ANN-CA Model Construction under SD Constraint: A Case Study on the Land-use Change Trend in Ya'an City

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Abstract

Land systems are closely related to various factors, including social issues, national economies, natural environments, etc. However, the dynamic evolution simulation of land systems is quite complex. There are many problems in terms of land use in China, such as extensive development, significant regional differences, and imbalanced development. From this perspective, it is imperative to study systematic land use evolution according to local contexts. In this study, two methods that are commonly used to solve complexity issues— “top-down” system dynamics and “bottom-up” cellular automata—were combined to investigate the land use evolutionary trend in Ya’an City. Firstly, a system dynamics model of land resource use was constructed based on the causal relationship between land and macroscopic elements, and the quantitative future predictions of land use structures in Ya’an were obtained. Next, an ANN-CA model containing three steps—artificial neural network training, optimization of cellular automata parameters, and model calibration—was constructed. The land use scenario in Ya’an City in 2018 was simulated and the quantity and space accuracy verification were conducted. Finally, the spatial layout of land use in Ya’an City in 2028 and 2038 was predicted, and the land use evolution trend was studied using the model under the constraint of the quantitative prediction results of system dynamics. The results demonstrated the good simulation effect of the ANN-CA model under the SD constraint. The overall simulation accuracy of the model is the highest (93.93%) when the threshold of transformation is 0.8 and the diffusion coefficient is 1. In the future, the spatial distribution of different land types in Ya’an City will change slightly, and construction land presents an expansion law from the center to surrounding areas.

1. Introduction

Land use is an important link between human socioeconomics and natural environmental evolution. Land use changes reflect the various activities of human beings, climate change, and ecological environmental changes, to a large extent. Humans’ understanding of land use changes has significantly developed in recent years (Aurélien et al.2012; Deng X.2011). Studies on land use have received further impetus since two large international organizations (IGBP and IHDP) have promoted research plans on “land use/coverage changes” in 1995. Currently, Chinese scholars have mainly investigated land use by using different research methods according to different research objectives of dynamic change analysis, the driving mechanism, and simulation predictions (Zhao et al.2016). With improving analyses on dynamic changes and studies on their driving mechanisms, the simulation of land use changes has developed rapidly. The relevant technological means have also become increasingly mature. Methods to simulate land use changes have developed from the earliest quantitative methods, which simply predict land use demand, to current spatial methods that simulate and rebuild the spatial layout of land use (Qian et al.2020).

Quantitative methods generally include system dynamics (SD), gray models (GMs), Markov models (Markov), artificial neural networks (ANNs), and the computable general equilibrium of land use change (CGELUC) (Rasmussen et al.2012; Liu et al.2021; Silburn et al. 2011; Al-Shaar et al. 2021; Lpes et al. 2020). Relevant studies have demonstrated that the abovementioned methods mainly build models based on historical experience, during which the model has to be calibrated continuously to achieve high-accuracy prediction results (Koko et al. 2020). In comparison to other methods, the SD model is applicable to many fields of study. It can not only predict land use demand in a region, but also understand the feedback mechanism in the system, which is remarkably advantageous (Xu and Luo 2018). In contrast to quantitative methods, spatial methods focus more on the prediction of the spatial structural layout of land use (Park et al.2011). Common spatial methods include the change of land use and effect (CLUE) model, dynamics of land system (DLS) model, cellular automata (CA) model, and multi-agent (MAS) model (Wang et al. 2019; Jin et al.2019; Almeida et al.2008; Xu et al. 2020). Among them, CA has proven to be an effective and convenient means to simulate urban dynamics and land use change. As a high-resolution microscale spatial dynamic model, the geographical CA model can easily be integrated with GIS spatial data and can reflect dynamic changes in spaces directly (Espíndola et al. 2021).

In terms of land use, cellular automata have been used to determine the model structure, set the transformation rules, and couple different models. White et al. built a CA rational model structure to understand urban land expansion evolution (White and Engelen 1994). Li et al. discussed how to integrate CA with GIS and geographic information systems in cities and farmlands (Li and Yeh 2000). Transformational rules are the core of CA modeling; initially, the transformation rules for CA were set according to experience, as was the case with CLUE-S. Subsequently, CA was coupled with other methods to simplify the definitions of the complex transformation rules. For example, Li and Yeh introduced principal component analysis and neural networks into CA modeling in 2002 (Yeh and Li 2002; Li et al. 2002). Later, they guided teams to continue to investigate CA modeling and established the theory of geographical simulation systems. Subsequently, they even coupled logic regression methods, decision trees, and CA, designing the geographical simulation optimization system (GeoSOS) and publishing an open-source version of the software in 2018. This software has been extensively used by scholars worldwide (Li et al.2011). Moreover, Liu Xiaoping et al. added the ant colony algorithm, artificial immune system, system dynamics, mixed particles, and double-integrated Kalman filter into the CA model (Liu et al.2008; Liu et al.2010; Huang et al.2013 Liu et al.2012; Ai L B 2013; Liu et al. 2015; Liu et al. 2017).

The issue of land use change is multi-disciplinary. Not only do human activity elements such as society, humanity, economy, and industrial structure have to be considered, but natural elements like the terrain and environment must also be accounted for. Therefore, it can be viewed as a complex systems engineering problem (Gao et al. 2021; Zhao et al. 2022). Therefore, this study combined two representative methods for addressing processing complexity, namely, the “top-down” system dynamics (SD) method, which describes variables from the objective level, and the “bottom-up” cellular automata (CA) method, which facilitates dynamic evolution from the framework of methods. In this process, artificial neural networks were added to simplify the transformation rules of CA, and a model was constructed to explore the land use evolutionary trend in the study area. The constructed model can not only couple macroscopic factors and microscopic factors, which influence land use changes, but also unify the quantity level and spatial level in the prediction method. It forms a basis to further understand relevant theory and supplements current research on land use.

2. Study area and data preparation

2.1 Study area

Ya’an City is a prefecture-level city in Sichuan Province and it is long from the south to north (about 220 km), but short from east to west (about 70 km). It has two municipal districts (Yucheng District and Mingshan District) and six counties (Xingjing County, Hanyuan County, Shimian County, Tianquan County, Lushan County, and Baoxing County). It covers an area of 15 046 km^2. Ya’an City is widely known as the “City of Rain”, “the throat of Western Sichuan”, “the gate of Tibet”, “the corridor of nationality”, the “lung of heaven”, and the “hometown of the panda”. Hence, it is important to study Ya’an City, the location of which is shown in Fig. 1.

2.2 Data preparation

This study requires two types of data: numerical data and geospatial information data (Table 1). To guarantee the operability of the model, spatial data was used as the standard for uniform environmental settings, and the vector data was transformed into raster data using the face transformation raster tool. The coordinate system was unified as WGS_1984_UTM_Zone_48N using the projection raster tool; the pixel size of all spatial data was set as 90 m using the resampling tool. The numbers of rows and columns of the raster data were unified using the clipping tool. To ensure ArcGIS and MATLAB data compatibility, making it convenient for the loose coupling development of the model, the raster format was further transformed into ASCII-GRID format.

Table 1
Abstraction of the dataset

Data	Criteria	Time	Description	Source	Format/resolution
Remote sensing images	Land use data	1998 2008 2018	Three phases of graphic data regarding land use status through interpretation of remote sensing images	Geospatial data cloud (http://www.gscloud.cn/search)	Raster, 30 m
DEM	Elevation Slope Aspect	2018	Slope and aspect were acquired through the 3D analysis of DEM, which are used as the constraints of the model	Geospatial data cloud (http://www.gscloud.cn/search)	Raster, 30 m
Road map	Distance to the road	2020	The arterial road map was acquired as a constraint of the model	Open Street Map (https://www.openstreetmap.org/)	Shapefile (line)
River chart	Distance to the river	2020	The major river chart was acquired as a constraint of the model	Open Street Map (https://www.openstreetmap.org/)	Shapefile (line)
Residential areas	Distance to the cities Distance to towns	2020	Major cities and towns were acquired as rated constraints of the model	Open Street Map (https://www.openstreetmap.org/)	Shapefile (point)
Natural reserve		2020	Used as the constraint of the model	The World Database on Protected Areas (WDPA)	Shapefile (polygon)
Administrative map		2020	Running boundary of the model	BIGEMAP software	Shapefile (polygon)
Data of influencing factors		1999–2018	Input data of the SD model	Statistical Yearbook of Ya'an City Statistical Yearbook of Sichuan Province	PDF

The data processing of land use status includes image mosaicking and clipping, radiation calibration, and monitoring classification. The land in Ya'an City was divided into six land use types, including cultivated land, forest land, grass land, water surface, construction land, and other land. The chart of ultimate land use status in Ya'an City in three phases is shown in Fig. 2.

