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Research Article

Simulating Intraurban Land Use Dynamics under Multiple Scenarios Based on Fuzzy Cellular Automata: A Case Study of Jinzhou District, Dalian

Jun Yang,[1,2] Weiling Liu,[1] Yonghua Li,[1] Xueming Li,[1] and Quansheng Ge[2]

[1]*Human Settlements Research Center, Liaoning Normal University, Dalian 116029, China*
[2]*Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographic Sciences and Natural Resources Research, CAS, Beijing, China*

Correspondence should be addressed to Weiling Liu; liuweiling_giser@163.com

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The spatial evolution of land use in Jinzhou area was simulated using fuzzy cellular automata to determine all factors influencing urban land use change. For this purpose, land use data of multiple sources and remote sensing images from 2003 to 2015 were analyzed. The following results were obtained: (1) real land use data and simulation data for 2015 were tested using four indices. Under the 5 m × 5 m scale, the model shows good performance for simulation of areas with various land use types. (2) Among simulations under four scenarios, the effect of traffic guidance on the development of construction land was more distinct under the economic development mode, which clearly showed the phenomenon of "agglomeration" along major traffic lines. (3) Jinshitan Street is adjacent to the sea, and land use changes are significant under the 4th scenario, and thus related departments should pay more attention. (4) Shortcomings of conventional cellular automata model in processing complex systems could be mitigated through the integration of fuzzy sets.

1. Introduction

Cities are open and large complex systems with complex characteristics such as uncertainty, nonlinearity, and self-organization. The interaction between the internal local behavior and the global order leads to complexities in the variation process of urban land use [1–8]. In order to reveal the evolution of urban land use, scholars have proposed many models. At present, mature models include the CLUE-S model [9], SD (system dynamics) model [10], CA (cellular automata) model [11–13], and geocellular automata model [14–17]. Among them, the CA model follows a bottom-up approach, which is very consistent with human understanding of the dynamic variation process of urban land use. Therefore, it has become an ideal mathematical model for effectively studying complex urban systems [18, 19].

CA is characterized by the simulation of complex phenomena using the interaction between cells and their surrounding neighborhood cells in the space domain [20, 21]. In the time domain, the state of a cell at a later time is determined by the state of the cell at a previous time and the conversion rules. Finally, the global complex state is evolved from simple local rules (micro level) [22–25]. Applying logistic regression, Markov, and CA, city expansions in the suburbs of Tehran, Iran, and around Poyang Lake, China, were simulated by Vaz and Arsanjani, Liu et al., Bidlo, and Arsanjani et al., respectively, which verified the simulation capabilities of CA in complex systems [26–29]. However, when the CA model is applied to urban systems with nonlinear, unbalanced, self-similar complexity, exact and complete information is lacing on many factors that affect land use change and these factors have the characteristics of fuzziness, thus making the CA simulation process more complicated and affecting the simulation accuracy of CA [30–32]. Therefore, uncertainty processing is necessary for factors with incomplete information and ambiguity. Zadeh et al., He and Zhang, Abbasi-Ghalehtaki et al., Tencer et al., Rajak et al., and Jafelice et al. proposed the concept of fuzzy set in 1965, which provided a method to solve fuzzy problems [33–38]. Since then, many scholars have extensively studied the combination of fuzzy sets and GIS (geographic information system), which provides a quantitative description method for handling complex systems [39–41]. Therefore, fuzzy sets can be combined with CA to solve fuzzy problems in simulation processes [28, 42–45].

The variation process of urban land use is influenced not only by micro level effects but also by macro level effects [46, 47]. For example, Xia et al. used the Markov method at the macro level and simulated dynamic spatiotemporal changes in tourists [48]. Li and Liu et al. simulated the spatial growth of a city by integrating landscape index and CA and adding a top-down global control factor of cell transition, through which the shortcomings of the bottom-up CA approach could be mitigated [49, 50]. Nevertheless, changes in urban land use occur because of the demand for land with the development of the population and economy, and therefore global control factors can be added on the basis of population and economic data. Hagenauer and Helbich developed the RegioClust model for the prediction and analysis of population and economy for the special geographical and demographic characteristics of Germany [51]; Nguyen et al. combined Markov and CA with logistic regression to simulate the impact of population growth on land use change in the Giao Thuy region of Nam Dinh Province, Vietnam [52]. Mirbagheri and Alimohammadi used global logistic regression (LR) to simulate the growth of the city of Islamshahr in southwestern Tehran, Iran, and conducted a comparative analysis with geographically weighted logistic regression (GWLR) [53]. Among these methods, logistic regression is widely used because of its good universality [54]. Therefore, in this study, logistic regression analysis was performed to obtain the global control factor. In addition, the policy factor is an important factor affecting land use variation. Based on the previous research experience, constrained cellular automata (constrained CA) can flexibly implement the quantification and spatialization of policy factors and couple the integration results into CA conversion rules [55, 56]. Therefore, this study quantified policy factors in the process of scenario simulation through the idea of constrained CA.

In addition, cell neighborhood, as an important part of CA, is an important factor affecting the accuracy of CA simulation. Shafizadeh-Moghadam et al. and Zheng et al. evaluated the effect of cell neighborhood size on the accuracy of CA simulation by selecting two cities in Iran, Tehran and Isfahan, as the research areas. Through PA (product accuracy), OA (overall accuracy), and FoM (the figure of merit), the accuracy of the simulation under the scales of $3\,\mathrm{m} \times 3\,\mathrm{m}$, $5\,\mathrm{m} \times 5\,\mathrm{m}$, $7\,\mathrm{m} \times 7\,\mathrm{m}$, and $9\,\mathrm{m} \times 9\,\mathrm{m}$ was verified, and the results showed that the best simulation was achieved under the scale of $7\,\mathrm{m} \times 7\,\mathrm{m}$ [57, 58]. Therefore, in order to determine the reliability of CA, the selection of cell neighborhood size must be verified.

In summary, based on previous methods and experiences of simulating land use variations, from the neighborhood scale, conversion rules, and simulation mechanisms that affect CA simulation accuracy, Jinzhou District of Dalian was selected as the research area in this study. The spatial distribution characteristics of future land use were simulated using data from multiple sources such as 1 : 10000 land use images of Jinzhou District from 2003–2015 and remote sensing images, with four cellular neighborhood scales ($3\,\mathrm{m} \times 3\,\mathrm{m}$, $5\,\mathrm{m} \times 5\,\mathrm{m}$, $7\,\mathrm{m} \times 7\,\mathrm{m}$, and $9\,\mathrm{m} \times 9\,\mathrm{m}$), and integration of the fuzzy set algorithm, logistic regression model, scenario analysis (SA), and constrained CA. Various factors (location, ecological, economic, etc.) under four scenarios (natural growth, farmland protection, ecological protection, and economic development) and the existing state (existing land use, future population and economic forecasting objectives, and different development planning policies) were considered in the simulations. The kappa, PA, OA, and FoM parameters were used to verify the simulation accuracy of the model. Through the simulations, the spatial distribution of land that may occur in the future under the existing development policy was revealed. This provides a reference for land use planning and urban planning staffing.

2. Study Area and Methods

2.1. Overview of the Study Area. Jinzhou District is located in Dalian City, Liaoning Province. It lies south of Liaodong Peninsula, 39°4′–39°23′ N and 121°26′–122°19′ E, and borders the Yellow Sea, Bohai Sea, and the Dalian Economic and Technological Development Zone. Jinzhou District has four functional areas, its development foundation is strong, and traffic is high (Figure 1). In 2003, the construction land area was $338.21\,\mathrm{km}^2$, and by 2015, it reached $458.36\,\mathrm{km}^2$, which will further increase to $120.15\,\mathrm{km}^2$ in 12 years with an annual growth rate of 3.5%. In the district, land use variation is significant. As such, the study of dynamic changes in land use in Jinzhou District is of great practical significance.

