



# Dynamic simulation of land use change based on logistic-CA-Markov and WLC-CA-Markov models: a case study in three gorges reservoir area of Chongqing, China

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## Abstract

The construction of The Three Gorges Reservoir has changed land use structure and reconstituted landscape pattern as imparts significant influence upon the land use structure and ecological environment of Three Gorges Reservoir Regions. The ecological safety of reservoir area is extremely dependent on unique location and special geological conditions of Zhongxian County, the center of Three Gorges Reservoir Regions in Chongqing, and therefore, ecological environment of reservoir area will be changed with the transition of land use in Zhongxian County. Based on land use data in 2000, 2005, 2010, this paper chooses influencing factors from aspects of natural topographic and geomorphological conditions, accessibility to economic development and land use expansion, and then establishes Logistic-CA-Markov (Logistic-Cellular Automata-Markov) and WLC-CA-Markov (Weighted Linear Combination- Cellular Automata- Markov) models so as to simulate spatial pattern of land use of Zhongxian County. The results demonstrate that WLC-CA-Markov model established here has better controllability and higher simulation precision (the kappa coefficient is 0.9295). In the future development of Zhongxian County, the area of grassland and plow land will be reduced continuously, the area of construction land will be expanded obviously mostly because of the added area both near the water and in the north of Zhongxian county, the area of woodland will be increased to a little extent, the area of water area and unused land has gentle change. In the sustainable scenario, the area of grassland will be reduced slightly, the area of water area keeps steady, the area of plow land is reduced but higher than red line of plow land, the area of construction land is increased with significantly smaller increase amplitude than that in the natural development scenario, and the woodland is increased. This scenario coordinates ecological environment with economic development of regional society and turns out to be the best development scenario of land use.

**Keywords** Land use change · Logistic-CA-Markov model · WLC-CA-Markov model · Scenario simulation · Zhongxian County

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## Introduction

Since the beginning of the twenty-first century, problems such as rapid population growth and waste of land resources have been occurring frequently in the ecologically sensitive areas in the Three Gorges Reservoir Region (Shi 2011; Zhou et al. 2011). As an important ecological protection area in the waters of the Yangtze River, the Three Gorges Reservoir Area of Chongqing (TGRAC) has self-evident ecological value. As the core zone of the TGRAC, Zhongxian's land use structure has undergone dramatic changes. In addition, with the rapid development of a market economy as well as the vigorous advancement of the urbanization process, Zhongxian's ecological environment has been impacted by human activity. For Zhongxian, how to transform land use types and how to

select land use patterns concern the guarantee of land for coordinated urban and rural development and affect intensive land use, thereby posing a threat to its ecological safety. On the other hand, whether the trend of land use changes in Zhongxian is reasonable affects the economic output of land and the results of different transformation models, i.e., environmental benefit stress. How to reasonably use land resources, how to adjust the relationships between different types of land, how to understand current land use conditions and how to determine future land use development have become urgent problems requiring in-depth study (Van and Verburg 2013; Long and Qu 2018).

Land use and land cover change (LUCC) is an important factor that affects the ecological environment and has become a central issue in global change and sustainable development research (Bathrellos et al. 2008; Samat et al. 2011; Li et al. 2017; Dang and Kawasaki 2017). LUCC is a very complex dynamic process driven by natural and human factors with a very complex mechanism (Xu et al. 2015; Wang et al. 2018a). Land use process modeling and simulation are among the main approaches for studying LUCC and are important tools for investigating the driving mechanisms of land use, supporting urban planning and policy formulation and evaluating the effects of land use on the ecological environment (He et al. 2017; Kuang 2011). The continuous development of geographic information technology, satellite remote sensing technology and data processing techniques has resulted in a continuous increase in the number of sources and resolution and accuracy of basic land use data and helped gradually advance their processing and management methods, allowing LUCC research to evolve from focusing on the effects of global climate change to focusing on LUCC processes of various spatial scales and their driving mechanisms and effects on resources, the environment and ecological conditions (Hao and Ren 2009; Li et al. 2017; Zhang et al. 2018). In regard to land use simulation, Guan et al. (2011) dynamically simulated future spatiotemporal land use changes in the Japanese city of Saga by introducing the natural and socioeconomic factors affecting land use into the cellular automata (CA)–Markov model. Peraltarivero et al. (2014) established various models based on Geographic Information Systems (GISs) and used them to study dynamic land use change in the Huasteca region between 1976 and 2007. In regard to the driving forces for land use, Loehr (2010) compared how external costs affected land use changes in Germany, China and Cambodia. Yang et al. (2012) proposed a spatiotemporal model for land use change analysis based on Markov chains, CA and ant colony optimization (ACO), in which ACO and CA are used to manage the spatial distribution of land use and Markov chains and CA are used to manage the total amount of land use cover. They used that model to simulate land use in the Changping district of Beijing. Wang et al. (2015) established a new differential evolution DE–CA model and employed a DE algorithm to optimize the quantitative structure of land use. By using the obtained results as the quantitative restraint condition for the CA model to optimize the spatial

pattern of land use, they successfully achieved a proper combination of the quantitative structure and spatial pattern of land use (Wang et al. 2011). Based on the current research status, CA models have outstanding advantages in land use simulation and thus have become the mainstream models for land use simulation (Xu et al. 2016; He et al. 2017; Parsa and Salehi 2016). CA models can be used to simulate complex land use patterns based on simple local transformational rules and can also be satisfactorily coupled with GISs and remote sensing data to significantly improve the capabilities of existing GISs to analyze complex natural phenomena and model spatiotemporal dynamics (He et al. 2008). Research on land use prediction models has gradually evolved from focusing on single models to focusing on the combination of multiple models and comprehensively considering various factors (e.g., natural, social and economic factors), rendering simulations of land use change processes more accurate (Liu et al. 2017).

Amidst this backdrop, this paper presents a case study of Zhongxian. Based on land use data for Zhongxian for 2000, 2005 and 2010 in combination with various factors, including natural terrain and geomorphological conditions, accessibility to economic development and land use expansion, a weighted linear combination WLC–CA–Markov model and a logistic–CA–Markov model with various transformational rules were established to simulate land use distribution patterns in Zhongxian in various scenarios (natural development, ecological protection and sustainable development), and the optimal land use pattern was determined. The results of this study provide a scientific basis for the reasonable use of regional land and formulation of structural optimization and land policies.

## Study area and data sources

### Study area

Situated on the northern bank of the Yangtze River in central Chongqing (30°03'03"N–30°35'35"N, 107°32'42"E–108°14'00"E) (Fig. 1), Zhongxian borders Wanzhou District and Shizhu County to the east, Fengdu County to the south, Dianjiang County to the west, and Liangping County and Wanzhou District to the north. In 2010, Zhongxian encompassed a total land area of 2182.911 km<sup>2</sup>, of which 903.271 km<sup>2</sup> (41.38%) were farmland, 1098.880 km<sup>2</sup> (50.34%) were forestland, 27.912 km<sup>2</sup> were grassland, 98.536 km<sup>2</sup> were waters, 54.298 km<sup>2</sup> were construction land, and 0.0144 km<sup>2</sup> were unused land. Zhongxian has high land use efficiency with low development potential for unused land. Agricultural land (farmland and forestland) is the major land use type in Zhongxian, whereas the proportion of construction land in Zhongxian is relatively small. The internal land use structure in Zhongxian is unreasonable. The Yangtze River separates the land of Zhongxian into two parts (one in the south

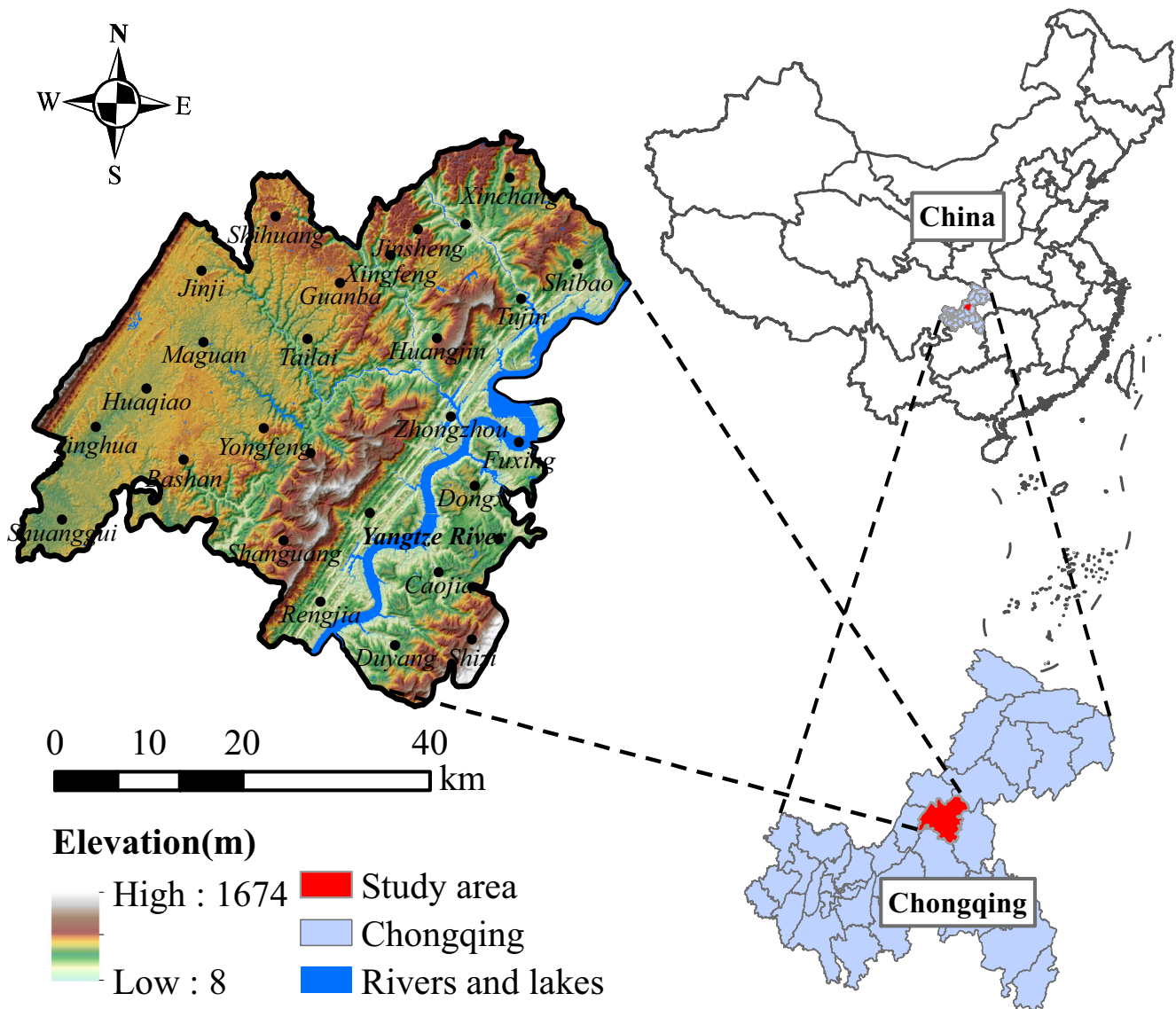


Fig. 1 Location of study area

and one in the north), which affects economic development. Between 2000 and 2015, Zhongxian experienced a significant decrease in the proportion of farmland and a dispersed land distribution pattern with land with steep slopes and at high altitudes that was difficult to develop and use, as well as extensive land use with a high ratio of unused land and low economic benefits from land in its rural settlements.