Influencing factor data of land use spaces in Ya'an City was acquired through the ArcGIS spatial analytical method. The slope and aspect processing of DEM data were performed using a 3D analysis tool, yielding the influencing factor map of the slope and aspect. The Euclidean distances in the distribution maps of roads, rivers, and administrative centers were calculated using the spatial analysis tool, thus yielding the corresponding influencing factor maps. The influencing factors of the DEM, slopes, aspects, roads, rivers, and administrative centers were normalized by using fuzzy membership tools to make numerical values distribute within the range of [0,1]. As a result, six types of influencing factor data were acquired (Fig. 3).

3. Model

3.1 Construction and simulation of the SD model

In this study, the causal feedback relationships among variables related to society, economy, and land use were analyzed from the perspective of the system. According to the land use change mechanism, an SD model that aims at the simulation and prediction of future land use demand in Ya'an City was constructed. The model boundaries include the time boundary and spatial boundary. The time boundary for model simulation is from 1999 to 2038. Specifically, years from 1999 to 2018 were historical data years, while years from 2019 to 2038 were prediction years. To decrease the error caused by period changes during prediction, the time step length was set to 1 year. The spatial boundary for model simulation was the administrative regions in Ya'an City, Sichuan Province.

The construction and simulation processes of land use by the SD model in Ya'an City include drawing the stock flow chart, establishment of system equations, verification of model validity, and model prediction. The stock-flow chart was the structural chart of model operation (Fig. 4). The system equation was mainly constructed according to logic relations among variables and statistical data laws. Verification of model validity included model mechanism tests, model history tests, and sensitivity analyses. Passing the verification of the model validity proves the reasonability and feasibility of model operation. In this study, model prediction involves predicting data in Ya'an City in the prediction years based on data from historical years. This is done to obtain the land use demands of different types in Ya'an City in 2028 and 2038, which are used as the quantitative constraints in the follow-up simulation process of the constructed ANN-CA model.

3.2 Construction and simulation of the ANN-CA model

3.2.1 Artificial neural network training

In this study, a three-layer BP neural network that contains a single hidden layer structure of 13-10-6 was built. Specifically, 13 neurons are present in the input layer, which correspond to six spatial influencing factor variables (DEM, slope, aspect, road, river, and administrative center), standardized statistical information of percentages of six land use types in neighbor regions (cultivated land, forest land, grass land, water surface, construction land, and other land), as well as the land use types of the current cells; 10 is the number of neurons in the hidden layer; 6 is the number of neurons in the output layer, which correspond to the transformation probability of 6 land use types. Here, the neighbor region used the expanded Moore-type neighbor type of $r = 3$ and cells used the raster grids with a resolution of 90 m×90 m.

The land use status in Ya'an City in 1998 and 2008 and binary data of spatial influencing factor charts were input into the model. Based on land use classification data in 1998, 5% of cells (raster) were randomly selected. The corresponding data of the input layer and output layer, a total of 92,924 sample data points, were input into the neural network model. The input layer data includes statistical information on cell/raster land use types in 1998 (1 item) and cell/raster land use types in neighboring regions in 1998 (6 items), which correspond to the data on spatial influencing factors (6 items). The data of the output layer corresponds to cell/raster land use types in 2008. Among these sample data, 80% and 20% were chosen as the training set and verification set of the neural network, respectively. The e-learning rate was set to 0.05 and the iterations were 200. A neural network model was constructed, and sample data was input for training the neural network. The neural network training accuracy is shown in Fig. 5. The training error of the model is 0.07898 when the iterations are 200. The accuracy of the training dataset reaches as high as 93.991%, and the accuracy of the verification set reaches as high as 93.855%, realizing the network training goal. This reflects that the neural network model in this study has a relatively high degree of fitting, and it can be coupled with CA for the subsequent land use simulation.

3.2.2 Setting of CA parameters

Based on the trained neural network model, relevant CA parameters were set to simulate the land use scenario in Ya'an City in 2018. In the specific simulation process, the land use status in Ya'an City in 2008 has to be input first and used as the land use data in the first year of the simulation. Moreover, the chart of the land use status in 2018 has to be input as the real land use data of the terminal year. The data for the final year serves two purposes: one is to set the total transformation quantity of model simulation. The quantity difference of urban land use raster in the land use data in the terminal year and the first year was used as the total transformation quantity for model simulation, which was calculated to be 6885. The other is to analyze simulation results. The simulation results and real data were compared to analyze whether the setting of the model parameters was reasonable.

Secondly, model parameters related to the transformation rules of cells must be set. The transformation rules of CA involve comparing the transformation probability of cells (θ) and the transformation threshold (η). Transformation was considered to be performed when $\theta \geq \eta$; no transformation was performed when $\theta < \eta$. The threshold of transformation ranges within [0,1]. Therefore, the cell state (land use types of raster) is more difficult to transform when the threshold of transformation is set higher. The calculation formula for θ is

$$\theta = f(\gamma) * \beta_{ann} * \rho * \Phi \ 1$$

where $f(\gamma)$ is the random disturbance function, where the diffusion coefficient (γ) is used as the independent variable and ranges within [1,10]. β_{ann} is the transformation probability calculated by the artificial neural network. ρ is the urban land use density in the cell neighbor window. Φ is the suitability of transformation.

Based on an analysis of the practical situation of land use transformation in Ya'an City, the setting of the suitability matrix for land use transformation in Ya'an City is shown in Table 2. The numerical values in the transformation suitability matrix are set to 0 or 1, where 0 represents that the land use type cannot be transformed into another land use type, while 1 represents that the given land use type can be transformed into another land use type.

Table 2
Matrix of transformation suitability

	Cultivated land	Forest land	Grass land	Water surface	Construction land	Other land
Cultivated land	1	1	1	1	1	0
Forest land	1	1	1	1	1	1
Grass land	1	1	1	1	1	1
Water surface	0	0	0	1	1	0
Construction land	0	0	0	0	1	0
Other land	0	0	0	0	0	1

The simulation of land use scenarios in 2018 showed that the values of η and γ in the model have significant influences on the ultimate operation results. The ranges of η and γ with relatively high fitting accuracy were chosen through the research process. Four different parameter combinations were set (η=0.8, γ=1; η=0.8, γ=2; η=0.9, γ=1; η=0.9, γ=1) to simulate land use scenarios in Ya’an City in 2018. The iterations were set to 50. The model operation results under different parameter combinations are shown in Fig. 6.

The overall accuracy of the simulation results under four parameter combination values were 93.93%, 92.91%, 93.56%, and 92.90%, respectively. The simulation accuracy under the first parameter combination is the highest. Hence, the threshold of transformation was set to 0.8 and the diffusion coefficient was set to 1 for subsequent analysis.

3.2.3 Model calibration and output of simulation results

The ANN-CA model in this study requires artificial neural network training, the optimization of CA parameters, and model calibration. To understand the land use evolutionary trend of different land use types in Ya’an City adequately and prevent abnormal offsets of the spatial centers of different land use types during simulation, the model was calibrated by using the spatial center migration analytical method, which is a relatively commonly used method in physics.

The land use scenario in Ya’an City in 2018 was simulated based on the neural network model built according to data on land use and spatial influencing factors in 1998 and 2008, as well as the CA model built according to land use data in 2008 and 2018, along with relevant parameter settings. The simulation results of land use in 2018 were output. The actual land use data in Ya’an City in 2008 and spatial centers of different land use types (cultivated land, forest land, grass land, water surface, construction land, and other land) in 2018 were calculated by using the average center tool in the spatial statistical toolkit. When a significant error is present between the calculated and simulated results for the actual center of a land use type, the parameters are modified appropriately; further, the processes in Section 3.2.1 and Section 3.2.2 were repeated until the error was within a permissible offset range. The model was calibrated according to land use simulation results in Ya’an City in 2018 (Fig. 7).