2.2. Global Control Factors Based on Logistic Regression. In addition to a series of spatial variables, the process of dynamic change of land use is closely related to population growth and economic development [59]. At present, research on land use change mainly establishes the relationship between population growth factor, economic development factor, and land use area through principal component analysis, simple correlation analysis, and typical correlation analysis to obtain the global control factor of cell conversion, improve cell conversion rules, and improve simulation accuracy [60]. In this study, through comparisons and significance tests considering various models, the most appropriate model was selected.

2.3. Influence Factor Based on Fuzzy Set Algorithm. The term "fuzzy" does not imply messy or chaotic thinking. Instead, fuzzy logic provides a means of handling imprecise problems. The fuzzy set serves as a very effective decision-making method for handling numerous influencing factors and provides a quantitative description method for managing complex geospatial systems [61, 62]. It is a type of the "soft-decision" approach in computing. The fuzzy set describes

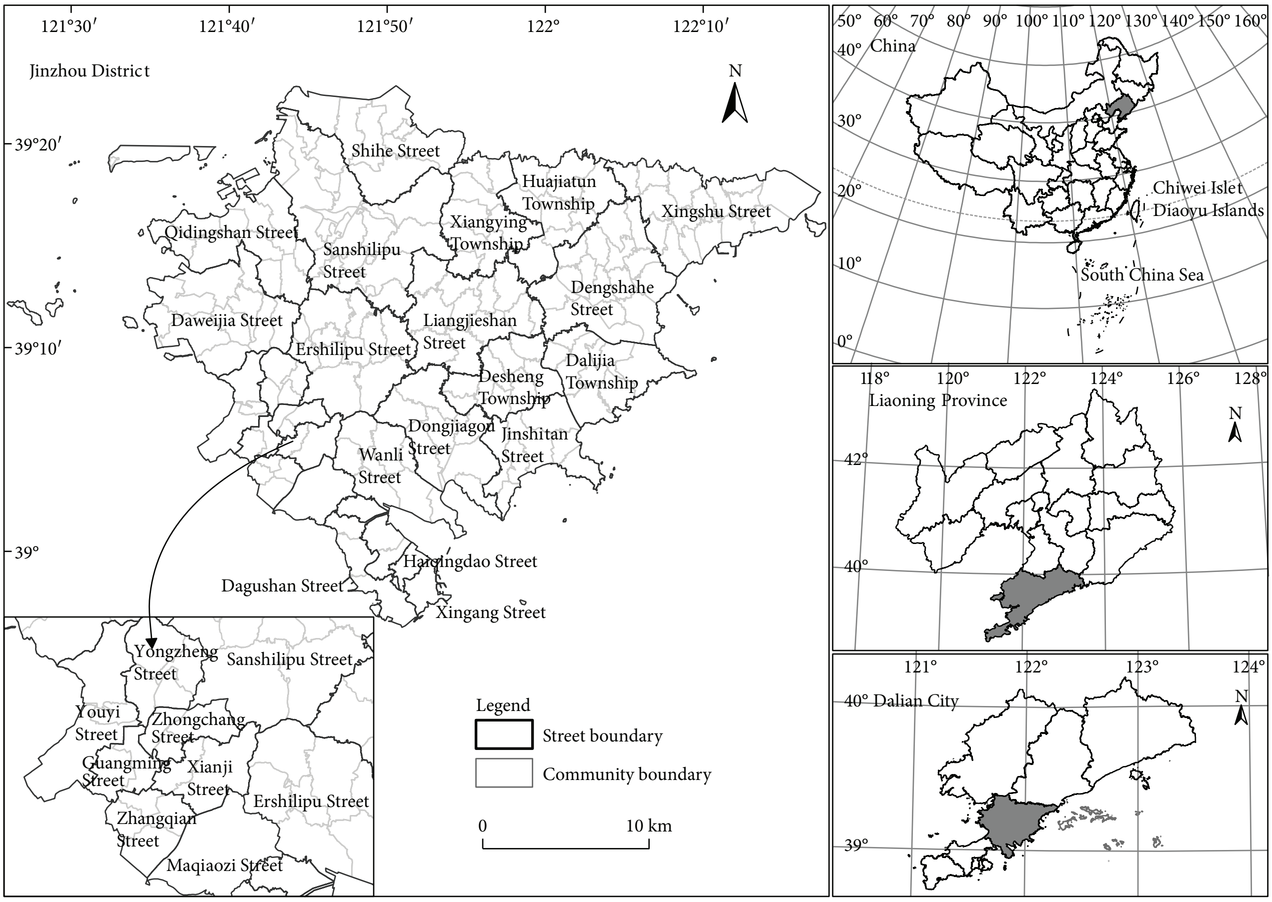


Figure 1: The location of the study area.

the relationship between an element and a set by the membership function [63, 64]. In the classical set theory, the relationship between the elements and the set has only two possibilities of "yes" or "no" (that element $x \subset U$ or element $x \not\subset U$ exists in two cases). However, in the fuzzy set theory, the relationship between the element and the set has some or more subordinate relationships [65–70]. In order to accurately describe the difference between the classical set theory and the fuzzy set theory, we define the symbol space: the domain U, the fuzzy set A, and the element $x (x \subset U)$; the relationship between the element and the fuzzy set can be described as

$$A = \{x, \mu(x)\}, \quad \mu_A(x) \in [0, 1], x \in X, \tag{1}$$

where μ_A represents the membership function of A and $\mu_A(x)$ represents the degree of subordination of element x to set A, that is, membership [71, 72].

The points in Figure 2(b) represent different elements, and the distance between the point and the set represents the membership degree of the element to the set. Figure 2(c) shows that, for a value of 170 cm, the low, medium, and high membership degrees to the set were 0.0, 0.3, and 0.7, respectively; that is, the low, medium, and high membership degrees (or probability) of 170 cm belong to the set. In the combination of fuzzy sets and CA, Burrough, Schmucker, and Zimmermann proposed that the influence factor should be fuzzified by J-type functions, serving as an example for applying fuzzy sets to CA [73–75]. The J-type function can be expressed as

$$\mu = \frac{1}{1 + ((x - p_2)/(p_2 - p_1))^2}, \tag{2}$$

where $p_1 = \text{point}_1$ and $p_2 = \text{point}_2$. When $x \geq \text{point}_2$, $u = 1$. When $x < \text{point}_2$, $u = 0$. When using the J membership function to process the factors, the influence of the limiting factor cannot reach zero. Therefore, the S-type membership function was added for processing the factors:

$$u(x) = \cos^2\alpha, \tag{3}$$

where

$$\begin{aligned} \alpha &= \frac{(x - \text{point } c)}{(\text{point } d - \text{point } c)} * \frac{pi}{2}, \quad \text{when } x < \text{point } c, u = 1, \\ \alpha &= \frac{1 - (x - \text{point } a)}{(\text{point } b - \text{point } a)} * \frac{pi}{2}, \quad \text{when } x > \text{point } b, u = 1. \end{aligned} \tag{4}$$

pi is the circular constant and point a, point b, point c, and point d represent the values of the inflection point of different membership functions.