**Data sources**

The land use data originated from the land use data for Chongqing, Sichuan, Guizhou and Yunnan for 1990 shared by the Chinese Academy of Sciences (CAS) as well as the phase 3 interpreted data (resolution: 30 m) of the Project of Survey and Evaluation of Changes in Ecological Environments Across China During the Ten-year Period from 2000 to 2010 based on

remote sensing data that was jointly conducted by the Ministry of Ecology and Environment of China and the CAS. The land use data for 2015 originated from the Resources and Environmental Science Data Center of the CAS (<http://www.resdc.cn>). The five phases of land use data were integrated and classified based on the Level 1 classification standard into data for construction land, forestland, grassland, farmland, waters, and unused land.

The digital elevation model (DEM) data (spatial resolution: 30 m) originated from the Geospatial Data Cloud platform. The population and gross domestic product (GDP) data originated from the National Earth System Science Data Sharing Infrastructure platform (<http://www.geodata.cn>)-a national science and technology infrastructure platform. The temperature and precipitation data originated from the Resources and Environmental Science Data Center of the CAS (<http://www.resdc.cn>). The road and administrative

center data were obtained by processing the data contained in the transport network and administrative maps of Zhongxian.

## Methods

### Analysis of driving factors for land use change in Zhongxian

#### Selection of driving factors for land use change in Zhongxian

A large number of factors affect land use change, mainly including natural, socioeconomic, accessibility and policy factors (Aroengbinang and Kaswanto 2015). Natural factors such as altitude, slope gradient and precipitation mainly reflect land productivity and its determinants (Li et al. 2016; Pang et al. 2010). Socioeconomic factors such as population and economy are mainly driven by relevant policies (Yu et al. 2011). Accessibility factors are mainly affected by human construction activity and policies. Natural and socioeconomic factors are the primary driving forces for land use change and significantly affect land use (Kleemann et al. 2017). In this study, by taking into consideration natural terrain and geomorphological conditions, accessibility to economic development and land use expansion, slope gradient, elevation, precipitation, temperature, population, GDP, distance from roads, distance from towns and distance from water systems were selected as factors affecting land use change, as in Fig. 2.

To further illustrate the relationships between the influencing factors and the land use distribution, each factor and the land use data were subjected to an overlay analysis using ArcGIS 10.1. Figure 3 shows the distribution of each land use type with respect to each factor.

#### Regression analysis of the driving factors for land use change in Zhongxian

As a type of analytical models used in mathematical statistics, logistic regression models have been extensively used to study driving factors for land use (Shu et al. 2014). The following shows the logistic model proposed in this study:

$$\text{Log}\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad (1)$$

where  $P_i$  is the probability that a certain land use type will appear in each grid cell;  $\beta_0$  is a constant term;  $\beta_1, \beta_2, \dots, \beta_n$  are the partial regression coefficients of the logistic model, which determine the quantitative relationships between and quantitative effects of the driving factors; and  $X_1, X_2, \dots, X_n$  are the driving factor variables.

The data for the influencing factors were standardized using ArcGIS 10.1 to eliminate their dimensional differences. Then,

each land use type in 2010 was subjected to a regression analysis using the Logistic Module in IDRISI 17.0. On a  $30 \times 30$ -m scale, the probability,  $P$ , for each land use type to appear ( $P_1$ : grassland;  $P_2$ : waters;  $P_3$ : farmland;  $P_4$ : construction land;  $P_5$ : unused land; and  $P_6$ : forestland) and the regression equation for each of the nine driving factors ( $X_1$ : precipitation;  $X_2$ : temperature;  $X_3$ : GDP;  $X_4$ : population;  $X_5$ : distance from roads;  $X_6$ : elevation;  $X_7$ : distance from the administrative center; and  $X_9$ : distance from waters) are as follows:

$$\text{logit}(P_1) = -8.2761 + 0.703896 * X_1 + 3.727430 * X_2 + 0.538227 * X_3 - 0.145127 * X_4 - 1.267489 * X_5 + 2.167064 * X_6 +$$

$$1.026549 * X_7 + 1.506291 * X_8 - 0.067997 * X_9.$$

$$\text{logit}(P_2) = -7.1071 + 2.468027 * X_1 + 9.184539 * X_2 + 0.623482 * X_3 - 0.580466 * X_4 + 1.722396 * X_5 - 2.833381 * X_6 +$$

$$0.769691 * X_7 - 2.726844 * X_8 - 143.078477 * X_9.$$

$$\text{logit}(P_3) = -4.7454 + 1.022051 * X_1 + 4.434327 * X_2 - 4.124062 * X_3 + 1.920963 * X_4 - 0.396890 * X_5 + 5.080801 * X_6 +$$

$$0.690240 * X_7 - 4.718226 * X_8 + 1.233122 * X_9.$$

$$\text{logit}(P_4) = -7.2083 - 0.244913 * X_1 + 5.159169 * X_2 + 3.574057 * X_3 + 2.552039 * X_4 - 6.342338 * X_5 + 4.907209 * X_6 -$$

$$1.558156 * X_7 - 2.430970 * X_8 + 0.906418 * X_9.$$

$$\text{logit}(P_5) = -19.8656 - 2.378513 * X_3 + 0.719825 * X_4 + 11.339201 * X_5 - 4.196382 * X_6 + 15.212837 * X_7 + 6.618604 * X_8 +$$

$$0.124018 * X_9.$$

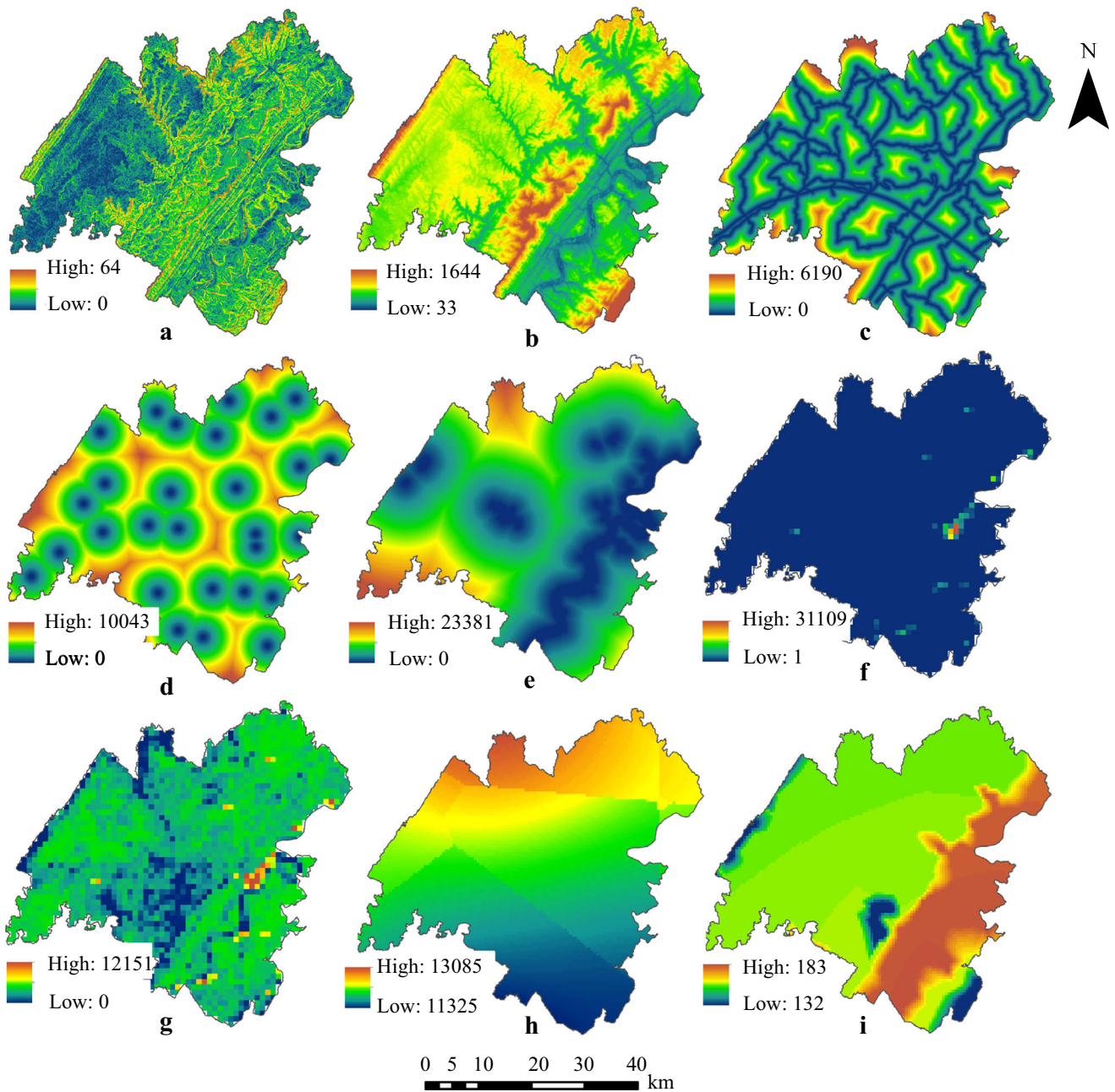
$$\text{logit}(P_6) = -4.8719 + 1.056975 * X_1 + 2.070273 * X_2 - 0.237339 * X_3 - 2.895698 * X_4 + 0.088240 * X_5 + 7.095712 * X_6 +$$

$$0.090904 * X_7 + 5.986750 * X_8 + 0.832643 * X_9.$$

The relative operating characteristic (ROC) method proposed by Pontius was employed to examine the goodness of fit (GoF) of the logistic regression model (Pontius and Schneider 2001). When the ROC value falls in the range of 0.5–1.0, the GoF of the regression model increases as the ROC value increases. When the ROC value exceeds 0.75, the GoF of the model is relatively high, suggesting that the model can meet the requirements. The results show that the ROC values of the logistic model for grassland, farmland, construction land, forestland, waters and unused land are 0.7877, 0.8525, 0.8854, 0.8863, 0.9864 and 0.9845, respectively. The ROC value for each land use type is greater than 0.75, suggesting a relatively high GoF and that the driving factors selected in this study can explain the spatial distribution of land use types to varying degrees.