3.2.4 Verification of model accuracy

(1) Verification of quantitative accuracy

The accuracy-error test method was applied to the simulation results at a quantitative level. The accuracy-error test formula is

$$P = \frac{W_{ir} - W_{it}}{W_{ir}} \quad 2$$

where P is the error accuracy of the land use type i. W_{ir} and W_{it} are the actual number of rasters and the simulated number of rasters of the land use type i. When $\mathrm{P} > 0$, the actual area of the land use type i is larger than the simulation area. When $\mathrm{P} < 0$, the actual area of the land use type i is smaller than the simulation area. The simulation accuracy is positively related to the absolute value of P.

The error accuracy of land use simulation results in 2018 was calculated using the accuracy-error test method, where the pixel size of grids was 90 m. The calculation results are shown in Table 3. It can be seen from Table 3 that the simulation errors of all land use types in Ya'an City in 2018 were lower than 10%, except water surfaces. Hence, it can be preliminarily determined from the quantitative accuracy verification that the ANN-CA model can predict land use in 2018 well.

Table 3
Simulation errors of land use types in Ya'an City in 2018

	Cultivated land	**Forest land**	**Grass land**	**Water surface**	**Construction land**	**Other land**
Actual number of raster	185868	1403516	233992	11520	18986	3159
Simulation number of raster	190987	1404623	234522	10013	18951	3145
$\lvert\mathrm{p}\rvert$	2.75%	0.08%	0.23%	13.08%	0.18%	0.44%
(2) Verification of spatial accuracy						

The verification of spatial accuracy mainly utilized the spatial center migration analytical method, which was used in the model calibration. The calculated results of actual and simulated spatial centers of construction land, cultivated land, forest land, and grass land in Ya'an City in 2018 are shown in Fig. 8. Clearly, the actual and simulation centers of these four land use types differ slightly in terms of spatial location. Therefore, the simulation results of land use in Ya'an City in 2018 have good performances for the verification of spatial accuracy.

4. Land use evolutionary trend in the study area

In this section, the ANN-CA model that passed the accuracy verification was used to simulate and predict the land use scenario in Ya'an City in the future, facilitating the analysis of the future land use evolutionary trend in the study area. Firstly, a hypothesis was proposed for the model, and simulation was performed under the premise of no significant changes in humanity, society, economy, and nature. Secondly, constraints against model operation were set and the ecological factor chart of Ya'an City was input into the model. A constraint that the land use types within the scope of a natural reserve are prohibited for transformation into construction land and cultivated land was set to protect the ecological environment in Ya'an City. Thirdly, the data of spatial influencing factors was input, and the neural network model was constructed based on land use data in 2008 and 2018 for training and extracting relevant laws. The CA parameters were set to simulate and predict land use situations in Ya'an City in 2028; the model was calibrated spatially and quantitatively. The offset between the calculated actual spatial centers of different land use types in 2018 and the calculated simulation space centers in 2028 was within the allowable range. Moreover, the land use prediction results in Ya'an City in 2028 were output when the errors between the quantitative prediction area based on the SD model and the simulation areas based on the ANN-CA model of four land use types (cultivated land, construction land, forest land, and grass land) in 2028 were lower than ± 5%. Finally, data of the spatial influencing factors, actual land use data in 2018 and simulated land use data in 2028, which were output in the previous step, were input into the model. A neural network model was constructed and trained to extract relevant laws. CA parameters were set to simulate and predict land use scenarios in Ya'an City in 2038. The model was calibrated spatially and quantitatively. The land use prediction results in Ya'an City in 2039 were output when the offset between the calculated spatial centers of different land use types in 2028 and 2038 was within the allowable range, and the error range between the quantitative prediction area based on the SD model and the simulation areas based on ANN-CA model of four land use types (cultivated land, construction land, forest land, and grass land) in 2038 was lower than ± 5%. The land use prediction results in 2028 and 2038 are shown in Fig. 9.

The system model in this study also simulated and predicted the evolution of urban construction land in Ya'an City. Urban construction land includes urban industrial land, urban tertiary industrial land, urban residential land, urban road and traffic facility land, and others. These urban construction land types increased from 851, 818, 989, 900, and 543 ha. in 2019 to 1870, 2872, 1053, 1552, and 1700 ha. in 2038, respectively. The area of urban tertiary industrial land in 2038 will be the largest, which agrees well with the predicted tertiary industrial development in 2038. The land use prediction results in 2038 are shown in Fig. 10–12. The prediction of different land use types in urban construction land can provide some references for urban development planning and policy formulation in Ya'an City.

The actual land use status in Ya'an City in 2018 was compared with land use simulation results in 2028 and 2038. It can be seen that the spatial location distributions of different land use types change slightly, indicating that the spatial center migration analytical method can calibrate the model very well. The prediction results of four land use types in Ya'an City in 2028 and 2038 based on the SD model were compared with simulation results based on the ANN-CA model, and the error was calculated. The results are shown in Table 4. Obviously, under the constraint of calculated results based on the SD model, the absolute error between simulation results based on the ANN-CA model and the predicted area based on the SD model of cultivated land, construction land, forest land, and grass land was lower than 5% in both 2028 and 2038.

Table 4
Prediction errors of land use areas in Ya'an City in 2028 and 2038

Years	**2028**			**2038**		
Land use types	SD (hectare)	ANN-CA (hectare)	|error| (%)	SD (hectare)	ANN-CA (hectare)	|error| (%)
Cultivated land	50661	52204	3.05%	51809	53014	2.27%
Construction land	16488	16750	1.59%	22806	23097	1.26%
Forest land	570353	551341	3.33%	603948	596583	1.23%
Grass land	39382	41032	4.19%	39699	41513	4.37%

For better observation of the construction land expansion trend in Ya'an City, the construction land was extracted from the land use simulation results in 2028 and 2038 based on the chart of the land use status in 2018. The construction lands were stacked from top to bottom in 2018, 2028, and 2038, the results of which are shown in Fig. 13.

In Fig. 13, the yellow region represents the construction land area in Ya'an City in 2018, the blue region represents the construction land expansion area from 2018 to 2028, and the red region represents the construction land expansion area from 2028 to 2038. It is clear that the construction land in the central and eastern regions (Tianquan County, Lushan County, Yucheng County, and Mingshan District) and southern regions (Hanyuan County) expanded significantly. The regions with great expansion of construction land are mainly distributed along rivers and roads, fully reflecting the driving and radiation effect of roads and rivers on urban construction in Ya'an City. To inform decisions regarding the traffic road network in Ya'an City, attention was paid to providing theoretical references for the implementation of policies like water resource management and protection. Generally, the construction land in Ya'an City presented a law of expansion from the center to surrounding areas, which was consistent with the open development pattern of "Four-way expansion" proposed by Ya'an City during the 13th Five-year plan. This confirms that the simulated evolutionary results of the ANN-CA model under the SD constraint are relatively accurate and reasonable. They can provide planning departments with reliable references to formulate related policies.

5. Conclusions

In this study, SD and CA, which are common methods to solve complexity problems, are combined to construct a model that simulates the land use evolutionary trend in Ya'an City. Results demonstrate that (1) when setting the CA parameters, under four parameter combinations with relatively high accuracy of fitting, the overall simulation accuracy of the model is the highest when the threshold of transformation is 0.8 and the diffusion coefficient is 1, reaching 93.93%. (2) When verifying the simulation accuracy, it can be seen from the collaborative analysis of the verification of quantitative and spatial accuracy that the ANN-CA model achieves relatively good simulation results. (3) It is found, by studying the land use evolutionary trend in the study area, that the construction land in Ya'an City from 2018 to 2038 presents an expansion law from the center to surrounding areas, which agrees well with the open development pattern of "Four-way expansion" in the study area. This confirms that the simulated evolutionary results of the ANN-CA model under the SD constraint can provide planning departments with reliable information to formulate related policies.

In this study, an ANN-CA model under the SD constraint is built and used to predict the spatial evolution of land use in Ya'an City. Although this study has achieved significant results in terms of model construction and simulation, there is still space for further improvement: (1) Influencing factors of different levels, including population, economy, terrain, river, road, and ecological factors, are used; the land use change laws of the study area are extracted; and the spatial simulation of the model is constrained. As a result, the simulation results of the ANN-CA model reach the expected effect. However, this study ignores some other factors that influence land use changes, such as climate, policy, and regulations. These variables should be integrated into the model in the future. (2) This study focuses on providing a tool to study the dynamic changes in land use and investigates the prediction and simulation of land use changes in Ya'an City. However, the prediction content has not been analyzed thoroughly. In the future, land use changes in Ya'an City should be simulated under different scenarios.