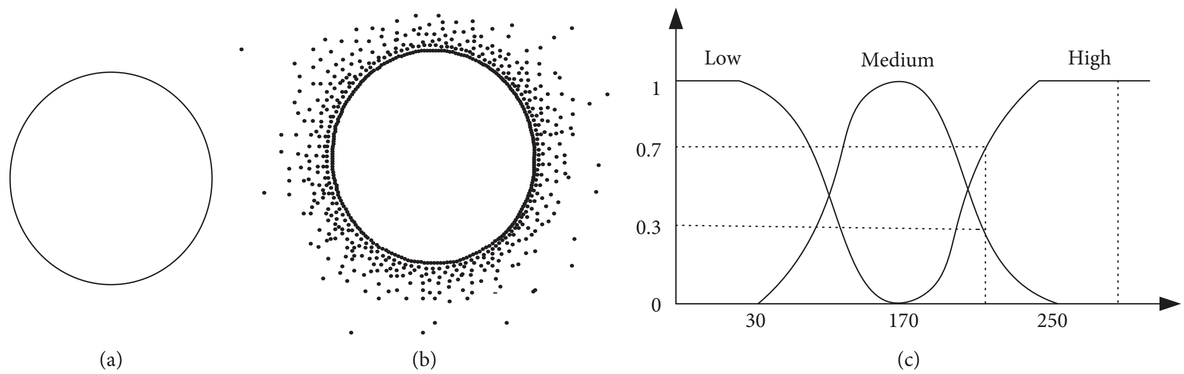


Figure 2: (a) Diagram representing the Boolean logic used in the classical set theory; (b) modified Venn diagram of a fuzzy set; (c) a membership function graph with height as an example.

2.4. Determination of Simulation Scenarios. SA is a method dedicated to exploring the impact of incidental and decision factors in the future. It is employed to determine incidental factors and decision factors that affect the development of things [76, 77] and to reflect the possible occurrence of future situations under the action of various factors and present conditions. Compared with the traditional forecasting method, SA can reflect multiple possibilities and dynamic characteristics of the development of things, such that the simulation results have more reference value. This study determined simulation scenarios based on the previous research experience and planning requirements of Jinzhou District.

2.5. Constrained CA Ideas. In the practice of land use planning in China, land use planning determines the use of land. For example, planning policies on basic farmland protection and land for construction planning largely determine the state of conversion of the cells at the next moment. Therefore, in the process of land use simulation, it is very important to improve the simulation accuracy of the model by quantifying and spatializing the constraints of basic farmland protection policies and planning policies for land use planning. Constraint cellular automaton is an effective tool to simulate complex geospatial space and is widely used in the simulation of urban spatial morphological changes and land use changes [78]. It can flexibly integrate the integration results of land use planning and policy constraints in urban planning CA conversion rules.

2.6. Modeling of Fuzzy CA Model. As shown in Figure 3, in this study, the fuzzy set algorithm, logistic regression model, SA method, and constrained CA approach were integrated, and the SA method was used to simulate land use under four scenarios of land use development including natural growth, basic farmland protection, ecological protection, and economic development [79, 80]. However, prior to the application of fuzzy CA, we assumed that no major policy changes occurred in built-up areas in the next five years during the simulation process, and there was no process of converting construction land into construction land and other types of land. First of all, through data processing software such as ArcGIS and ERDAS, the original data were processed by Molder Builder modeling, data classification, data fusion, image classification and resampling preprocessing, unified data coordinate system, and database. Then, to determine the rules of cell transformation under the CA bottom-up simulation mechanism, the fuzzy set algorithm is used to fuzzify the location factors and ecological factors that affect the conversion of cells. The constrained CA idea determines the policy in the rules of cell conversion factors (such as farmland protection and forest protection and other restrictions). In addition, in order to compensate for the shortcomings of CA bottom-up research ideas, regression analysis of population and economic data in the study area was performed by principal component analysis, regression analysis, and weight analysis, and an accuracy test was performed (for the results, see Section 3.3 and Table 1). The regression analysis method with the highest accuracy was selected to determine the top-down cell transition area (i.e., the global control factor) in the cell iteration process. Then, the CA bottom-up conversion rules were applied to employ top-down and random factors in the CA model for iterative computing within $3\,\mathrm{m} \times 3\,\mathrm{m}$, $5\,\mathrm{m} \times 5\,\mathrm{m}$, $7\,\mathrm{m} \times 7\,\mathrm{m}$, and $9\,\mathrm{m} \times 9\,\mathrm{m}$ scales. The accuracy of the kappa, PA, OA, and FoM indices was tested using real land use data and the simulated land use data in 2015 on the cell scale of the cell to determine the reliability of the CA. At last, four scenarios of natural growth, basic farmland protection, ecological protection, and economic growth were determined using the scenario analysis method (based on the trend of land use change), the simulation results were analyzed, and predictions were made.

3. Model Application and Validation

3.1. Data Sources and Processing. The data including multi-source data of land use and remote sensing data from 2003 to 2015 are presented in Table 2. Land use was classified according to the land classification standard (GB/T 21010-2007) promulgated by the state, which divides it into five categories: construction land, agricultural land, forestland, water area, and other land use. The grid unit size is $5\,\mathrm{m} \times 5\,\mathrm{m}$. The land use classification is shown in Table 3.

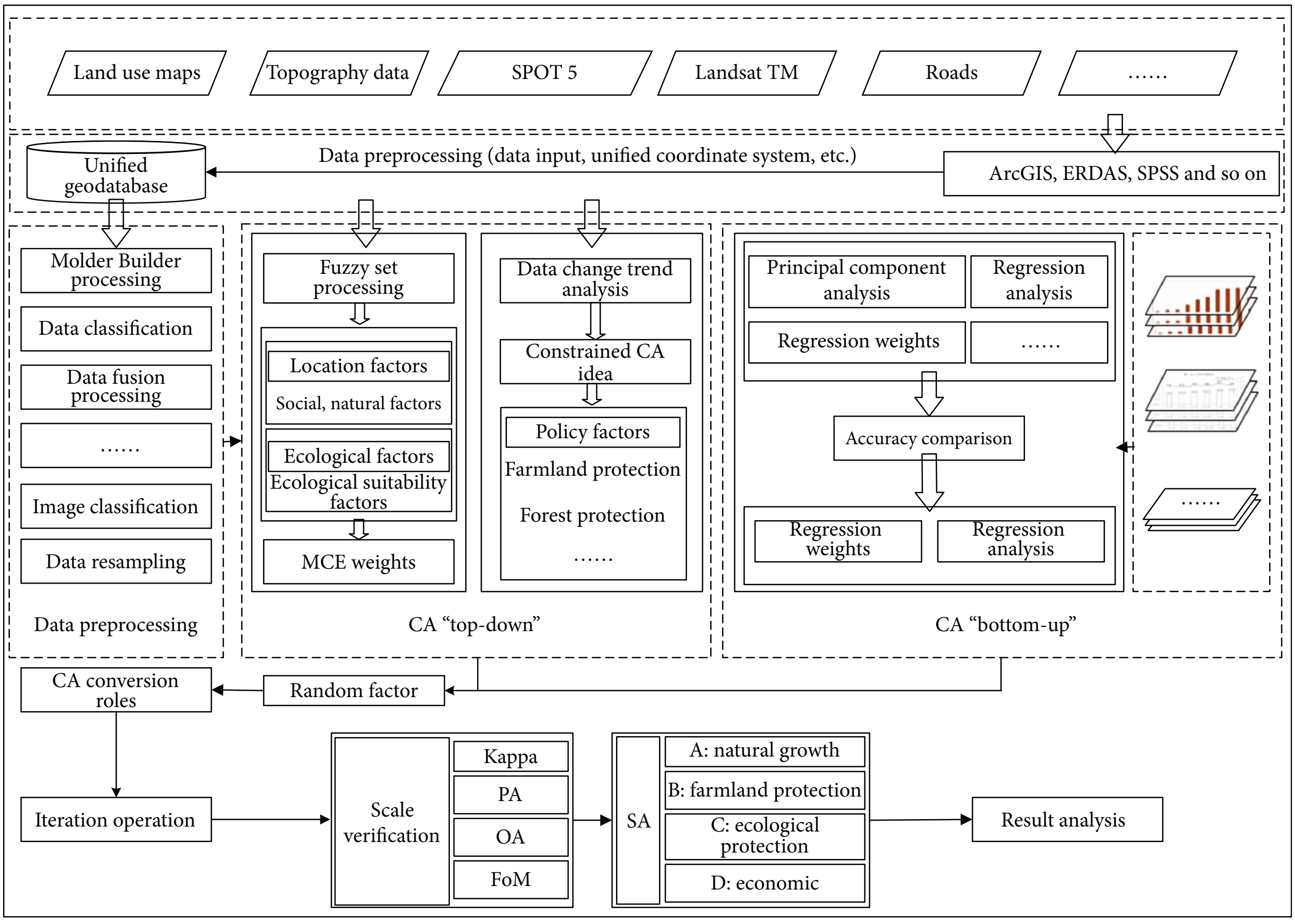


Figure 3: Cellular automata land use simulation based on the fuzzy set technology roadmap.