#### Prediction of land use change based on the CA–Markov model

The CA–Markov model is a type of complex dynamic model established by combining CA and the Markov model and can be used to simulate the spatiotemporal evolution of complex systems (Kasetkasem et al. 2005; Aaviksoo 1995; Yang et al. 2014). The transformational rules of CA control changes in spatial positions, while the Markov area transformation matrix controls



a: Slope      b: Elevation      c: Distance to the nearest road      d: Distance to nearest administrative center  
 e: Distance to the nearest river      f: GDP      g: Population density      h: Amount of precipitation      i: Temperature  
**Fig. 2** The main driving factors of land use change in Zhongxian

temporal changes. The combination of CA and the Markov model can facilitate dynamic simulation of land use (Fu et al. 2017). In addition, data for economic, social and natural factors can also be added into the CA–Markov model to allow the prediction to be more consistent with actual development (Subedi et al. 2013; Halmy et al. 2015; Mondal et al. 2016).

The probabilities for land transformation in 2015 were predicted using the Markov module in IDRISI 17.0 based on the

land use data for 2005 and 2010. The time interval was set to 5. By running the software program, the area transformation matrix for 2005–2010 and the predicted transformation probability matrix were obtained (Fig. 4). In Fig. 4, the red areas represent the land use types with the highest probability of occurrence. When the probability for a certain land use type is higher, there is a higher probability of transformation to that land use type.

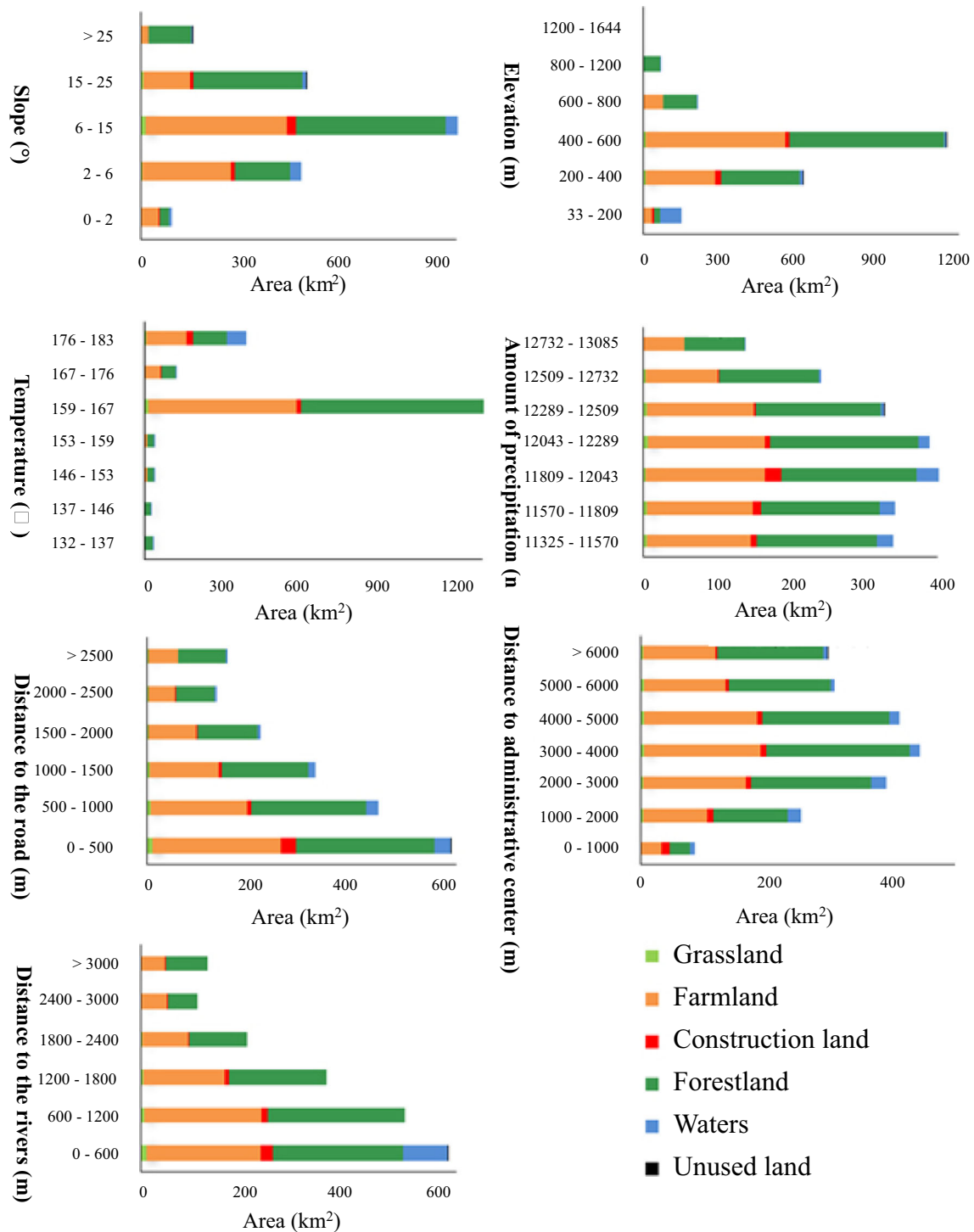


Fig. 3 statistics of land use areas in different driving factors

**WLC–CA–Markov model**

The WLC–CA–Markov model, which is established on the basis of the CA–Markov model, uses the WLC method to establish a collection of land transformation suitability maps to simulate land use. Figure 5 shows the modeling process. The

establishment of a collection of transformation suitability maps is the most important and complex component of the model. Whether the collection of transformation suitability maps is reasonable will affect the simulation accuracy of the model. In the WLC–CA–Markov model, waters are considered restricted areas that cannot be transformed into other land use types. The weights

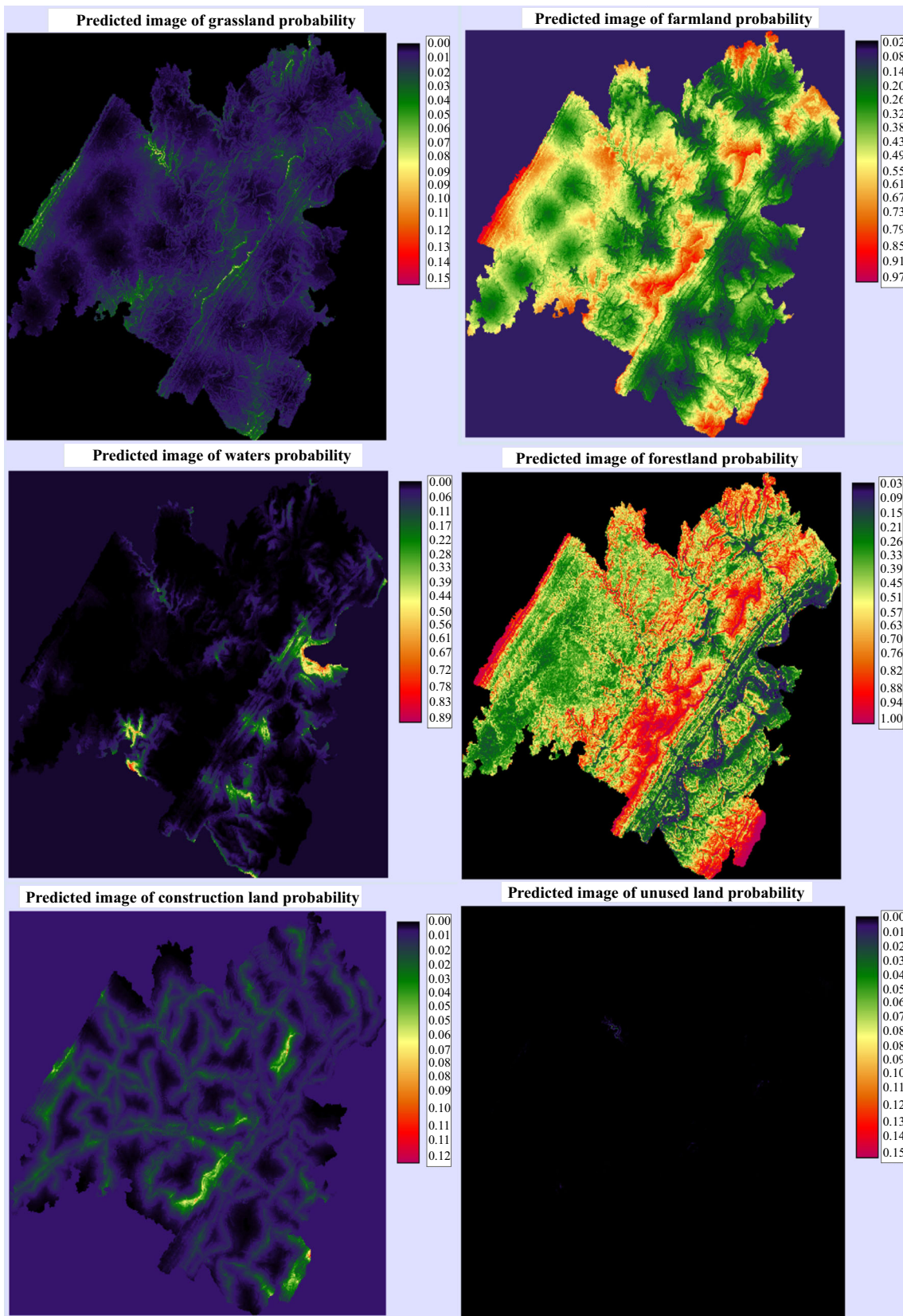
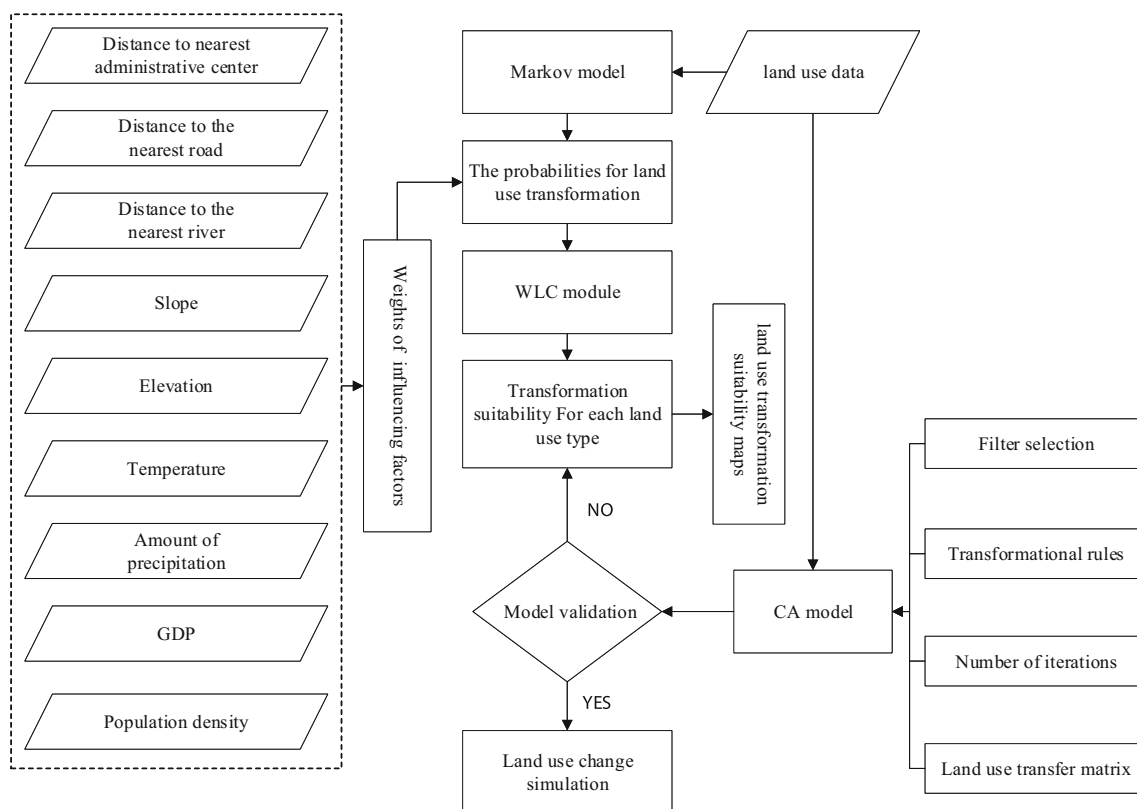


