramic Bureau, specially supervising ceramic production for government. Under the influence, the production of folk kilns which mainly processed ceramic materials in Fu Liang developed greatly. The development of ceramic-making scale make Fu Liang more prosperous, attracting many people to migrate to Fu Liang, which can be seen from "History of Fu Liang County" of "History of Yuan Dynasty"---the population of Fu Liang county increased from 121,507 in A.D.1215 to 192,140 in A.D. 1290.

2) A.D.1*350*-A.D.1362

From the history, we can find the leader of Red Scarf Army—Xiang pulv conquered Fu Liang in A.D.1350, and this county was at war until the year of 1357. In addition, from the reference, in A.D.1360, Li Yong defended Fun Liang and stabilized the local political situation. The political institution involved in ceramic almost is not in the period. Until A.D.1362, the production of ceramics began to recover .So we defined the political situation is wartime, and the ceramic production in this period was basically stagnant.

*3) A.D.136*3-A.D.1401

This period of time is claimed late Yuan dynasty and early Ming dynasty, during which Fu Liang were dominated Yuanzhang Zhu, so we defined the political situation to tend towards stability. During this period, the taboo of "royal clay" were broken, at the same time, many skilled official craftsmen were stranded in folk due to the demise of the Yuan dynasty. They put the technology into folk, as well as the royal clay of high quality, leading to prosperous production of ceramics.

4) A.D.1402-A.D.1554

During this period, Ming dynasty had been established and the society was stable, besides Ming dynasty paid great attention to the development of handicraft industry and agriculture. In 1402 the government set "Royal Kiln" factory, specially firing ceramics for the royal family and monopolizing ceramic clay of good quality as "official clay", which can only be used by "Royal Kiln" factory. In 1530, "Distribute official task to folk"---one of political institutions was appeared. Under this system, the production of folk kilns in Fu Liang faded gradually.

In this model, we design two variables to denote the function of two type political agents. Then, these agents will impact on the land use conversion probability through adjusting the two variables.

3.1.2. Artificial Agents: Artificial agents are used to solve the allocation problem of kilns. Essentially, the problem is a spatial optimization problem. Evolution Algorithms is one common way solving the problem. Among them, PSO is highly robust and can offer different routes through the problem hyperspace than other evolution algorithms. In this article, basic PSO is modified by redefining fitness function to be suitable for solving spatial combinatorial optimization problems. Depending on the value of the fitness function, agents are allowed to compete in a variety of environments and act solely to maximize their own expected utility.

1) Basic PSO

PSO is a stochastic optimization technique developed by Eberhart and Kennedy. A particle in PSO represents a candidate solution. Each particle moves through the problem space with a velocity, which is dynamically adjusted by its own moving experience and those of its companions. Similar to GA, PSO also has a fitness function that evaluates the position of the particle. At each time step, all particles are updated by the following equations (Eberhart & Kennedy 1995):

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

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

Where X and V respectively shows the i-th particle's position and velocity, ω 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, $Pbest_{ij}^{t}$ is the local best solution found by the i-th particle in j-th dimension at t-th iteration, where $Gbest_{gj}^{t}$ represents the global best.

2）Definition of Fitness Function

In ancient times, Ceramic production used clay as raw material and wood as fuel, and finished products were transported through rivers, so the position of kiln was affected by the distance from the dock, the distance from the mountain and the distance from the clay mine. Moreover, because the ancient ceramic production needed a large number of kiln craftsman and the traffic was not convenient at that time, kiln craftsman could only perch on the local village. Based on above analysis, meantime, considering the important extent of the traffic and craftsman, we shall enhance the weight of the distance from the dock and village. As a result, the fitness function of particle swarm optimization algorithm is defined as Equation 3.

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

Among them, $\left(x_1, y_1\right)$ is the nearest dock away from the current grid, $\left(x_2, y_2\right)$ is nearest mountain from the current grid, $\left(x_3, y_3\right)$ is nearest clay mine from the current grid, $\left(x_4, y_4\right)$ is nearest clay mine from the current grid, $\left(x, y\right)$ is current grid coordinates. w_1, w_2, w_3 and w_4 are the corresponding weight coefficient. Moreover, $\sum_{i=1}^{4} w_i = 1$.

3.2. A CA Model

In the CA model, each cell has a state representing the land use type (Zhao and Peng, 2010). According to the transition rules, the state of each cell is updated simultaneously at each time step by its physical attributes of land cells and the number of developed cells in Moore neighborhoods. In practice, we diminish the total computing time through only compute the candidate cells of artificial agents rather than each cell. The CA model is used to capture the effects of spatial properties of land use changing from certain type to kiln. Thus, we track land use change from one of type set (*i.e.*, mountain, shrub, resident, river, farmland.) to kiln.