Table 1: Forecasted area of land use in 2020 based on the logistical model.

	Construction land	Forestland	Agricultural land	Other land use	Water area
Area (km^2)	508.50	450.00	447.30	81.00	73.80

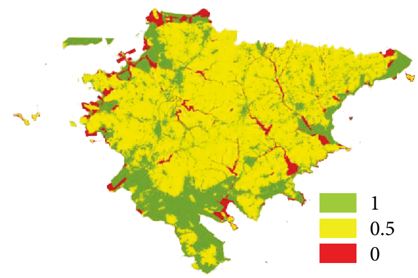
Table 2: Data sources and processing.

Data type	Data features	Data sources	Data processing
Land use data	1 : 10000 topography data	Dalian Land Resources and Housing Bureau	Molder Builder
Administrative divisions data	Including city, street, and other regional boundaries	Dalian Land Resources and Housing Bureau	Extract administrative divisions
Roads data	1 : 10000 linear data	Dalian Land Resources and Housing Bureau	Euclidean distance
Remote sensing image	SPOT5 image (resolution of 2.5 m), TM image	National Marine Environmental Monitoring Center	Interpret, extraction, and analysis
Statistical Yearbook	Text format Statistical Yearbook of Jinzhou District	National Bureau of Statistics of China	Summary and analysis
Land Use Planning in Dalian (2006–2020)	Text format	Dalian Land Resources and Housing Bureau	Summary and analysis
Dalian City Master Plan (2001–2020)	Text format	Dalian Land Resources and Housing Bureau	Summary and analysis

Table 3: Land use type classification of Jinzhou District in Dalian.

Number	Land use type	Meaning
1	Construction land	Refers to the transportation land, place of residence, town-industry land, special land, urban construction land, rural residents, and so on
2	Forestland	Refers to the growth of arbor, bamboo, and shrub land, including woodland, grass, and artificial grass
3	Agricultural land	Refers to the cultivation of crops of land, including paddy fields, irrigated land, dry land, orchards, and tea garden
4	Other land use	Refers to the grassland, naked rock, sand dunes, and other unused land
5	Water area	Refers to the river surface, reservoirs, coastal beach, and so on

Table 4: Selection and processing of natural factors.

Number	Factor selection	Division standards	Process result
1	Land use status	(A) Water area, assigned 0 (B) Agricultural land and forestland, assigned 0.5 (C) Construction land and other land use, assigned 1	

3.2. Extraction of Parameters

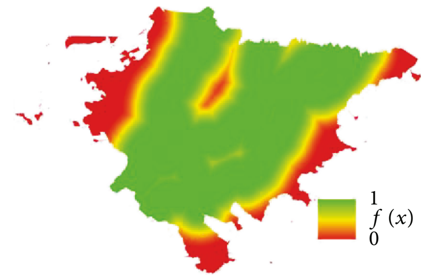
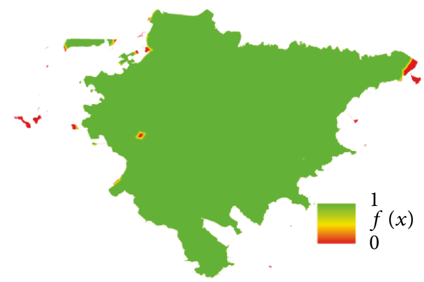
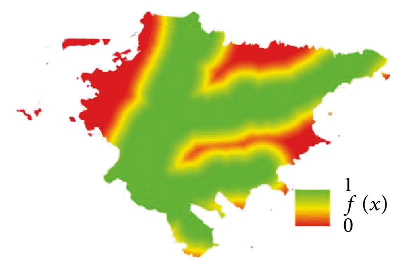
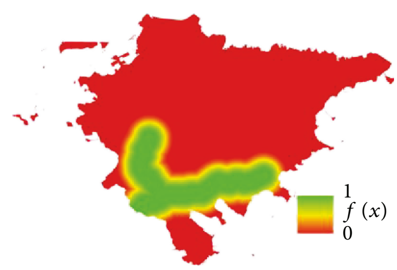
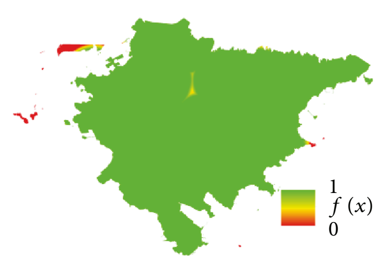
3.2.1. Global Control Factors. In order to obtain the global control factor of the cell transformation, GDP data and population growth data from 2003 to 2015 in Jinzhou District were taken as independent variables and land use type area as the dependent variable in SPSS for principal component analysis, weighted regression analysis, and logistic regression analysis. Regression analysis of a model to verify the effect of the final choice of the regression model is a logistic regression analysis and weight regression analysis. The regression coefficients R^2 were 0.679, 0.742, 0.727, 0.714, and 0.696, and the statistics p were 0.042, 0.038, 0.044, 0.030, and 0.045 [81, 82]. From the viewpoint of statistics, each regression equation is reasonable, and the regression effect is significant. Hence, it is possible to obtain areas of different land use types in Jinzhou District in 2020 through the established regression models and the development planning data for Jinzhou District in 2020, as shown in Table 1.

Compared with the actual land use data in 2015, the construction land area is increased in 2020, and the other types of land use area show a decreasing trend to a certain extent.

3.2.2. Location Factor. Obvious functional zoning phenomena occur in the land within the city due to the influence of natural and social attributes, which reflect changes and differentiation of land use types. Therefore, in the process of simulating variations in land use, consideration of natural and social attributes is necessary to achieve more scientific and rational simulations [83]. In this study, location factors of natural factors were classified and fuzzed according to the relevant research of Shu [84], the land use planning of Dalian (2006–2020), and the relevant provisions of the Dalian City Master Plan (2001–2020). The social factor is based on the "Restrictions on Construction and Mining along Highways and Railways" (Articles 10, 11, 14, 17, and 18), Regulations of the People's Republic of China on Highway Administration, and *Geographic Information System Practice Tutorial* [84, 85]. The characteristics of the study area were constantly adjusted to the values of point a, point b, point c, and point d for fuzzification, and the values in Tables 4 and 5 were the final selected values (recorded as C_0). In addition, to further prove the scientific simulation of the selected point and increase the rigor of the article, according to the natural breakpoint method [86], two values were selected at the left and right ends of point C_0 for verification (verification results are shown in the discussion part of Figure 4).