Declarations

Data availability statement

Data and code will be made available on reasonable request.

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Conflict of interest disclosure

There is no conflict of interest associated with this research work.

Ethics approval statement

This article does not contain any studies with human participants performed by any of the authors.

Declaration of competing interest

The author declares that there is no conflict of interest associated with the research work.

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Figures

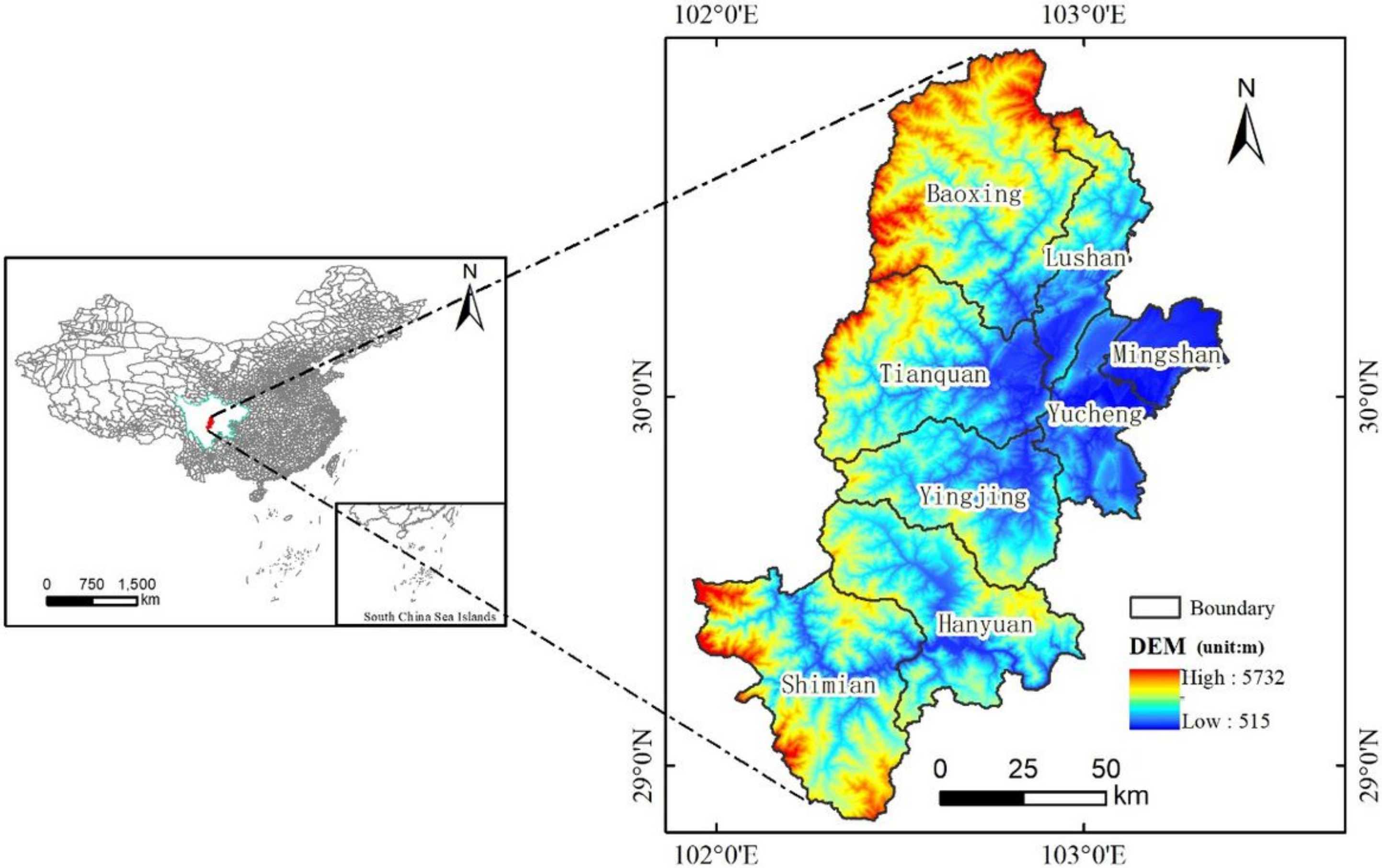

Figure 1

Location of Ya'an City

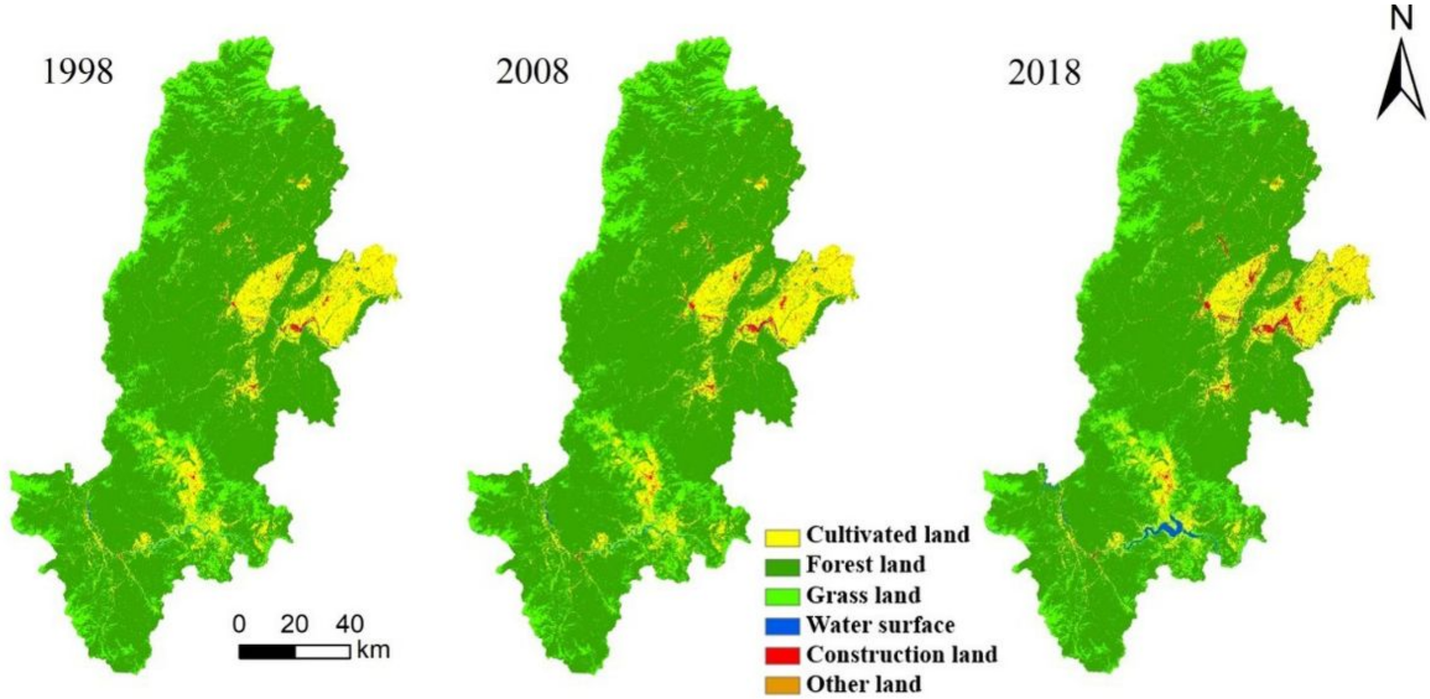

Figure 2

Chart of land use status in Ya'an City in three phases