In this study, the division of the CA of the square grid space as an experimental basis, using the Moore neighborhood, fixed value boundary. After the data are processed by a set of tools (*e.g.* Matlab, ArcGis), cellular space $L = \left\{ cells_{i,j} \mid 1 \le i \le 2392, 1 \le j \le 2264 \right\}$, dimension $d = 2$,and state set $s = \left\{1,2,3,4,5,6,7\right\}$, number 1-7 respectively stands for mountain, shrub, resident, river, background, farmland, kiln. The transition rules f described as follows:

1. Through artificial agents constantly moves in 2392×2264 cellular space to seek the location of candidate kilns. These locations will be developed into candidate land of the kiln.

2. We derive the value of the suitability to development from each of candidate lands according to its land type and slope. The formula (Equation 4) will return the real value between 0 and 1, such as if the land type is river, else is 0.

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

Among them, S_{ij}^{t} represents the state of (i,j) land at t-th iteration.

3. We count the number of developed cells in Moore neighborhoods through the neighborhood function (Equation 5).

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

4. Whether a candidate land can be developed into a kiln can be obtained by the formula 6, compare obtained conversion probabilities with set the conversion probability threshold, if the result is greater than the probability threshold, it can evolve into the kiln; otherwise, it can’t. The conversion probability threshold is influenced by political agent and assigned different values in different research stage through two variables.

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

4. Model Simulation and Evaluation

Hereafter, simulation results are presented in order to demonstrate the essential principle of the model. The study area is located in the Northeast part of the Jiang Xi Province, China. The initial cellular domain (of 2392*2264 cells) represents the original land use type of study area. This domain is representative of all possible cells and agents combinations. At each time step, some parameters of the model and the states of the affected cells are changed under the control of the interaction of agents. As a result, the simulation result is also changed with time go. The simulation results of the different stages show Table 1. The detailed data of the main land type change in the different stages show Table 2.

Table 1. The Simulation Results under Different Stages

research stage	years	simulation results
stage 1	A.D.1271-A.D.1349	Fig.5.
stage 2	A.D.1350-A.D.1362	Fig.6.
stage 3	A.D.1363-A.D.1401	Fig.7.
stage 4	A.D.1402-A.D.1554	Fig.8.

Table 2. The Statistics of Cells in ArcGis10.0

Research stage	mountain	Shrub	Resident	Farmland	kiln
Stage 1	783145	261295	379910	104350	1850
Stage 2	814809	292843	317983	104960	0
Stage 3	800517	278213	330652	112697	8471
Stage 4	799802	277059	330661	121079	1949