3.2.3. Ecological Suitability Factor. With the economic development and expansion of construction land, the city's ecological environment has been damaged to varying degrees. With the high frequency of environmental problems, ecological suitability has become an important factor in urban construction land expansion [87, 88]. Therefore, based on the research experience of the literature on ecological suitability [84, 89, 90], "CJJ-83-99" (Urban Land Use Planning Regulations), "Basic Farmland Protection Regulations," "Notice of the Ministry of Land and Resources on Implementing the Comprehensive Protection of Permanent Basic Farmland," *Geographic Information System Practice Tutorial*, and National Outline of Ecological Protection "Thirteenth Five-Year Plan," study area characteristics were continuously

Table 5: Selection and processing of social factors.

Number	Factor selection	Division standards	Process result
1	Distance to national highway and provincial highway	(A) ≤2000 m, fuzzy membership degree is 1 (B) 2000–8000 m, fuzzy membership degree is $f(x)$ (C) ≥8000 m, fuzzy membership degree is 0	
2	Distance to highway (including one to four highways)	(A) ≤1000 m, fuzzy membership degree is 1 (B) 1000–6000 m, fuzzy membership degree is $f(x)$ (C) ≥6000 m, fuzzy membership degree is 0	
3	Distance to railway	(A) ≤1000 m, fuzzy membership degree is 1 (B)1000–8000 m, fuzzy membership degree is $f(x)$ (C) ≥8000 m, fuzzy membership degree is 0	
4	Distance to subway	(A) ≤1000 m, fuzzy membership degree is 1 (B) 1000–5000 m, fuzzy membership degree is $f(x)$ (C) ≥5000 m, fuzzy membership degree is 0	
5	Distance to city center	(A) ≤5000 m, fuzzy membership degree is 1 (B) 5000–10000 m, fuzzy membership degree is $f(x)$ (C) ≥10000 m, fuzzy membership degree is 0	

adjusted to point a, point b, point c, and point d values for fuzzification, and the values in Table 6 were the final selected value (the values selected in Table 6 and the values selected in Tables 4 and 5 are collectively recorded as C_0). In addition, to further prove the scientific simulation of the selected point and increase the rigor of the article, according to the natural breakpoint method [86], two values were selected at the left and right ends of point C_0 for verification (verification results are shown in the discussion part of Figure 4). "CJJ-83-99" clearly stipulates that it is forbidden to construct buildings with slopes greater than 25°. Therefore, only two points on the left were selected during the verification process.

3.2.4. Constrained Policy Factors. Based on previous research experience, constrained CA ideas, and current situation of research area, this study quantified and spatialized basic farmland protection policies and ecological protection policies in the conversion rules of CA. Therefore, according

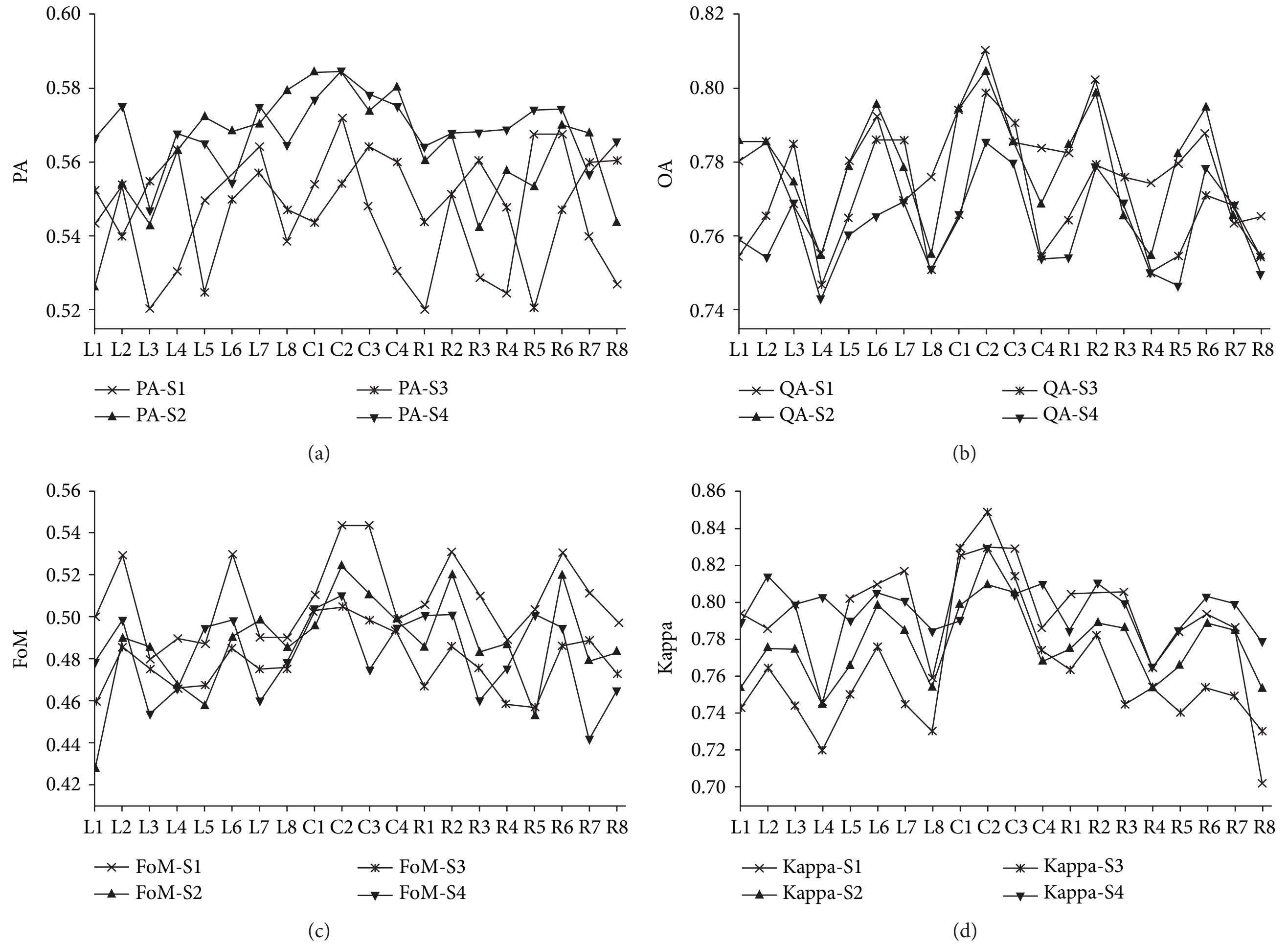


Figure 4: Influence of point *a*, point *b*, point *c*, and point *d* values for the simulation accuracy of S1, S2, S3, and S4 at four cell neighborhoods. L1, L2, L3, and L4 and L5, L6, L7, and L8 are the verification results of two points at the left end of C_0 in different cell neighborhoods: R1, R2, R3, and R4 and R5, R6, R7, and R8, respectively. Verification results of two points on the right side of *C* in different cell neighborhoods, where 1 and 5 represent 3 m × 3 m neighbors; 2 and 6 represent 5 m × 5 m neighbors; 3 and 7 represent 7 m × 7 m Cell neighborhood; 4 and 8 represent 9 m × 9 m cell neighborhoods.

to the general plan for land use in Dalian (2006–2020), the cell set in the basic farmland protection policy and ecological protection policy was set to 0; that is, the cell state does not change in the next iteration calculation in the simulation of the specific definition of the scene [91–93]. In addition, when the fuzzy membership degree of location factor and ecological suitability factor $f(x)$ is set to 0 and 1, the idea of constrained CA is also applied.