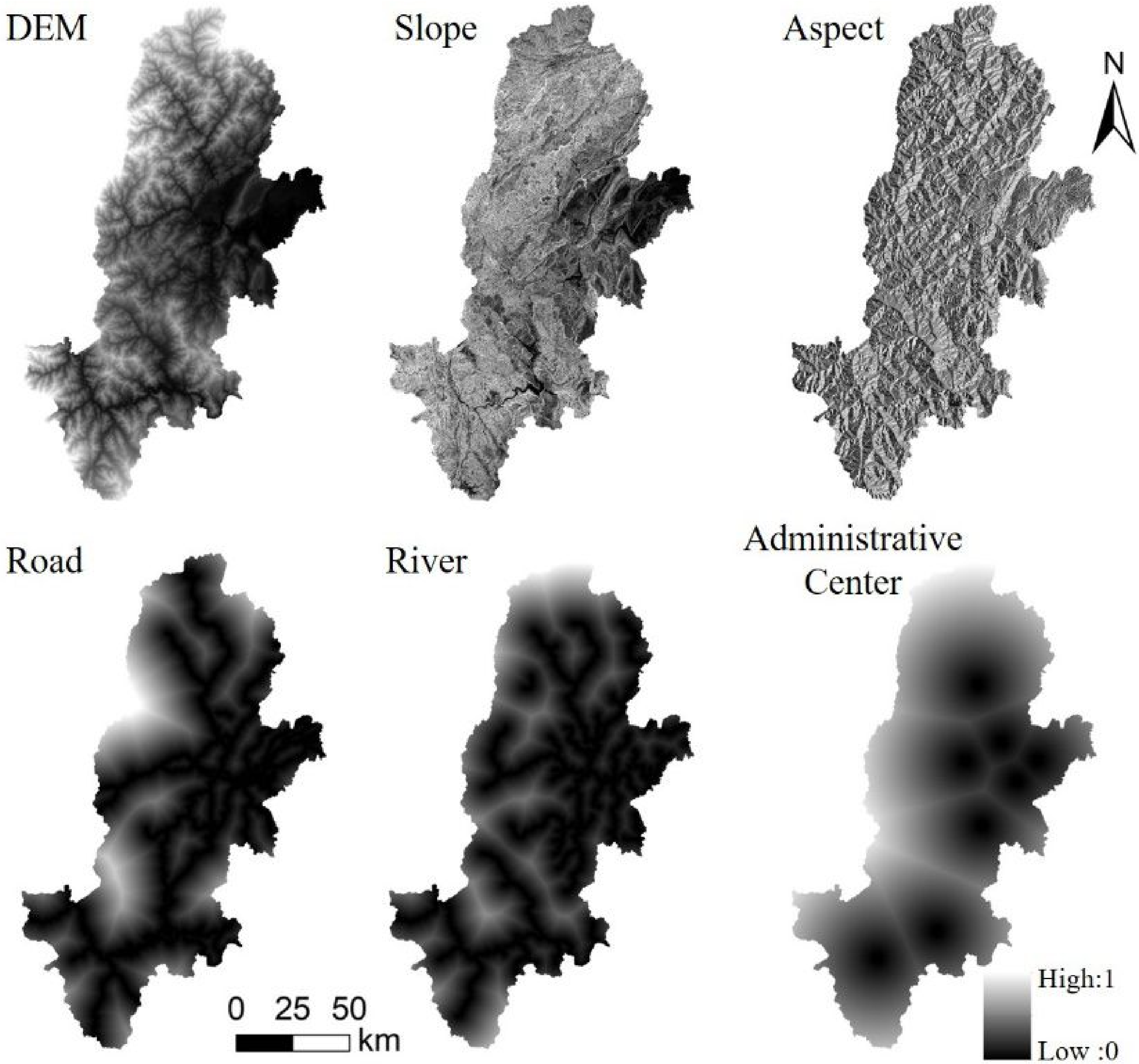

Figure 3

Analysis chart of influencing factors

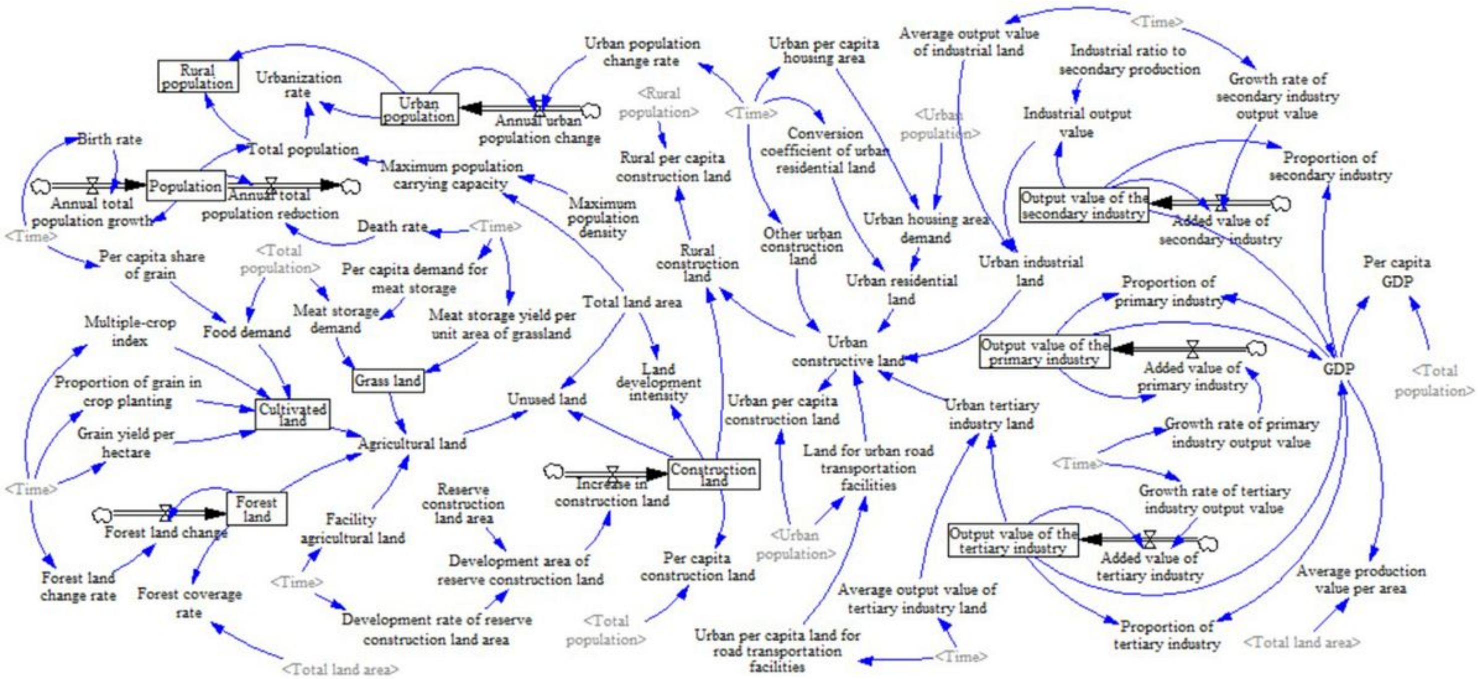

Figure 4

Stock flow chart of land use systems

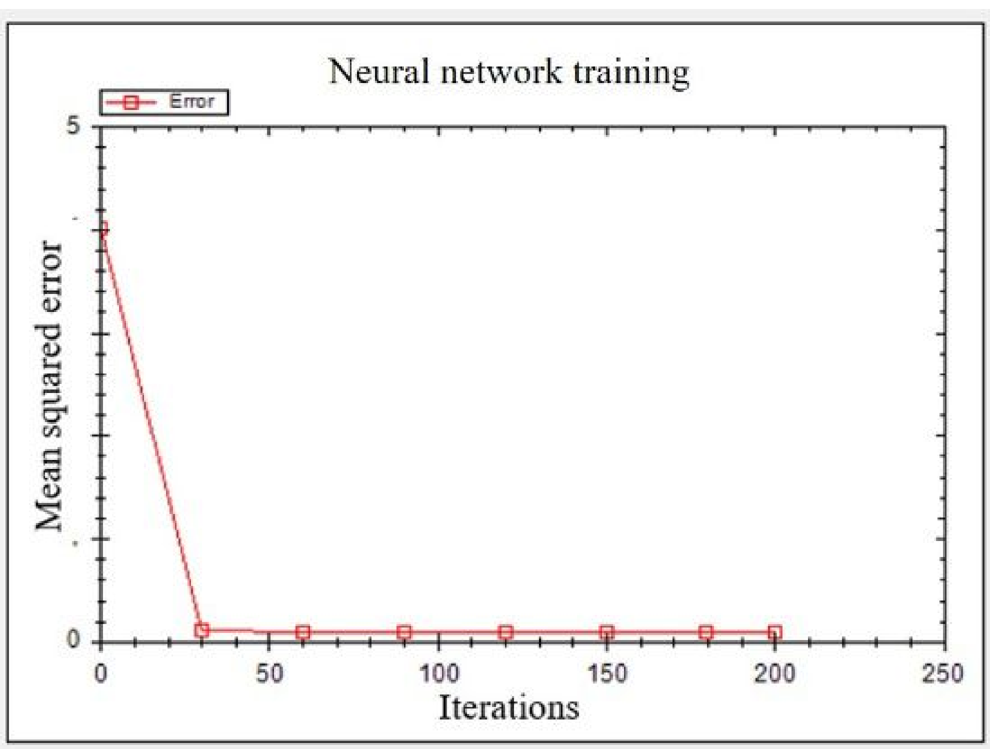

Figure 5

Accuracy of neural network training

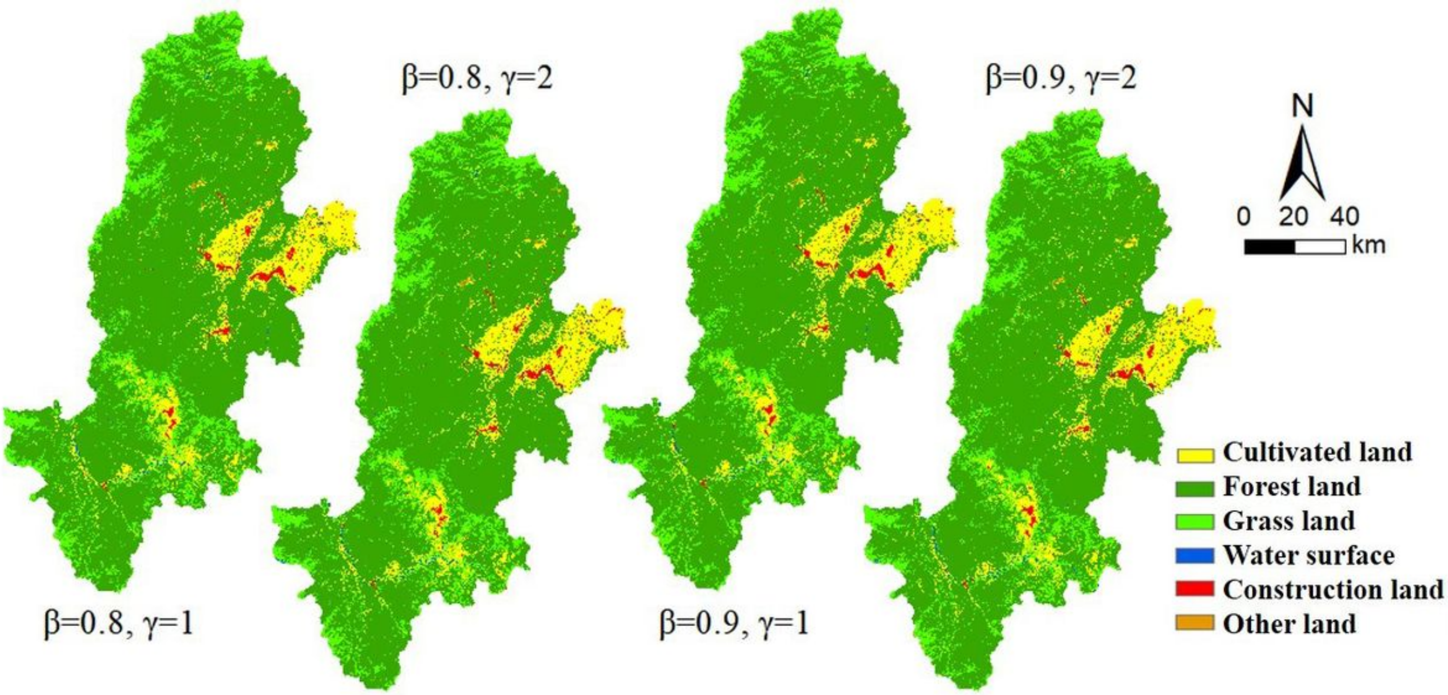

Figure 6