Fig. 4 Probability-of-occurrence of land use change



**Fig. 5** The modeling process of WLC–CA–Markov model

of the nine influencing factors were determined using an analytical hierarchy process (Ying et al. 2007; Kundu et al. 2017). Subsequently, the obtained suitability maps for the six land use types were combined using the Collection Editor Module to form a collection of land use transformation suitability maps (i.e., transformational rules) needed for the CA–Markov model (Fig. 6).

### Logistic–CA–Markov model

The logistic model proposed in this study clarifies the relevance between the land use types and each factor and renders the transformational rules more convincing. The logistic–CA–Markov model established in this study obtains a collection of transformation suitability maps for CA by using the proposed logistic model to fit each land use type to each influencing factor and then uses the Markov model to simulate future land use in Zhongxian. Figure 7 shows the modeling process. The transformation suitability map for each land use type was obtained using the logistic model. The transformational rules for the model were obtained by combining the suitability maps (Fig. 8).

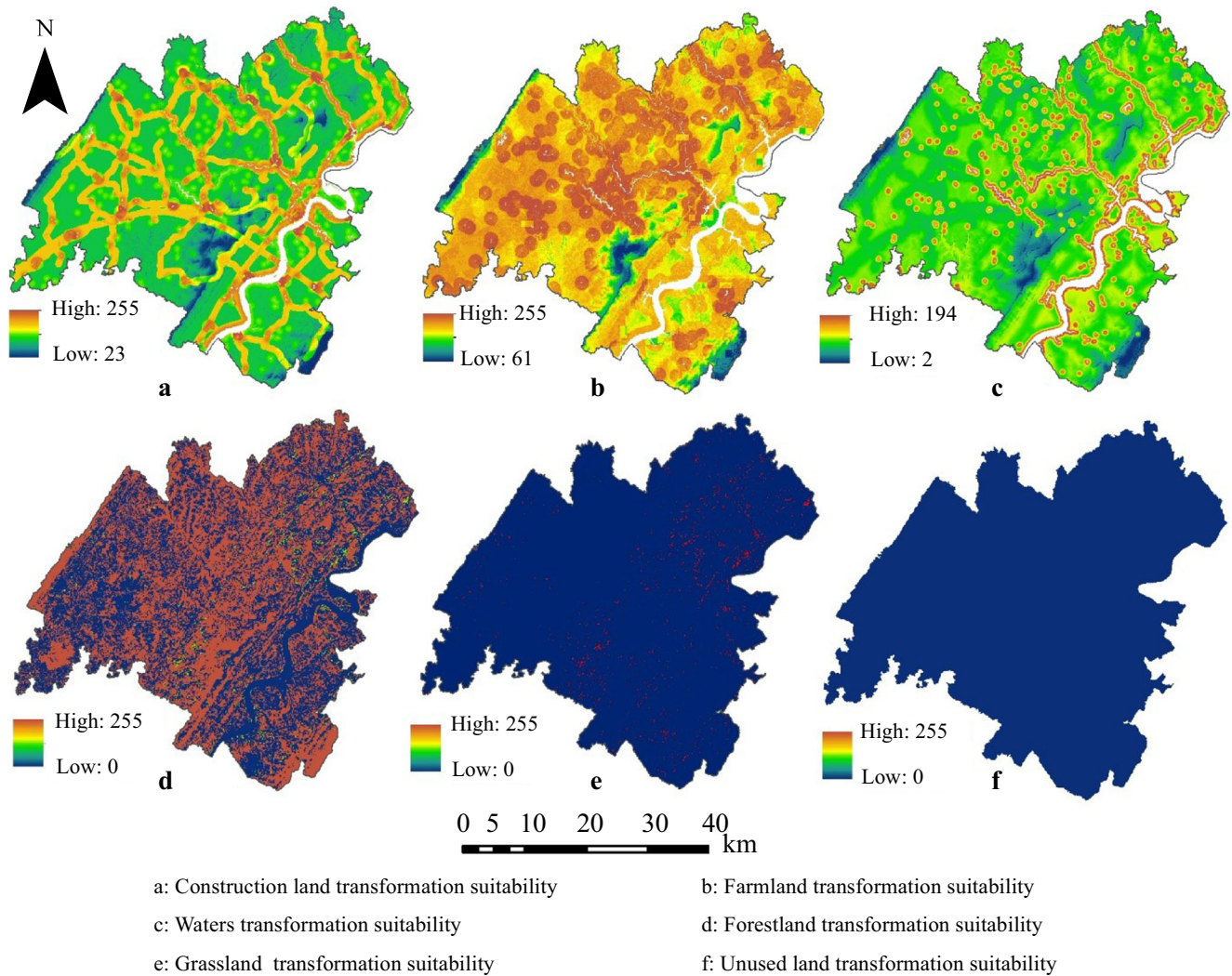
### Model validation and comparison

To examine the accuracy of the WLC–CA–Markov and logistic–CA–Markov models, the land use data for 2015

predicted by the two models were compared with the actual data (Table 1 and Fig. 9). The model validation results show that except for unused land, the difference between the predicted and actual areas of each land use type is less than 6%, suggesting small model errors. The unused land encompasses a small area and is distributed randomly and thus cannot be predicted accurately. The effects of unused land on land use in the whole region are insignificant. Therefore, the difference between the predicted and actual areas of unused land will not affect the evaluation of the quantitative model validation results.

Based on the value of the kappa coefficient, the WLC–CA–Markov model is more accurate than the logistic–CA–Markov model. The errors in the areas predicted by the WLC–CA–Markov model are smaller than those in the areas predicted by the logistic–CA–Markov model. The logistic method used in the logistic–CA–Markov model linearly fits each land use type to each influencing factor and performs a regression on all the factors based on one trend. However, the land use pattern is relatively dispersed. As a result, an overall fit cannot illustrate the relationships between local land use distribution patterns and the factors. The logistic model reflects only the relationship between each factor and each land use type in the entirety of Zhongxian and equalizes multiple local





**Fig. 6** A collection of land use transformation suitability maps based on WLC-CA-Markov model

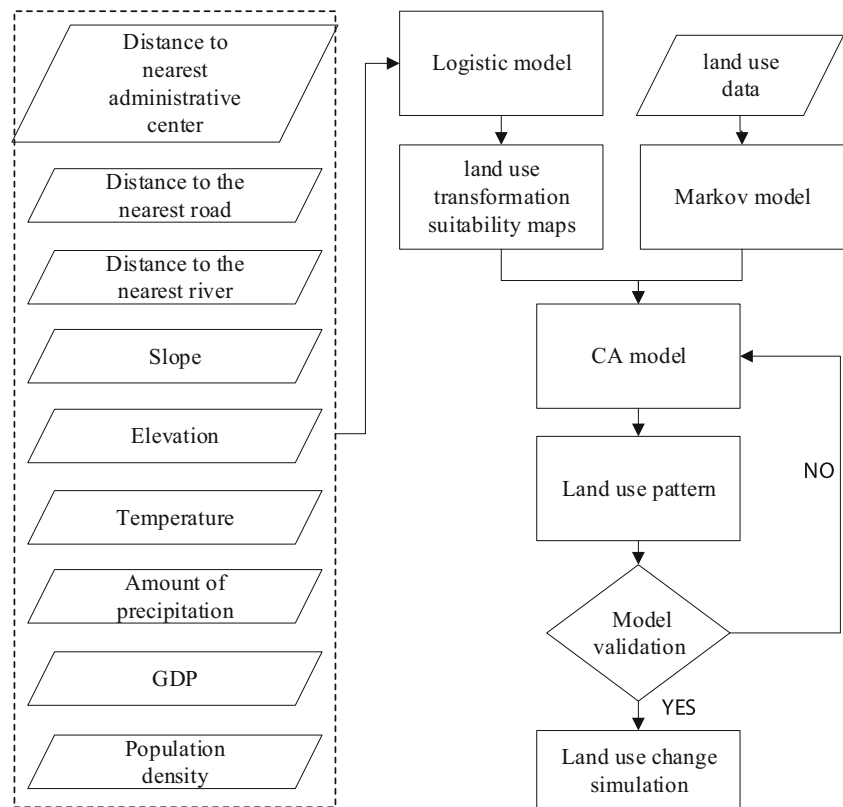
relationships or ignores local impact trends. In addition, it is not easy to add policy-related impacts into the logistic-CA-Markov model, making it difficult to correct the weights of the influencing factors to improve model accuracy. By contrast, based on the distribution of each land use type with respect to each factor in combination with relevant land policies, the WLC-CA-Markov model macroscopically determines the weight of each factor. In addition, in the WLC-CA-Markov model, the formulation of the collection of land use transformation suitability maps is relatively highly adjustable, allowing the model to be combined with the actual conditions and thus rendering the model more scientific, reasonable and consistent with the socioeconomic development trend. By comprehensively considering accuracy and the adjustability of transformational rules, the WLC-CA-Markov model was found to be superior to the logistic-CA-Markov model. Thus, the WLC-CA-Markov model was employed to simulate future land use change scenarios.