3.2.5. Random Factors. There are often uncertain factors and random factors in the change of land use type. To improve the simulation precision, the random factor variable was added, as shown in the following formula:

$$P_{ij}^{t}(i,j) = P_{ij}^{t} \times \left(1 + (-In\gamma)^{\lambda}\right), \quad (5)$$

where γ is the changing random variable and $\gamma \in [0,1]$; λ is the parameter to control the amplitude of the random variable.

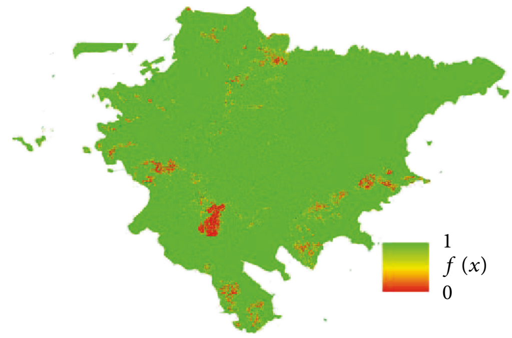
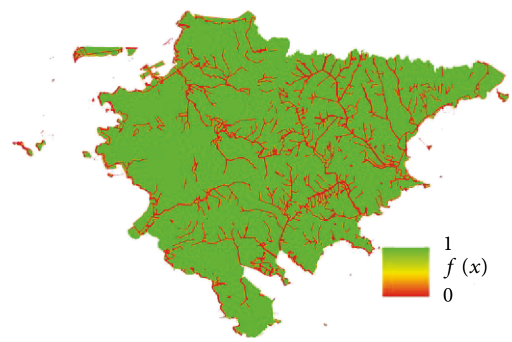
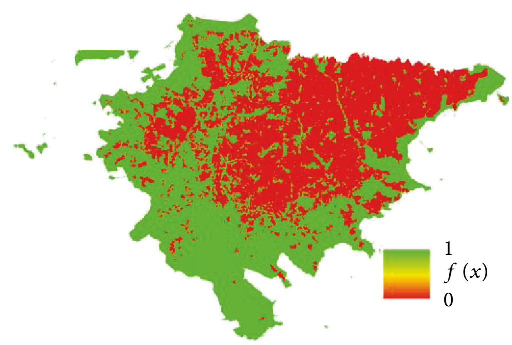
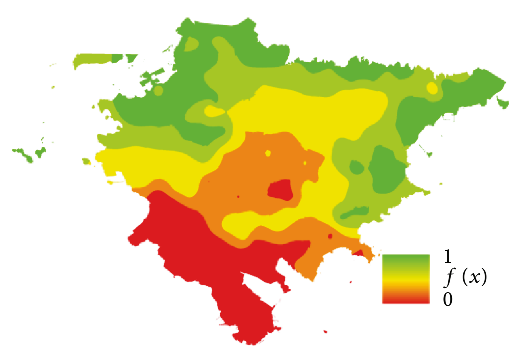
3.2.6. Probability of Cell Transformation. In simulations of land use variation, each variable has different degrees of impact on land use variation. Therefore, weight processing must be performed for the variables. $w_{(ij)m}$ is defined as the weight of the *m*th spatial variable that affects the probability of cell transformation. Then formula (6) is obtained.

$$P = \sum_{m}^{n} w_{(ij)m} \times P_{ij}^{t}(i,j), \quad m = 1,2,\ldots,n. \quad (6)$$

According to formula (6), the weight of each factor is identified and calculated by MCE (multicriteria evaluation) [94–97]. The results are shown in Table 7.

3.3. Validation of the Model. The land use simulation data of 2015 obtained from the model are shown in Figure 5. To determine the feasibility of the model, several simulations of land use in 2015 must be validated. At present, many scholars use the kappa coefficient to verify the simulation

Table 6: Selection and processing of ecological suitability factors.

Number	Factor selection	Division standards	Process result
1	Slope	(A) ≤10°, fuzzy membership degree is 1 (B) 10°–25°, fuzzy membership degree is $f(x)$ (C) ≥25°, fuzzy membership degree is 0	
2	Distance to water	(A) ≤50 m, fuzzy membership degree is 0 (B) 50–100 m, fuzzy membership degree is $f(x)$ (C) ≥150 m, fuzzy membership degree is 1	
3	Distance to basic farmland protection	(A) ≤50 m, fuzzy membership degree is 0 (B) 50–100 m, fuzzy membership degree is $f(x)$ (C) ≥100 m, fuzzy membership degree is 1	
4	Distance to ecological protection zone	(A) ≤50 m, membership degree is 0 (B) 50–100 m, membership degree is $f(x)$ (C) ≥100 m, membership degree is 1	

accuracy of the model and believe that the kappa coefficient has a good advantage in model verification. However, Pontius and Millones emphasize that the kappa coefficient uses randomness as the baseline and neglects the conversion from the observed sample matrix to the estimated population matrix [98]. Therefore, the study used the kappa, PA, OA, and FoM indices to verify the accuracy of the model—reliability of model simulation results at different neighborhood scales. According to the calculation formula and operation procedure of Li [49], the real land use data of Jinzhou District in 2003 and 2015 were taken as reference, and the simulated land use data of 2015 were used as the observation data to calculate A, B, C, D, and E. Each error parameter was substituted into PA, OA, and FoM formulas to calculate the simulation accuracy of each type of land use. The test results are shown in Figure 5.

Table 7: Weight settings of each factor.

Land-use type/factors	Natural factors	Location suitability					Ecological suitability			
		Social factors								
	1	1	2	3	4	5	1	2	3	4
Construction land	0.1473	0.1393	0.1512	0.1604	0.1806	0.2212	0.2942	0.2725	0.2733	0.1600
Forestland	0.1834	0.1846	0.1934	0.1402	0.1675	0.1309	0.2978	0.2459	0.2641	0.1922
Agricultural land	0.1993	0.1952	0.1567	0.1862	0.1409	0.1217	0.2541	0.2983	0.2239	0.2237
Other land use	0.1673	0.1779	0.1662	0.1633	0.1533	0.1720	0.2317	0.2403	0.2391	0.2889
Other land use	0.1527	0.1549	0.1672	0.1748	0.1612	0.1892	0.2614	0.2398	0.2467	0.2521

Figure 5 shows that when the kappa coefficient reaches the highest value (such as land for construction in Figure 5(a), agricultural land (Figure 5(c)), other land (Figure 5(d)), and water (Figure 5(e))), the best effect under PA, OA, and FoM indices cannot be achieved, and asynchrony exists. At the same time, construction land, forestland, and agricultural land have higher index values at the $5\,m \times 5\,m$ neighborhood scale; other land uses have higher exponent values at the $3\,m \times 3\,m$ and $5\,m \times 5\,m$ neighborhood scales. The $5\,m \times 5\,m$ neighborhood scale has a high index value, whereas the index value difference of the $7\,m \times 7\,m$ scale is not large. According to Shafizadeh-Moghadam et al.'s introduction and summary of the parameters, the simulation effect of other lands and waters in $5\,m \times 5\,m$ is within an acceptable range. Therefore, Jinzhou District in 2020 at the neighborhood scale of $5\,m \times 5\,m$ was considered for further analyses.

4. Analysis under Multiple Scenarios

The four scenarios (natural growth mode, farmland protection mode, ecological protection mode, and economic development mode) based on the variation trend and planning requirements of land use in Jinzhou District are shown in Table 8.

Simulation parameters were adjusted according to the four scenarios. Through this, land use data of Jinzhou District in 2020 was obtained (Figure 6).

From the simulation results and the spatial distribution of land use, differences in the simulation results under the four scenarios could be observed as follows:

(1) Influenced by economic development, under the natural growth mode without any other preexisting conditions, the characteristics of the quantity of different types of land use are as follows: the area of construction land increased by 22%, agricultural land area decreased by 12%, forestland area decreased by 8%, area of the water region decreased by 2%, and other land area decreased by 0.7%. The spatial distribution characteristics are as follows: the spontaneous distribution showed a phenomenon of "agglomeration," which is inconsistent with the existing development policy, and is not conducive to meeting the requirements of sustainable development.