Land use simulation results in 2018 under different parameters

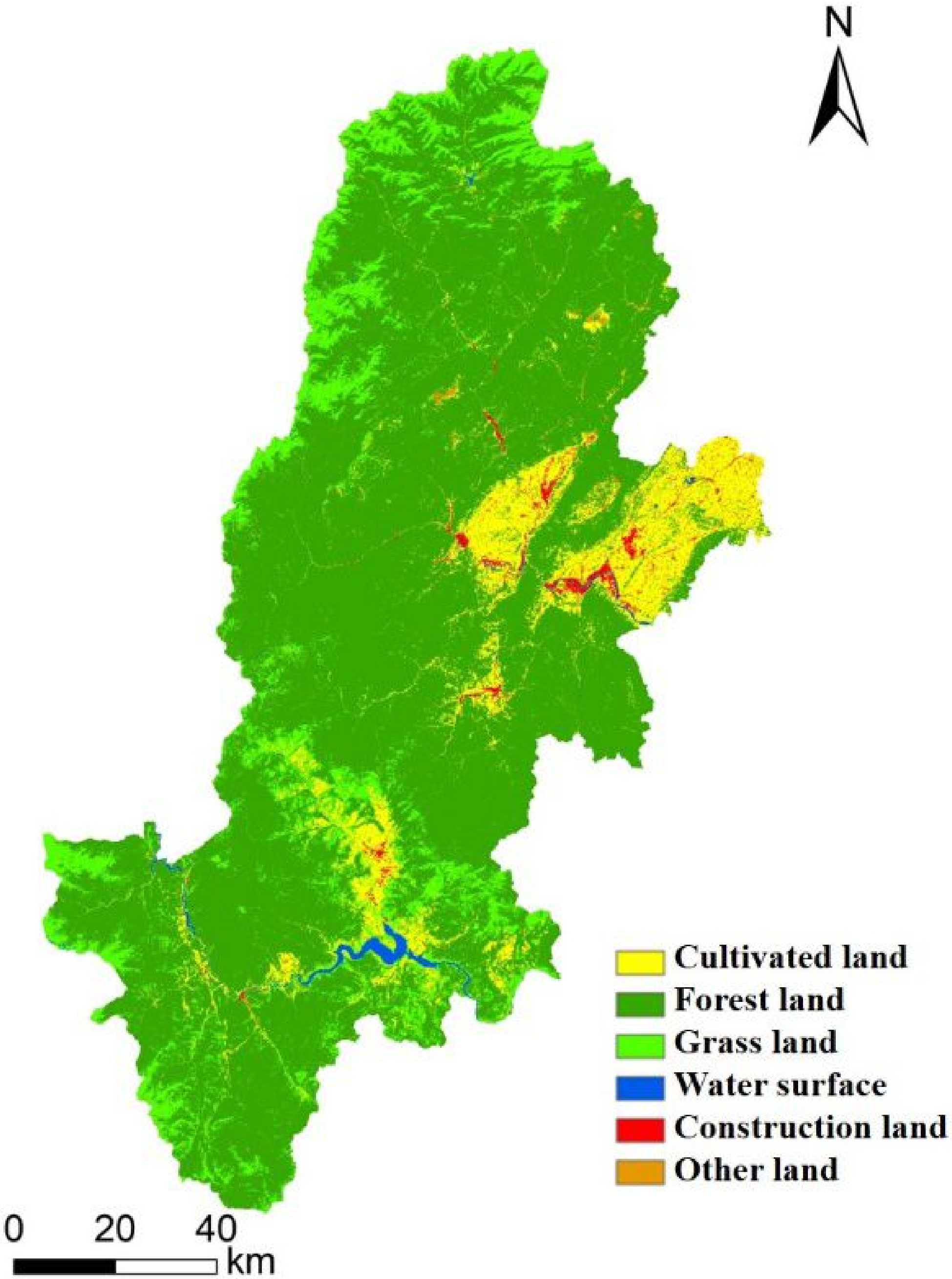

Figure 7

Land use simulation chart in 2018

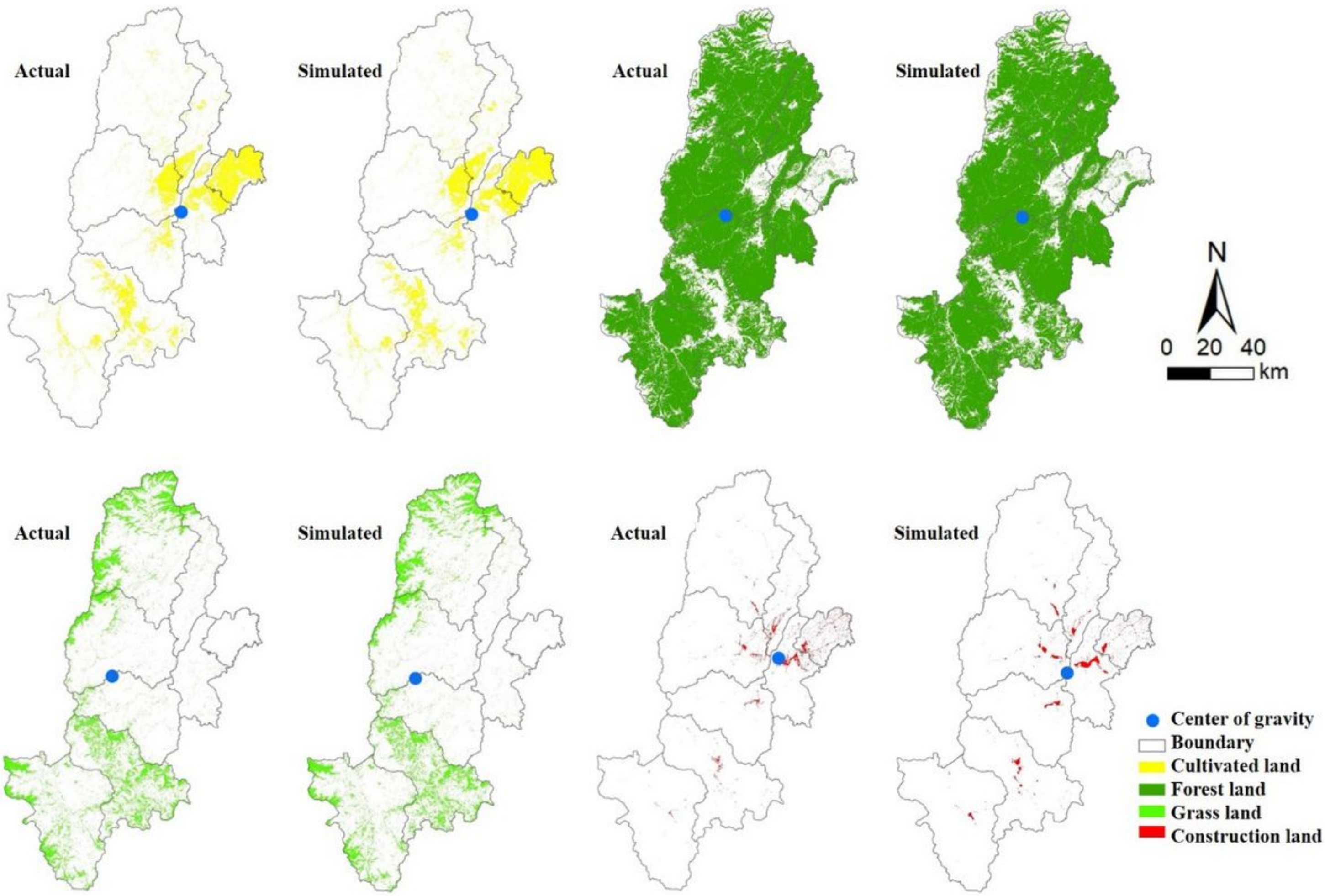

Figure 8

Actual and simulated centers of land use types in Ya’an City in 2018

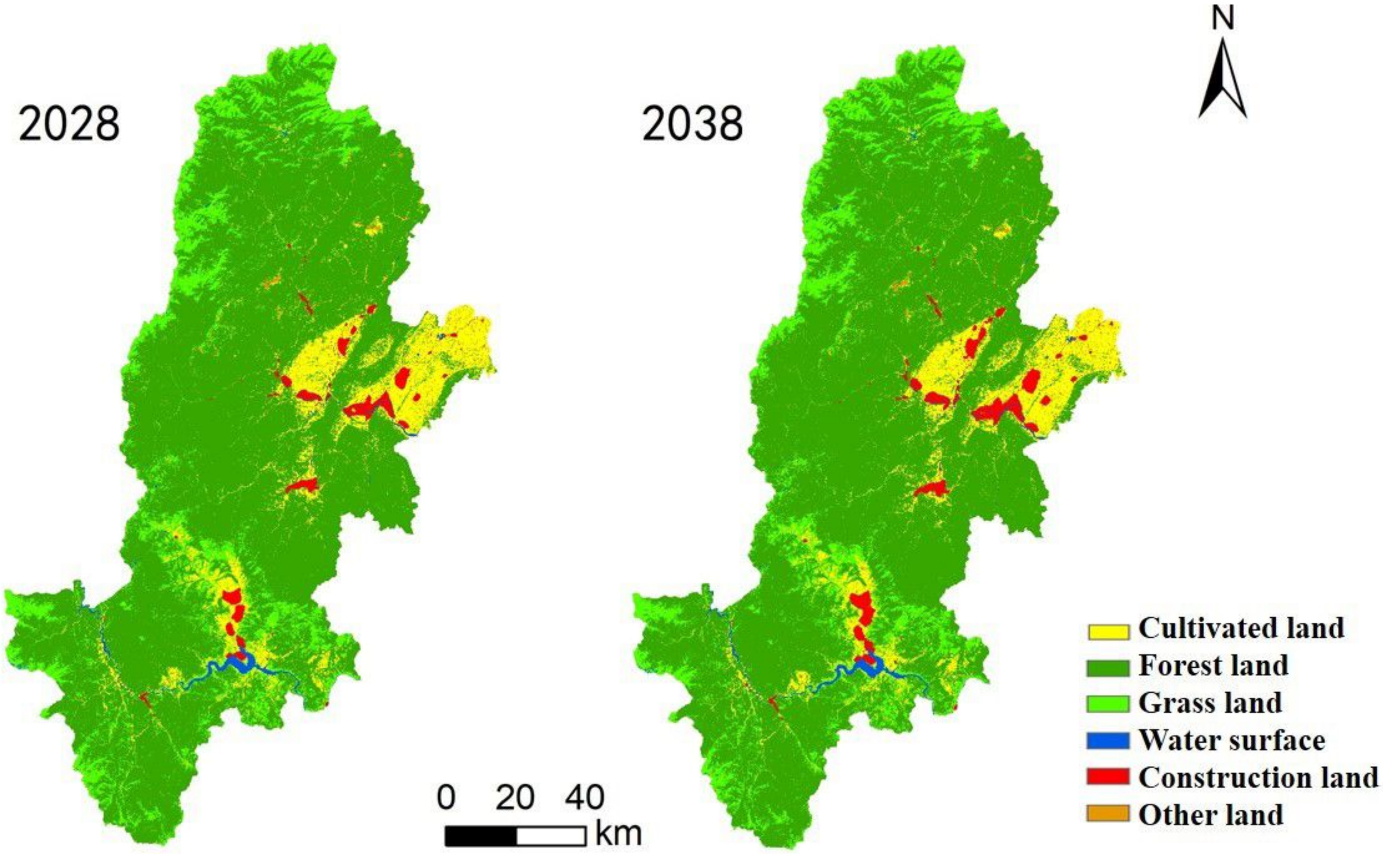

Figure 9

Land use simulation results in Ya’an City in 2028 and 2038