## Results

### Land use change in Zhongxian from 1990 to 2015

Construction land in Zhongxian increased rapidly from 8.5237 km<sup>2</sup> in 1990 to 87.3859km<sup>2</sup> in 2015, with an annual growth rate of 9.76% (Fig. 10, Table 2). Waters in Zhongxian increased rapidly from 59.17 km<sup>2</sup> in 1990 to 100.10 km<sup>2</sup> in 2015, with an annual growth rate of 2.13% (Fig. 10, Table 1). Forestland in Zhongxian increased rapidly from 1081.05 km<sup>2</sup> in 1990 to 1112.18 km<sup>2</sup> in 2015, with an annual growth rate of 1.25%. In particular, Unused land in Zhongxian increased rapidly from 2.78 km<sup>2</sup> in 1990 to 0.007 km<sup>2</sup> in 2015, with an annual growth rate of 21.19%. Grassland in Zhongxian increased rapidly from 30.44 km<sup>2</sup> in 1990 to 26.07 km<sup>2</sup> in 2015, with an annual growth rate of 0.62%. Farmland in Zhongxian increased rapidly from 999.72 km<sup>2</sup> in 1990 to 855.92 km<sup>2</sup> in 2015, with an annual growth rate of 0.62%.

**Fig. 7** The modeling process of Logistic-CA-Markov model



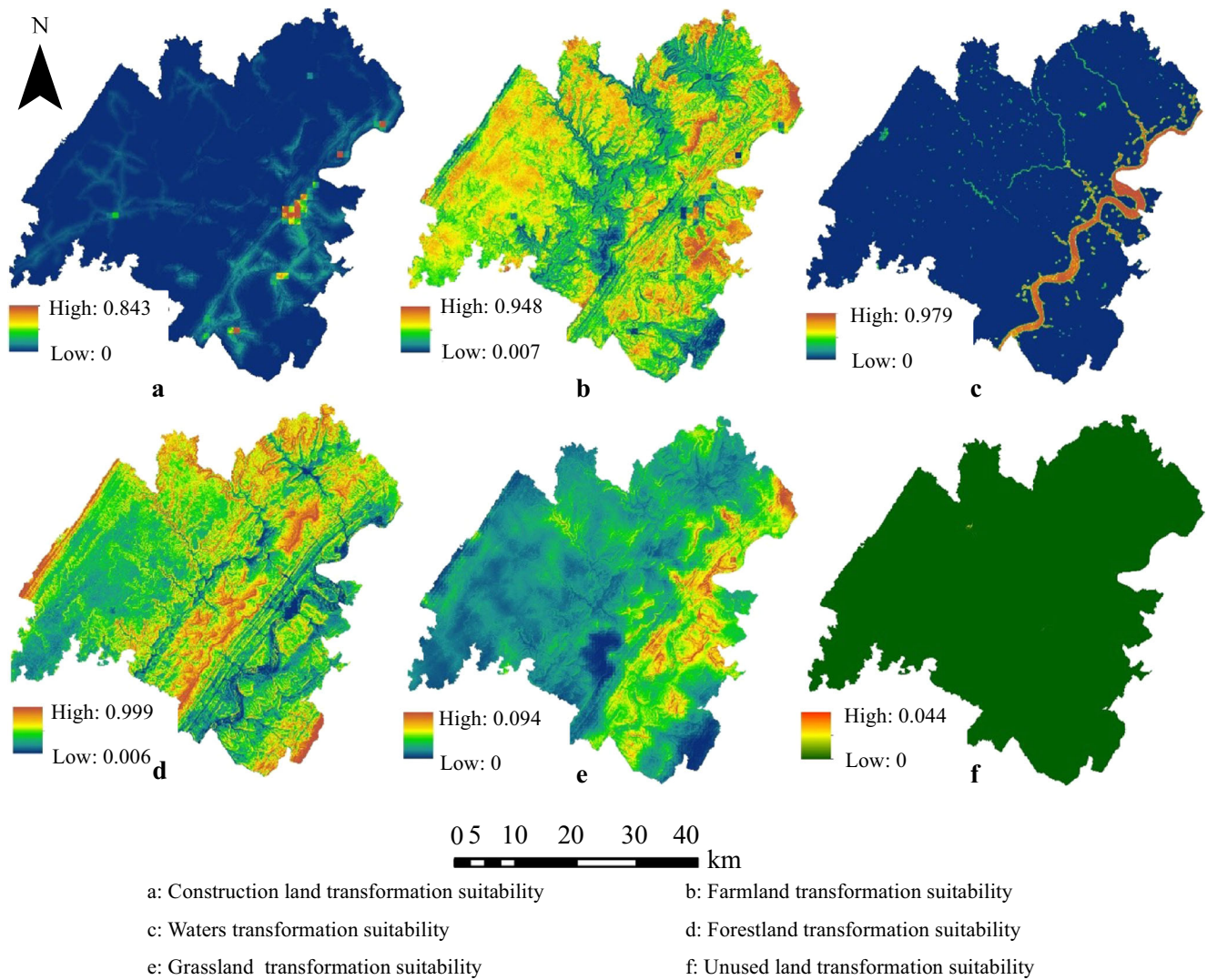
In addition, the six land use type in Zhongxian were undergoing rapid inter transformation (Fig. 11, Table 3). Farmland and forestland were the dominant land use types in the region, and there were relatively intense transformations of farmland to construction land, forestland and waters. Between 1990 and 2015, 53.5169, 125.9994 and 14.2756 km<sup>2</sup> of farmland were transformed to construction land, forestland and waters, respectively. Forestland was mostly transformed to construction land and waters. While no notable quantitative transformations occurred between the remaining land use types, spatially, there were discernible changes in the locations of these land use types. For construction land, a significant increase in its area and an evolution from a central distribution pattern to a dispersed distribution pattern can be observed in Fig. 11. Between 1990 and 2015, the construction land area increased significantly, most of which was a result of transformation from farmland and forestland. In terms of spatial distribution, there was a notable increase in the construction land area on the banks of the Yangtze River, which, overall, was towards the direction away from the waters. Most of the increased construction land was distributed in the townships of Zhongzhou, Wuyang, Xinsheng and Huangjin. Most of the grassland, farmland, construction land, unused land and forestland distributed near the river basin were transformed to waters. This transformation trend was closely linked to the construction of the Three Gorges Dam. The impounding of water in the dam reservoir resulted in an increase in the water levels and the water

surface area. As a result, the nearby land was inundated, and other land use types were transformed to waters.

### Prediction of land use change

Based on the land use data for Zhongxian for 2015, the land use in Zhongxian in 2020, 2025 and 2030 was predicted using the WLC–CA–Markov model to investigate future land use distribution patterns in Zhongxian (Fig. 12).

According to the prediction results, there will be a significant increase in the construction land area between 2020 and 2030, mostly occurring near the main stream of the Yangtze River. As the urbanization process advances, the villages and towns near waters will become relatively highly appealing and have a higher cluster effect. Large numbers of people and enterprises will swarm into these areas, resulting in a further increase in the construction land area. By 2030, there will have been an increase in the construction land area in northern Zhongxian. The expansion of construction land towards northern and central Zhongxian will become an inevitable trend due to socio-economic development. The increase in the construction land area will come from farmland and grassland. The distribution of grassland will be in line with the direction of the Yangtze River. Most of the grassland will be distributed near the river basin. Most of the forestland will be



**Fig. 8** A collection of land use transformation suitability maps based on Logistic-CA-Markov model

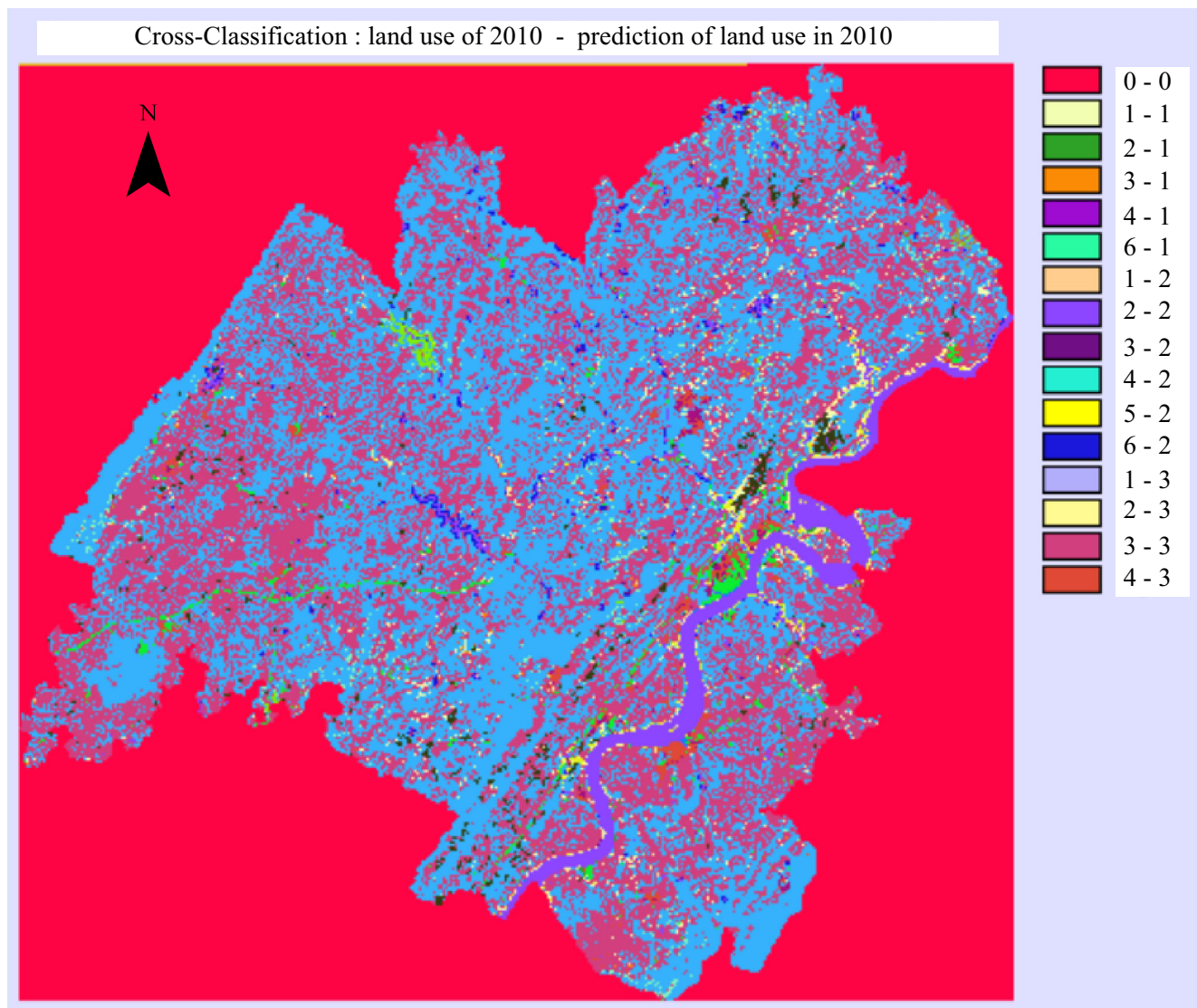
distributed in high-altitude areas in central-western Zhongxian. There will be a relatively balanced distribution of the farmland area. The waters will have a relatively stable area.