(2) In the basic farmland protection mode, that is, in the next five years, farmland protection area does not change. When the development of agricultural land reaches the predicted level, construction land increases mainly through the conversion of forestland and other land. Forestland in the southwest of Jinzhou District is significantly reduced. Consequently, the ecological fragility of southwest Jinzhou District increases, and the probability of occurrence of urban thermal effect in the study area also increases. Figure 5 shows that social factors such as subways and highways have guidance effects for land use development, but the mode has a certain limit on economic development through the protection of agricultural land.

(3) In the ecological protection mode, strict constraints of ecological protection were added. The development of southwest Jinzhou District was limited to a certain extent. Urban construction land developed slightly northwest along transportation routes, but because of the natural attribute, namely, spatial restrictions due to the slope, this development mode is bound to increase the cost of development. In addition, it will present some challenges to the ecological system in the new development region.

(4) In the economic development mode, that is, meeting the requirement of increasing construction land, conditions of farmland protection and ecological protection were added. The expansion pattern of construction land showed a trend of growth along major transportation routes, and changes in the area of forestland in the southwest are small, thereby relieving the ecological stress in southwest Jinzhou District. The water area reaches the global area restriction (see Table 1), and the spatial distribution becomes more dispersed, with the locations becoming more consistent with the spatial distribution of agricultural land. However, compared with the total area of the water region in 2015, the overall area of the water region is decreased. Other types of land use are also decreased compared with those in 2015.

5. Discussions and Conclusions

In this study, all the factors influencing land use variation, including population and economic factors, were taken into

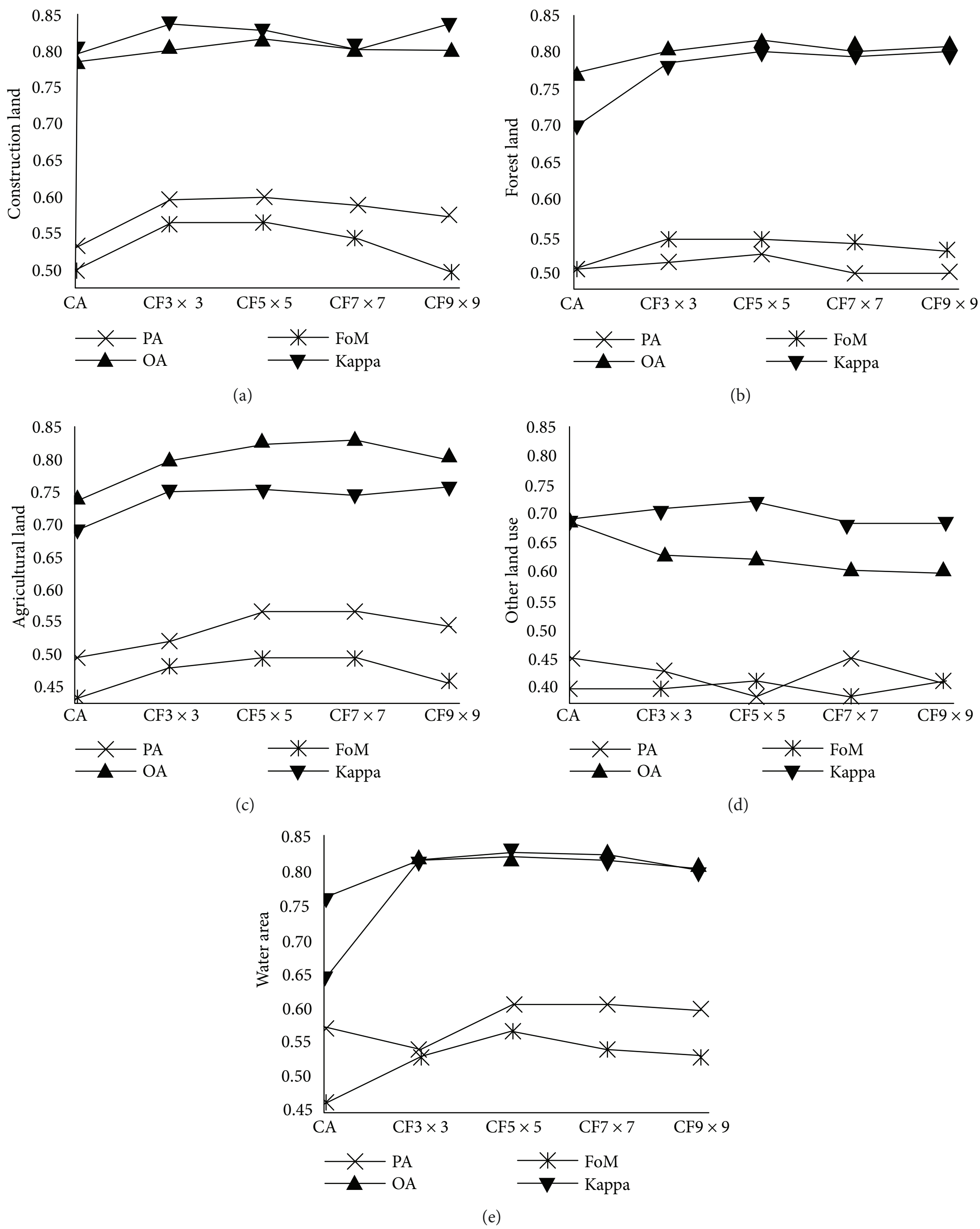


Figure 5: Comparison of simulation accuracy of land use types under different neighborhood scales under the traditional CA and fuzzy CA models (CA is the PA, OA, FoM, and Kappa parameter values of the traditional CA model; CF3 × 3, CF5 × 5, CF7 × 7, and CF9 × 9 are the fuzzy CA models at 3 m × 3 m, 5 m × 5 m, 7 m × 7 m, and 9 m × 9 m neighborhood cells with different PA, OA, FoM, and Kappa parameter values).

account during model construction. The conclusions are as follows:

(1) The advantages of using the CA model in simulating the dynamic variation of land use were fully utilized. The fuzzy CA model was established by integrating the fuzzy set algorithm, logistic regression algorithm, and SA method. The simulation accuracy of the model was tested on the 3 m × 3 m, 5 m × 5 m, 7 m × 7 m, and 9 m × 9 m neighborhood scales, and

Table 8: Definitions of the four scenarios used in the simulations.

Scenario definitions	Number	Meaning
Natural growth mode	S1	According to the city's existing development model development, without any adjustments
Farmland protection mode	S2	Farmland is not converted to any other land use type, and other types are preferentially converted to agricultural land
Ecological protection mode	S3	To minimize the ecological footprint of land for construction purposes and to increase the protection limit for areas with more sensitivity
Economic protection mode	S4	To ensure that regions with rapid economic growth meet construction land requirements (see Table 1) while increasing farmland protection restrictions and ecological protection restrictions

it was determined that the simulated effect of the model on each land use type can be achieved at the $5\,m \times 5\,m$ cell neighbor scale. The simulations met the requirements and were reasonable, indicating the high performance of the model in simulating land use for 2020.