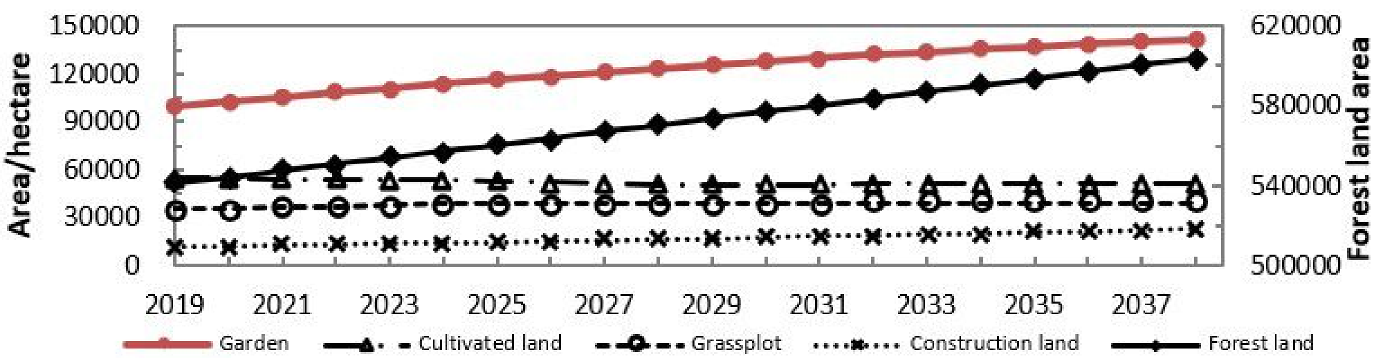

Figure 10

Predicted results of land use evolution

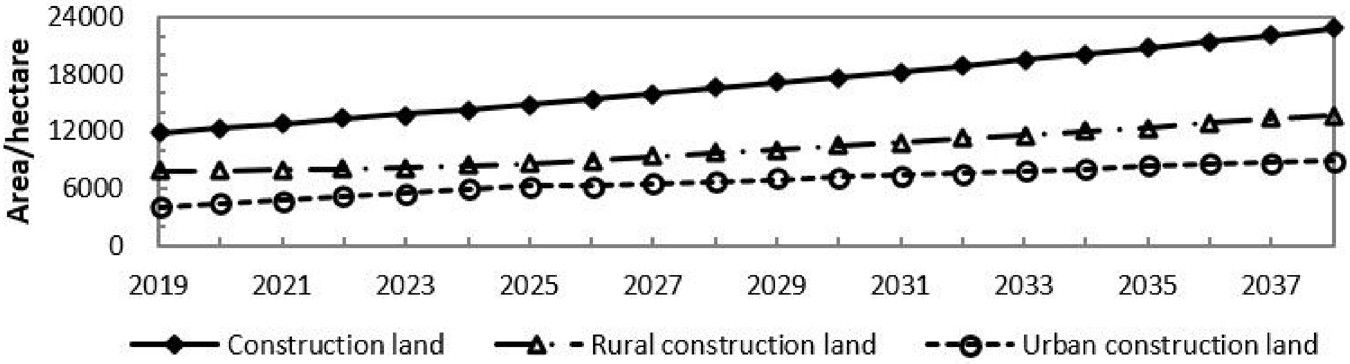

Figure 11

Predicted results of construction land

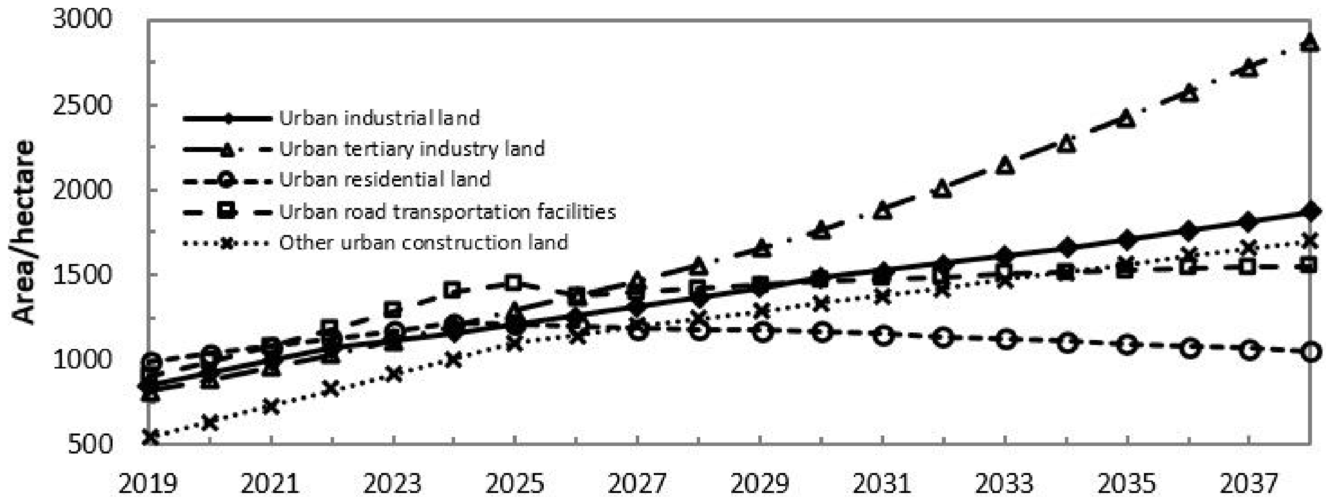

Figure 12

Urban construction land use scenarios

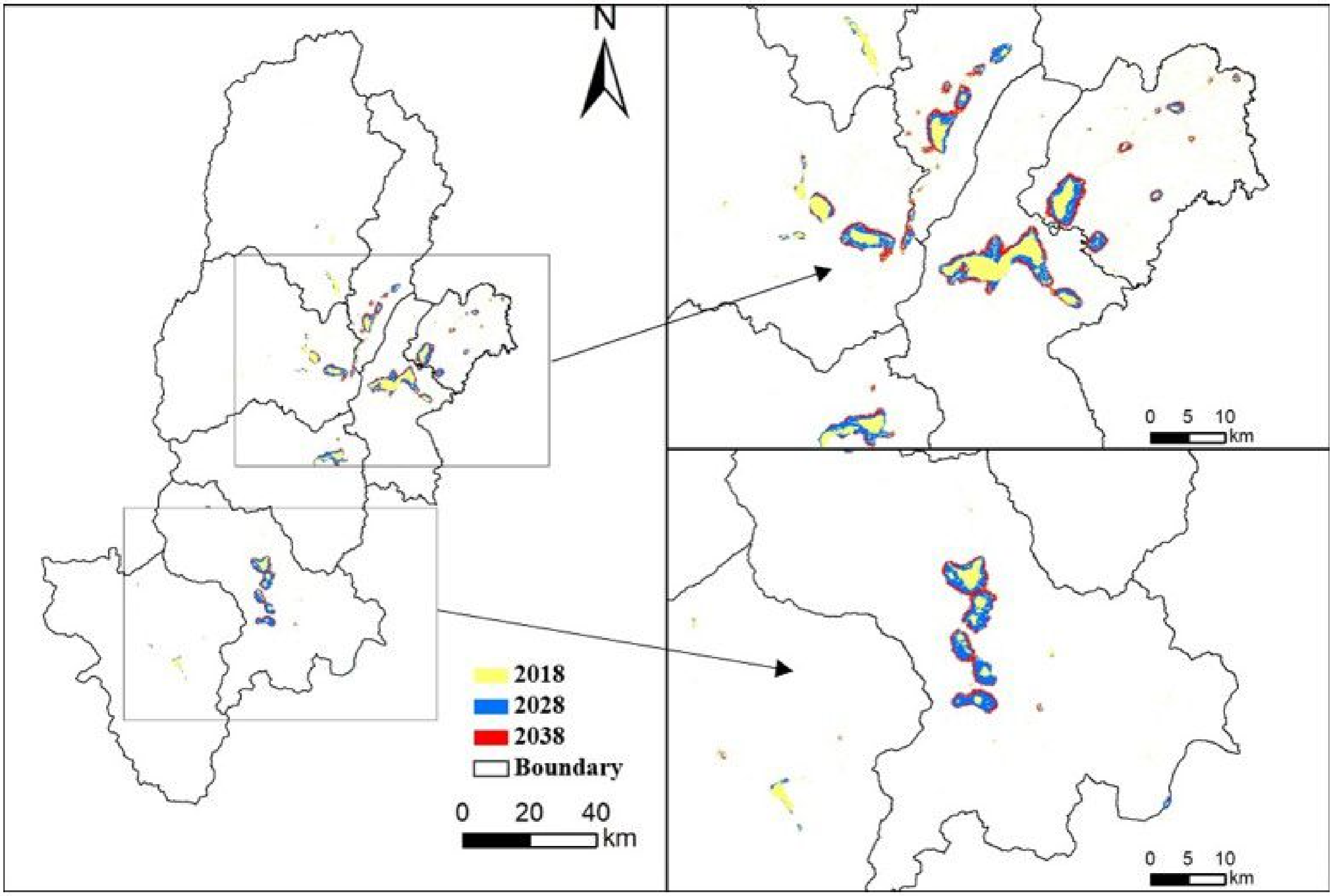

Figure 13

Construction land expansion trend in Ya’an City