Compared to 2015, in 2020, Zhongxian will see an increase of 0.67 km<sup>2</sup> in its grassland area (the increased grassland area

will mostly be distributed in central-southern and eastern Zhongxian), an increase of 21.80 km<sup>2</sup> (annual rate in 2015 and 2010: 4.36 km<sup>2</sup>) in its construction land area, a decrease of 39.57 km<sup>2</sup> in its farmland area (most of the reduction occurs due to transformation to construction land, particularly along the river basin), an increase of 19.90 km<sup>2</sup> in its forestland area,

**Table 1** The model validation results of the WLC-CA-Markov and logistic-CA-Markov models

Land use types	Actual area (km <sup>2</sup> )	WLC-CA-Markov			Logistic-CA-Markov		
		Predicted area(km <sup>2</sup> )	Error range(%)	Kappa index	Predicted area(km <sup>2</sup> )	Error range(%)	Kappa index
Grassland	26.0709	26.9373	3.32	0.9295	27.3153	4.77	0.9027
Waters	100.1039	98.3416	-1.76		119.3516	19.23	
Farmland	855.9245	857.8317	0.22		848.6978	-0.84	
Construction land	87.3858	82.9562	-5.07		80.6183	-7.74	
Unused land	0.0072	0.0096	33.33		0.0141	95.18	
Forestland	1112.1846	1116.632	0.4		1106.717	-0.49	



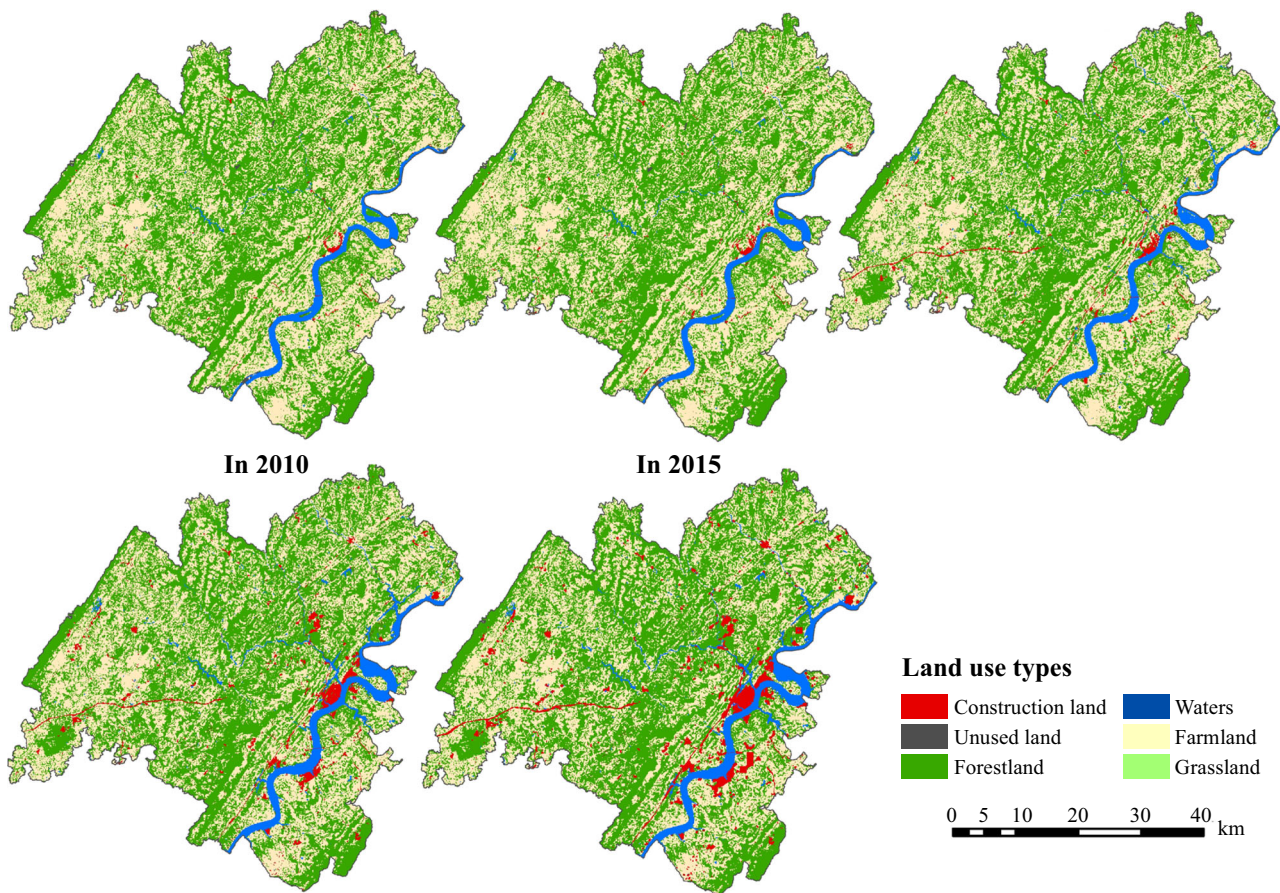
**Fig. 9** Model validation

and an decrease of 1.77 km<sup>2</sup> in the area of its waters. Relatively significant land use changes will occur between 2020 and 2025. Compared to 2020, in 2025, Zhongxian will see a decrease of 0.17 km<sup>2</sup> in its grassland area, an increase of 24.10 km<sup>2</sup> in its construction land, a decrease of 37.91 km<sup>2</sup> in its farmland area, an increase of 14.01 km<sup>2</sup> in its forestland area, and a relatively insignificant change in the areas of its waters and unused land. Compared to 2025, in 2030, Zhongxian will see a continuous decrease in its grassland area, albeit to a relatively small extent, an unchanged area of its waters, a continuous increase of 22.08 km<sup>2</sup> in its construction land area, an increase of 12.54 km<sup>2</sup> in its forestland area, and an unchanged unused land area. Between 2015 and 2030, overall, Zhongxian will see a slight decrease in the areas of its grassland, waters and unused land, increases of 67.99 and 46.44 km<sup>2</sup> in its construction land area and forestland area, respectively, and a decrease of 111.91 km<sup>2</sup> in its farmland

area. The large area of construction land needed for future development in Zhongxian will mostly come from farmland.

### Simulation of land use in various scenarios

Based on the future land use development trend and policy adjustment in Zhongxian, three scenarios are set, namely, a natural development scenario, an ecological protection scenario and a sustainable development scenario. In the natural development scenario, no restrictions are imposed on land use development in Zhongxian; the current socioeconomic development trend and land use evolution pattern are followed, and free transformations between land use types are allowed. In the ecological protection scenario, restrictions are imposed on the transformation of waters, grassland land and forestland within the ecological conservation zones in Zhongxian to construction land, unused land and farmland. In addition, the



**Fig. 10** Spatial distribution of land use type in Zhongxian from 1990 to 2015

distances from construction land to waters are increased to prevent urban development from affecting the ecological environment of the waters. Moreover, the transformation of farmland land to construction land is also slowed. In the sustainable development scenario, consideration is given to both ecological and economic development. Some waters, grassland and forestland can be transformed to construction land,

the transformation of farmland with a slope gradient of 0–6° to other land use types is prohibited, high-quality farmland is protected, the rate of expansion of construction land is controlled, and construction within the construction land control zones is prohibited.

Predictions were made on land use conditions in the three scenarios. Figure 13 shows the land use conditions in

**Table. 2** Land use change in Zhongxian from 1990 to 2015 (km<sup>2</sup>)

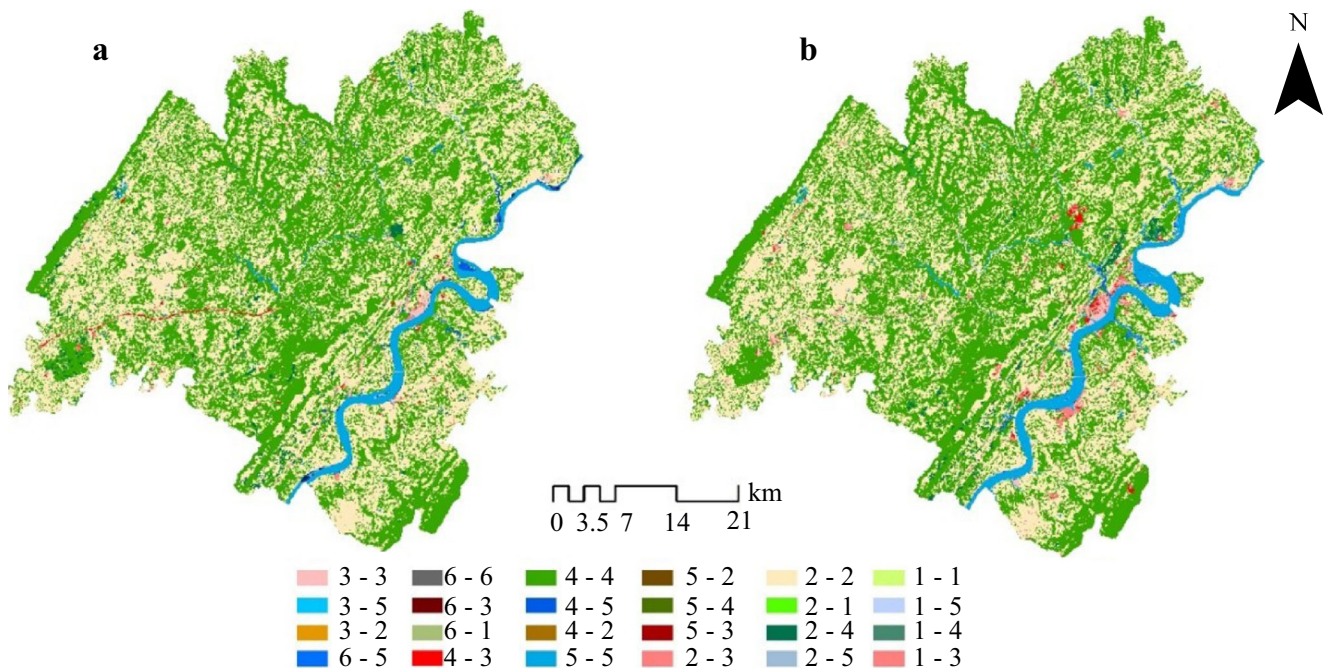
Land use type	Urban land(km <sup>2</sup> )					CAL*	ACL**	ACR***
	1990	2000	2005	2010	2015			
Grassland	30.4525	30.538	28.7943	27.9117	26.0707	-4.3818	-0.1753	-0.6195
Waters	59.2141	59.3422	78.0682	98.5361	100.104	40.8899	1.6356	2.1224
Farmland	1000.194	996.1621	961.5299	903.2711	855.9244	-144.2695	-5.7708	-0.6211
Construction land	8.5323	11.7622	25.6433	54.2981	87.3859	78.8536	3.1541	9.7526
Unused land	2.7791	2.7779	0.0266	0.0144	0.0072	-2.7719	-0.1109	-21.1980
Forestland	1081.738	1082.328	1088.849	1098.88	1112.185	30.4466	1.2179	0.1111

Notes

\*Change area of land use type.