(2) Based on the logistic regression model, the global control factors of land use variation were added. The spatial distribution of land use in the future under different development policies was revealed under four scenarios. The results show that in the natural development scenario, construction land increases by 22%, and the other types of land use decrease. Agricultural land decreases by 12%, and a significant amount of high-quality farmland is occupied by construction land. In the farmland protection mode, woodland in the southwest of Jinzhou is largely transformed to construction land, increasing the ecological fragility of the area. In the ecological protection mode, urban construction land was slightly developed towards the northeast along major traffic roads, but the phenomenon of agglomeration is not observed. Under the economic development mode, the expansion of construction land exhibits agglomeration along the main traffic roads. The variation of forestland in the southwest is small, thus alleviating the ecological stress in southwest Jinzhou. The water region area reaches the global constraint, and its spatial distribution is simultaneously more dispersed, becoming more consistent with the distribution of agricultural land. However, compared with 2015, the overall area of the water region showed a decreasing trend; the size of other land use types also decreases in comparison with that in 2015.

(3) Jinshitan Street, as a national scenic area, shows obvious changes in construction land under the four kinds of simulation scenarios. In addition, in the rocky beach south of the sea, an increase of construction land exacerbated the marine environment to some extent, thus making protection more difficult; therefore, the relevant planning section should pay more attention to this phenomenon.

(4) The fuzzy set algorithm can be used to solve the problem of incomplete information and ambiguity in the simulation process, thus mitigating the shortcomings of CA in processing complex systems.

Although PA, OA, FoM, and kappa parameters were used to verify the simulation accuracy of the traditional CA and fuzzy CA under the neighborhood of $3\,m \times 3\,m$, $5\,m \times 5\,m$, $7\,m \times 7\,m$, and $9\,m \times 9\,m$ cells, it was not given that different values of point a, point b, point c, and point d were selected for different simulation scenarios. To enhance the rigor and logic of the study, this paper conducts exploratory tests based on the land use data in 2015 and the condition settings in the scenes S1, S2, S3, and S4. It is the two points that were selected at the left and right ends of point C_0 according to the natural breakpoint method. The parameters PA, OA, FoM, and kappa were used to verify the simulation accuracy at the four neighboring cell scales and four simulation scenarios. The verification results are given in Figure 4.

In Figure 4, the two values at the left and right ends of C_0 appear to be slightly higher than those of C_0 in terms of simulation accuracy, but in general, they have higher simulation accuracy under the values of point C_0. Therefore, the selection of C_0 points is reliable in the S1, S2, S3, and S4 scenarios and revealed the reliability of simulation results of land use in 2020.

According to scholars' opinions and the research on the simulation process of land use in Jinzhou District, in the follow-up study, the following aspects should be emphasized: (1) due to limitations of data acquisition, further in-depth factors that affect land use variation could not be considered. For instance, factors such as soil characteristics and cultivated land suitability will also affect the land use variation. (2) It is very important to validate the accuracy of the model. Although four kinds of parameters were used to verify the accuracy of the model at four kinds of cell neighborhood scales, the verification results of each index are different for each type of land use. Therefore, selecting the representative parameters to validate the model is also the focus of the next step. (3) Logistic regression has universal characteristics. The global factor control factor used in this study, RegioClust model, was proposed by Arefiev et al. for Germany's special population and geographical features [43]. Therefore, targeted models of population and economic factors on the evolution of land use should be developed to conduct an accurate study. The follow-up study will further focus on this issue to improve the results.

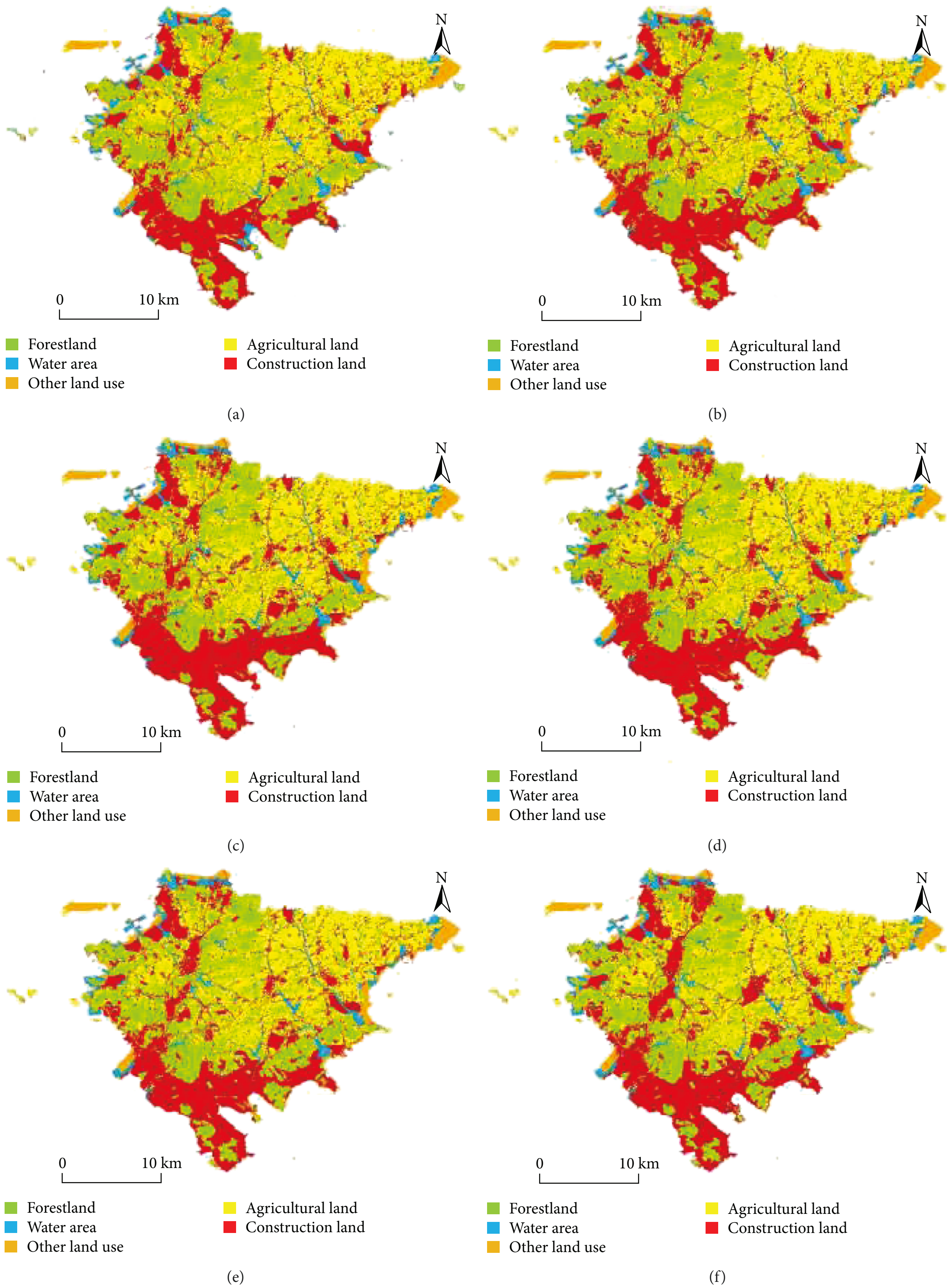


Figure 6: (a) Actual data of land use in 2015; (b) simulated data of land use in 2015; (c–f) land use simulation data under S1, S2, S3, and S4 scenarios, respectively, for Jinzhou District in 2020.

Disclosure

The funding sources had no role in the study design, data collection, analysis or interpretation, or the writing of this manuscript. The authors have read and understood the journal's policies, and they believe that neither the manuscript nor the study violates any of these.

Conflicts of Interest

The authors declare that they have no competing interests.

Authors' Contributions

Jun Yang contributed to all aspects of this work. Weiling Liu wrote the main manuscript text, conducted the experiment, and analyzed the data. Yonghua Li, Xueming Li, and Quansheng Ge revised the paper. All authors reviewed the manuscript.

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