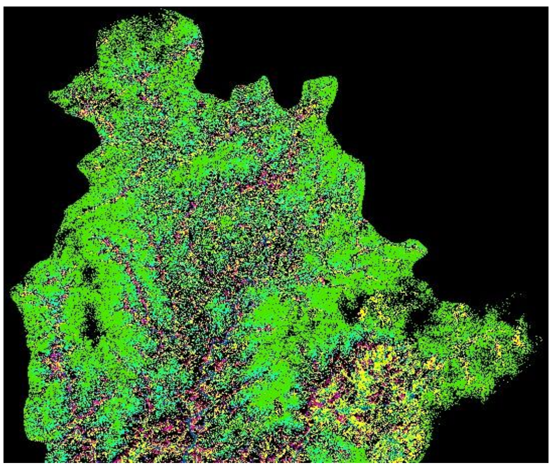

Figure 5. The Simulation Result of Stage 1

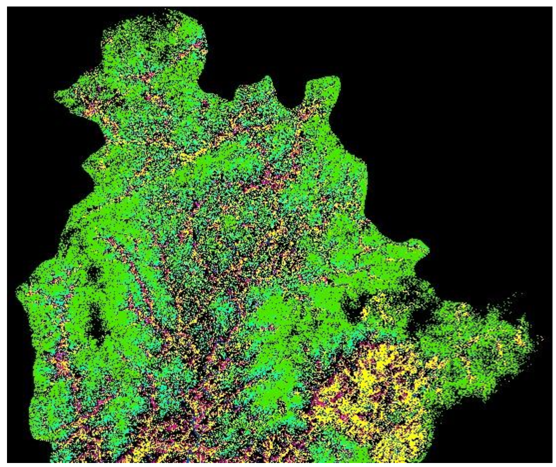

Figure 6. The Simulation Result of Stage 2

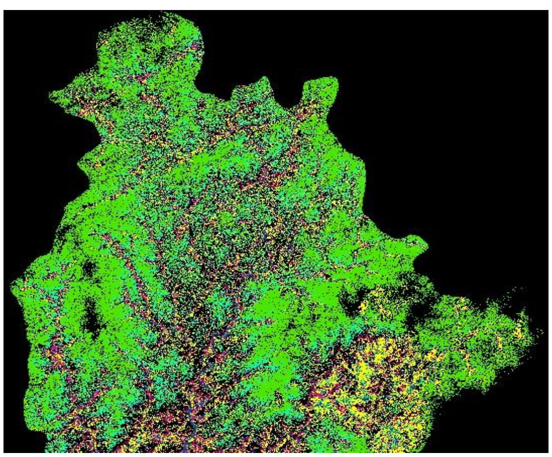

Figure 7. The Simulation Result of Stage 3

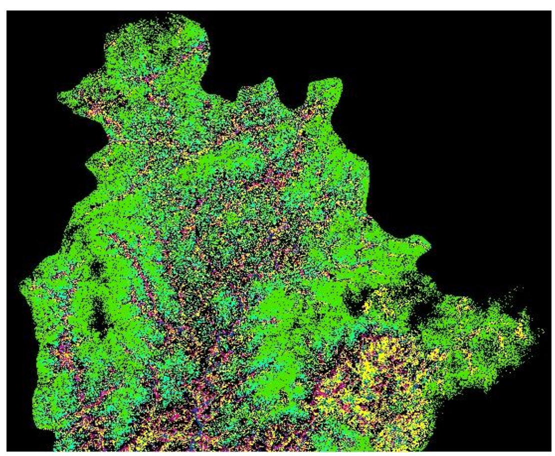

Figure 8. The Simulation Result of Stage 4

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At present, the model test methods are generally the point-by-point comparison and the overall comparison (Hashemi & Meybodi 2009). 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:

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

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 3.

Table 3. Moran's I Index Contrast

years	Moran' s I Index	
	actual value	simulate value
A.D.1271-A.D.1349	0.6626	0.6614
A.D.1350-A.D.1362	0.6196	0.6471
A.D.1363-A.D.1401	0.5931	0.6445
A.D.1402-A.D.1554	0.6078	0.6452

From Table 2 and Table 3, we can find:

1. The kilns growth in the third stage are fastest than that in other stages, because the political situation is stable and the skilled craftsmen can utilize good raw materials to produce ceramic. Furthermore, the development of the folk kilns had slow down in the fourth stage and become the verge of extinction in the second stage because of the official kiln's emergence and war. It indicated the development of the folk is constrained by the official kiln and war.

2. The simulation of integration model is of richer changing hierarchy, which reflects the evolving situation of kiln in different times. The evolution regularity of kilns is that the location of kilns distribute along river and around village. With time go, the location of kiln spread out from northeast to southwest. The interaction and information communication between these two kinds of agents help the model to modify the suitability of land and probability threshold dynamically, which better reflects the interaction between complex political factors and natural environment.

3. Because of continuous evolvement, from the entire research phase, we can find that the number of the farmland continuous increase from stage 2 to stage 4, which shows the policies of Ming dynasty and wartime pay high attention to agriculture product in spite of farmland was so few in ancient Fu Liang area. Moreover, our model

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not only reflects the evolution of kilns but also reflects other land type change with time. In the third stage, the numbers of mountain and shrub were decreased due to the expansion of the ceramic product. As a result, the number of the craftsman increase lead resident land increase.

5. Conclusion

Our model is a novel land use model developed by combining CA and multi-agent models. Multi-agent system models are increasingly recognized as a powerful tool to simulate social systems because they can capture important human decision and behavior that are difficult to formulate by using other tools (Lempert, 2002). In our model, the agents are equipped with land use related preferences and information extracted from political policies. Artificial agents may change their behavior in response to their environmental change based on their political development. The heterogeneity of agents is represented by adjusting diverse sets of weights according to GIS data. Eventually, we simulate the human-environment system and the evolution process of kilns in Fu Liang from 1271 to 1554 by using the integration model. The simulation results indicate that this novel model is of richer changing hierarchy and can better reflect the whole evolution process of kilns and land use change due to the interaction between political environment and the natural environment can dynamically modify transition probability threshold and look for the preferable location.

Moreover, the fused model as a new method that is a primary attempt to dispose of the land use change with the lack of ancient GIS spatial data and is effective in spite of the index Moran's I of simulation is not much closer to the actual Moran's I. As such it might provide a research with additional information and insight.

Acknowledgments

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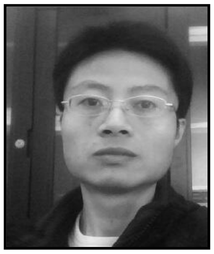

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