\*\*Annual change of land use type.

\*\*\*Annual change rate of land use type.



**Fig. 11** Temporal and spatial variation of land use in Zhongxian

Zhongxian in 2020 and 2025. Table 4 shows the area of each land use type in each of the three scenarios.

Under the natural development scenario. Compared to 2015, in 2020, Zhongxian will have a grassland area of 26.74 km<sup>2</sup>, a slightly reduced water area, a significantly reduced farmland area (by approximately 40 km<sup>2</sup>) (most of the reduced farmland area will have been transformed to construction land), a most significantly increased construction land area, a slightly reduced unused land area, and an increased forestland area. Between 2020 and 2030, Zhongxian will see the most significant changes in its farmland and construction land areas. The farmland area will decrease at an excessive rate, whereas the construction land area will increase rapidly.

Under the ecological protection scenario. Compared to 2015, in 2020, Zhongxian will have inconspicuously changed areas of grassland and waters, an increased forestland area (by 35.85 km<sup>2</sup>), a reduced farmland area (by 39.94 km<sup>2</sup>) (most of the reduced farmland area will have been transformed to forestland), an increased construction land area (by 5.66 km<sup>2</sup>) (the increase in construction area will have originated from farmland alone), and a slightly increased unused land area. Overall, in the ecological protection scenario, the farmland and forestland areas will have undergone the most significant fluctuations by 2020, primarily due to the implementation of the Returning Farmland to Forestland project. A stable area of waters is favorable to ecological regulation on the banks of the Yangtze River. However, according to this trend, compared to 2020, in 2030, Zhongxian will see a sharp decrease of 45.23 km<sup>2</sup> in its construction land area (the decrease will have occurred near the waters), a decrease of 3.99 km<sup>2</sup> in its

forestland area, and a decrease of 45.23 km<sup>2</sup> in its farmland area. Overall, Zhongxian will see an increase in its ecological land area, indicating environmental improvement. However, a significant expansion of waters will be detrimental to economic development in Zhongxian and pose a threat to production and people's living conditions.

Under the sustainable development scenario. Compared to 2015, in 2020, Zhongxian will see a decrease of 0.56 km<sup>2</sup> in its grassland area, a decrease of 19.75 km<sup>2</sup> in its farmland area, an increase of 10.09 km<sup>2</sup> in its construction land area, and an increase of 15.35 km<sup>2</sup> in its forestland area. Compared to 2020, in 2030, Zhongxian will see an increase, albeit relatively insignificant, of 0.23 km<sup>2</sup> in its grassland area, an increase of 21.96 km<sup>2</sup> in its construction land area, respectively, and a decrease of 40.20 km<sup>2</sup> in its farmland area. Overall, Zhongxian will see the most significant decrease in its farmland area (most of the reduced farmland will have been transformed to construction land and forestland). Most of the increase in construction land area will not have occurred near Zhongxian but instead in the region north of it. The increase in forestland area will facilitate ecological environmental protection.

## Discussion

### The best land use scenario

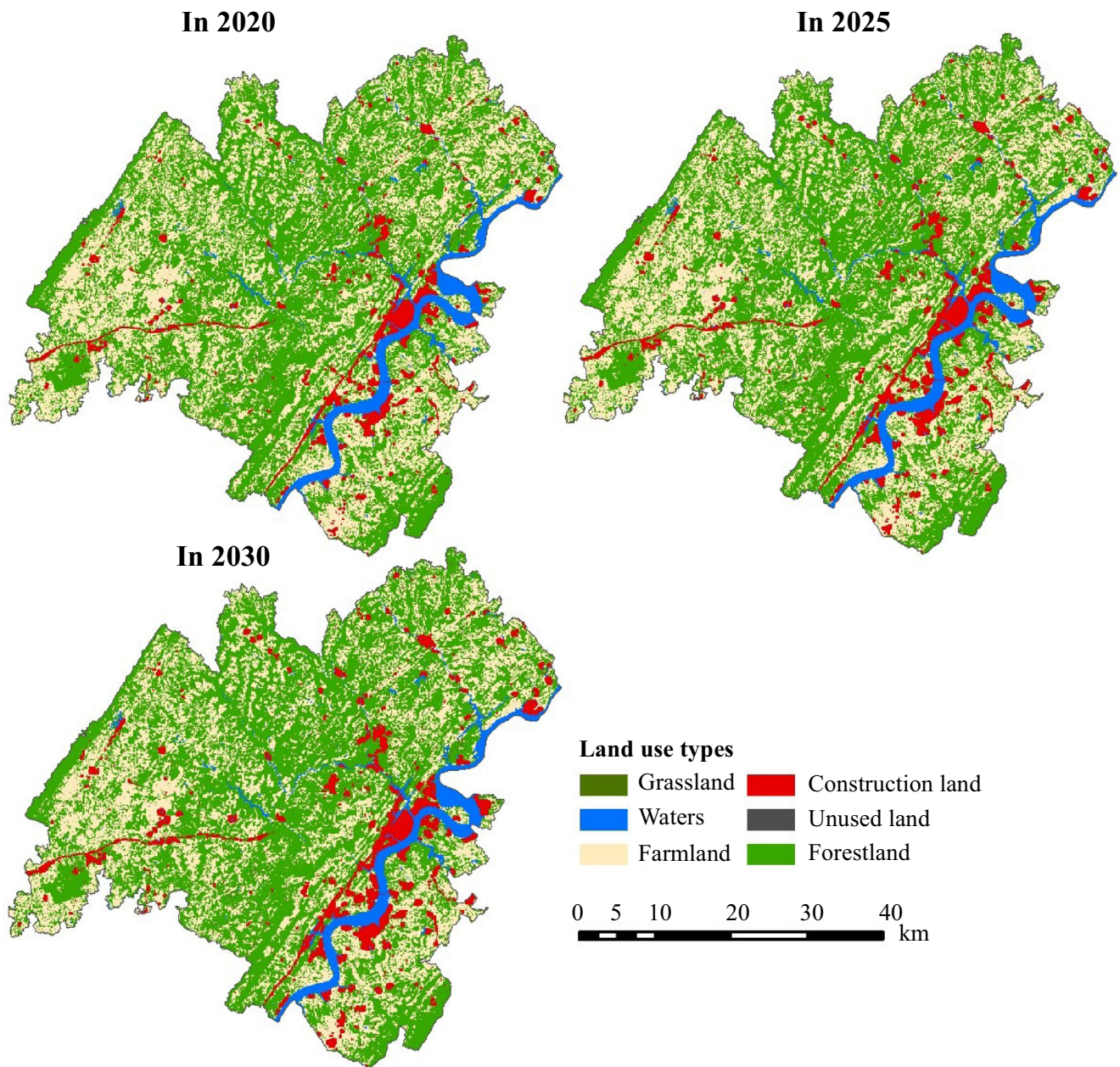
In the natural development scenario, compared to 2015, in 2020, Zhongxian will see a dramatic decrease in the farmland

**Table 3** Transition matrix of land use in Zhongxian from 1990 to 2015 (km<sup>2</sup>)

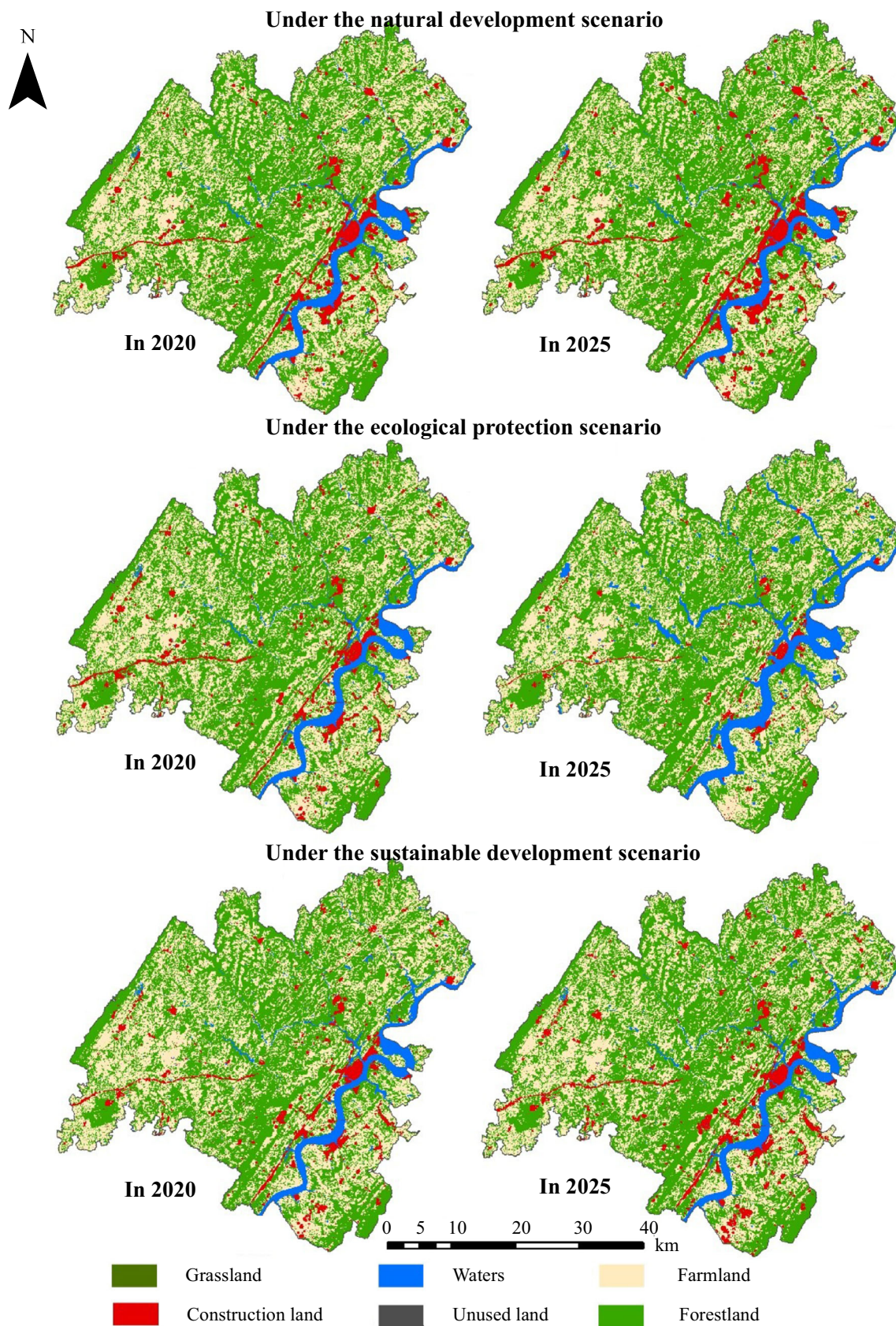
Land use types	Grassland	Waters	Farmland	Construction land	Unused land	Forestland
Grassland	20.7704	1.9867	2.2374	1.1732	0	4.2736
Waters	0.0287	58.6947	0.3162	0.0087	0	0.1217
Farmland	3.9466	14.2756	801.9813	53.5169	0	125.9994
Construction land	0.0025	0.8926	0.0045	7.6207	0	0.0034
Unused land	0	2.1186	0.0062	0.0018	0.0072	0.6423
Forestland	1.3225	22.1359	51.379	25.0646	0	981.1442

area to 816.35 km<sup>2</sup>, which is smaller than the red-line farmland area stipulated in Zhongxian’s *Overall Plan for Land Use*. As a result, grain production will decrease and will not

meet the supply requirement. An imbalance between supply and demand will affect the stability of socioeconomic development in Zhongxian. Although the grassland and forestland



**Fig. 12** Future land use simulation in Zhongxian



**Fig. 13** Land use simulation of various scenarios in Zhongxian



**Table 4** Simulation of land use in three scenarios in Zhongxian in 2020 and 2025(km<sup>2</sup>)

Scenarios	Years	Grassland	Waters	Farmland	Construction land	Unused land	Forestland
Natural development scenario	2020	26.7415	98.3368	816.3542	109.1856	0.0046	1132.0854
	2025	26.5759	98.3127	778.4477	133.2896	0.0006	1146.0859
Ecological protection scenario	2020	25.876	99.7212	815.9831	93.0817	0.0141	1148.0363
	2025	25.2377	162.7262	802.857	47.8549	0.0009	1144.0418
Sustainable development scenario	2020	25.5149	99.998	836.1758	97.4744	0.0141	1127.5376
	2025	25.7466	99.8013	795.9732	119.4326	0.0141	1141.7462

areas will increase, they will decrease over a long-term period of development because they will be occupied by construction land. There will be a significant decrease in the farmland area and an imbalanced ratio of the total farmland area to the population. This trend will lead to rapid socioeconomic development, a dense population along the main stream of the Yangtze River, a deteriorating ecological environment, a reduction of farmland, and a tense man–land relationship; consequently, the trend will be deleterious to sustainable development in Zhongxian as a whole. The ecological environmental

protection scenario focuses on ecological protection, controls construction land, and restricts the development of primary and tertiary industries. In this scenario, population growth will inevitably lead to an excessively high population density in the current construction land zones and will place a heavier load on the urban system, thereby causing problems such as traffic congestion and an adverse urban environment. Increasing the ecological land area will protect the environments of other villages and towns in Zhongxian but will also add, instead of lessen, the pressure on Zhongxian. This

**Table 5** Comparison of different land use simulation models

Study area	Method / Model	Years	Prediction accuracy / Kappa coefficient	Scenarios	Author
Zhong county	Logistic-CA-Markov, WLC -CA-Markov	2015–2030	kappa coefficients: 0.9027 kappa coefficients: 0.9295	(a)Natural development (b)Ecological protection (c)Sustainable development	<b>This study</b>
Sangong watershedin Xinjiang	Combining SD model with CLUE-S model	2004–2030	The values of the kappa statistic are 0.83, 0.84 and 0.81 in 1987, 1998 and 1994	(a)Reference scenario (b)Economic scenario (c)Ecological scenario	Luo et al. (2010)
the Stubai Valley	SPA-LUCC	1973–2003	Overall accuracy: 73%	(a)Continuation of previous LUCC (b)Reduction of use and (c)Diversification of use	Schirpke et al. (2012)
Guangzhou city	Patch-Logistic-CA	2012–2020	Mean pattern-level similarity of 79.66% to actual development patterns	(a)Diffusion scenario (b)Business-as-usual (c)Coalescence scenario	Chen et al. (2014)
Erhai Lake Basin	Agent-based model, ant colony optimization	2010–2020	Maximum accuracy: 78.01%	–	Xu et al. (2015)
Shenzhen city	Monte Carlo approach, CA-ANN model	2004–2020	Overall accuracies: greater than 81.91%, kappa coefficients: greater than 0.71	–	Li and Li (2015)
Dawa County and Liaoning Province	Differential evolution-cellular automata (DE-CA) model	2005–2020	Overall accuracy: 84.56% Kappa coefficient: 0.7860	–	Wang et al. (2015)
Hong Kong	CLUE-S and Markov model	2000–2018	Overall accuracy: 81.53% Kappa coefficient: 0.7753	(a)The baseline scenario (b)The open space scenario (c)The residential scenario (d)The balanced scenario	Zheng et al. (2015)
Foshan city	Markov-logistic-CA	2005–2025	Kappa coefficients: between 0.78 to 0.80	(a)Business as usual (b)New transportation (c)Growth with limits	Han and Jia (2017)
Dongying city	CA-Markov model	1995–2025	Kappa coefficient: 0.61	–	Wang et al. (2018b)
the Ahvaz region of south-west Iran	DoTRules and random forest, CA model	1985–2015	Overall accuracy: DoTRules (75.4%) and random forest (75.8%)	–	Roodposhti et al. (2018)

measure will not be able to attend to both areas. According to this trend, there will be an excessively dense urban population and a poor urban environment in Zhongxian, particularly in Zhongzhou Township. By contrast, other villages and towns will have a vast but sparsely populated area with a pleasant environment and will see a reduction in industrial activity. In addition, these villages and towns will rely heavily on primary industries, have insufficient construction land to attract investment, and derive poor economic benefits from the land. Their gap in economic development from other districts and counties in Chongqing will widen. In the sustainable development scenario, the barycenter of construction land will move northward. In addition, the northern areas will develop the citrus industry vigorously, focus on simultaneous economic and environmental development, protect the core ecological protection zones, and develop some ecological land into construction land and thereby lessen the farmland pressure while ensuring the red-line farmland area in Zhongxian, guaranteeing food security, mitigating the tense man–land relationship, and reducing the environmental pressure. Spatially, there will be a relatively balanced increase in the construction land area in each village and town. As the leader in economic development, Zhongzhou Township will stimulate the coordinated development between the villages and towns and will help narrow the gap between urban and rural areas. The sustainable development model will facilitate future development in Zhongxian.

Here, the three scenarios for Zhongxian are analyzed from the ecological environment and economic development perspectives. In the natural development scenario, Zhongxian considers both ecological environmental protection and economic development. However, the rate of increase in the construction land area is too high, and the extent of decrease in the farmland area is too large. In 2020, the total farmland area in Zhongxian will be smaller than the red-line area and will thus be undesirable for development. The ecological protection scenario focuses only on ecological protection and has no stimulating effect on economic development. The sustainable development scenario strengthens the protection on farmland, particularly basic farm fields; optimizes the agricultural land structure; and protects the ecological environment of Zhongxian. By 2020, the total farmland area will be no smaller than 829.60 km<sup>2</sup>; the scale of urban and rural construction land within the whole county will be controlled within 137.40 km<sup>2</sup>; and the farmland and construction land areas will be 836.18 and 97.48 km<sup>2</sup>, respectively, thus meeting the requirements stipulated in the plan. The sustainable development scenario strictly controls the scale of construction land; focuses on the unified, coordinated development of urban and rural construction land; moves the barycenter of construction land to the northern areas

(which is favorable for the protection of ecological waters in the southeast); and facilitates the integration of collective construction land. Therefore, the sustainable development scenario is the best land use model.

### Comparison of different land use simulation models

Models of land use changes are useful tools for analyzing the driving forces and processes of land use changes, and the decision-making for land use planning. In the past 10 years, researchers have developed many different models of land use simulation depending on their objective and background. But no single model is capable of seizing all crucial processes of land use change at different scales. Each LUCC model has its own potentials and constrains (Luo et al. 2010). Summarized in Table 5 shows the accuracies, study areas, scenarios of land use change simulations conducted by different scholars using various models. All of them are not single, but coupled models, which reflect the updating trend of coupled models in land use simulations. In this study, we determine influencing factors from the aspects of natural topographic and geomorphological conditions, accessibility to economic development and land use expansion, and then establish Logistic-CA-Markov and WLC-CA-Markov models so as to simulate spatial patterns of land use in Zhongxian County. The results illustrate that the WLC-CA-Markov model established here has better controllability and higher simulation precision (the kappa coefficient is 0.9295) than other coupled models. From Table 5 we can find that Han and Jia (2017) also adopted the Logistic-CA-Markov model, but in their simulation results, the kappa coefficient did not exceed 0.8, therefore, we boldly suppose that the difference between the study area and the driving factor could affect the simulation accuracy of the model significantly.

Although our WLC-CA-Markov model has a good overall kappa accuracy in the simulation process, it falls lack of fully reflecting the variety of LUCC in the study area. One reason for this is that land use change is a complex process, and more comprehensive influence factors need to be considered in order to accurately demonstrate the mechanism. In addition, CA models are spatially explicit and temporally dynamic simulation methods, nevertheless, the lack of an ability to access individual characteristics is a limitation when LUCC to be simulated is involved in the integrated systems. In future endeavor, more influence factors and individual characteristics should be considered deliberately.

### Conclusions

There were frequent transformations between various land use types in Zhongxian between 1990 and 2015, particularly between 2005 and 2010, during which time there was a one-fold

increase in the construction land area (most of which originated from farmland), an increase of 20.47 km<sup>2</sup> in the area of waters, an increase in the forestland area (mainly due to the vigorous promotion of the citrus industry), and an increase in the forestland area (due to a change in the agricultural business model), whereas the grassland and unused land areas remained relatively stable.

The WLC–CA–Markov model was found to be notably superior to the logistic–CA–Markov model and was thus employed to predict the land use conditions in Zhongxian in 2020, 2025, and 2030. There are some land use problems in Zhongxian. It is thus necessary to increase the policy interventions on farmland, strengthen land use regulation, improve the market mechanism, and enhance the supervision of land use.

Three scenarios for Zhongxian were analyzed from the ecological environment and economic development perspectives. In the natural development scenario, Zhongxian considers both ecological environmental protection and economic development. However, in this scenario, the rate of increase in the construction land area is too high, and the extent of decrease in the farmland area is too large; by 2020, the total farmland area in Zhongxian will be reduced to below the red line, which will be detrimental to development. The ecological protection scenario focuses on ecological protection and has no stimulating effect on economic development. The sustainable development scenario considers both ecological and economic development and is thus both more suitable for land use development and favorable for future development in Zhongxian.

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