

Article

Enhancing Land Use Functions Through the Optimised Allocation of Land Use

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Abstract

Land use functions refer to the capacity of land systems to provide goods and services, either directly or indirectly. They reflect the intensity of land use and the demands of social development at different stages and serve as an important reference for future land use planning. This study establishes a land use allocation optimisation framework that integrates top-down and bottom-up approaches to enhance land use functions. At the bottom-up level, an artificial neural network (ANN) model is employed to evaluate land suitability based on neighbourhood rules and driving factors. At the top-down level, a multi-agent system (MAS) model is used to integrate trade-offs among land use functions with supply–demand relationships, thereby defining land use constraints during the allocation process. Subsequently, the two models were integrated into a cellular automata (CA) model to achieve the spatial allocation of optimised land use patterns. Xintai City, located in Shandong Province, was selected as the study area. The results indicate that, compared with the 2021 baseline, ecological functions exhibited the greatest improvement, increasing by 24.11%, whereas living and production functions decreased slightly by 4.35% and 0.87%, respectively, resulting in an overall comprehensive functional improvement of 9.32%. Regarding trade-off relationships among land use functions, the intensity of trade-offs between production and ecological functions, as well as between living and ecological functions, decreased significantly by 28.72% and 25.56%, respectively, whereas the trade-off intensity between production and living functions increased slightly by 1.68%. Regarding the supply–demand relationships of land use functions in Xintai City, the surplus of production functions decreased by 13.46%, the surplus of living functions increased by 16.67%, the deficit in ecological functions improved by 33.33%, and the comprehensive functional surplus increased by 23.53%. The proposed method demonstrates substantial effectiveness in enhancing land use functions, alleviating trade-offs among land use functions, and optimising their supply–demand relationships.

Keywords: land use functions; optimisation and enhancement; multi-agent system; artificial neural network; cellular automaton



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1. Introduction

Land is a natural complex composed of multiple natural elements, including geology, topography, hydrology, soil, and vegetation [1]. Through human transformation and utilization, land has become not only a key factor of production that provides food and raw materials essential for human survival [2], but also a fundamental support system for human life through functions such as housing provision and livelihood security. In

addition, land possesses ecological functions, including ecological conservation and environmental regulation, which are essential for maintaining regional ecological balance [3]. Consequently, the land system constitutes a complex system integrating socio-economic and natural dimensions. Driven by the Global Land Project (GLP) [4], studies focusing solely on land use and land use cover change (LUCC) have struggled to comprehensively capture the complex and coupled characteristics of land systems [5]. Consequently, increasing attention has been directed towards the study of land use functions [6]. Land use functions refer to the capacities of land systems to generate products and services that satisfy human survival and development needs [7]. Establishing a methodological framework for measuring land use functions and clarifying their connotations and interrelationships can provide important guidance for promoting harmonious human–land relationships at the regional scale, optimising the utilisation of land use functions, and identifying pathways for land use transformation [8].

Land serves as the spatial carrier of land use functions, and the optimisation of land allocation provides an effective means of enhancing these functions. Land use allocation optimisation can generally be categorised into two approaches: top-down and bottom-up [9]. The top-down approach is based on macro-level systemic objectives and aggregate controls; land-use indicators are broken down step by step to spatial units using methods such as global optimisation or system dynamics at aggregated or zonal scales [10]. Representative top-down models include conventional mathematical approaches, such as linear programming models [11–13]. In addition, intelligent optimisation algorithms are widely applied, including the Shuffled Frog Leaping Algorithm (SFLA), Simulated Annealing Algorithm (SAA), Particle Swarm Optimisation (PSO), and Ant Colony Optimisation (ACO) [14–17]. The bottom-up approach simulates the decision-making processes of multiple actors and micro-scale land use changes within local land systems [18]. It emphasises the influence of the surrounding geographical environment on optimisation units and is therefore more consistent with the mechanisms of natural evolution [19]. Among bottom-up approaches, artificial neural network (ANN) models have been widely applied in land use optimisation research. ANN models can integrate multiple factors influencing land use and effectively capture the transformation rules governing land use evolution in response to the surrounding environment [20]. However, this approach has limited capacity in terms of interpretability; policy constraints; and a clear, rule-based decision-making structure, failing to reflect the constraints of regional policies and human decision-making [21].

In summary, top-down models primarily emphasise the constraints imposed by socio-economic development objectives and policy regulations on land use, whereas bottom-up models are primarily driven by local environmental and spatial factors surrounding land use. Both approaches possess inherent limitations that restrict the achievement of optimal land use allocation. Therefore, integrating the two approaches by combining their respective strengths and compensating for their limitations is essential for developing a more rational land use optimisation framework. Against this backdrop, this study adopts an integrated top-down and bottom-up framework to optimise land use allocation and enhance land use functions. The bottom-up model is employed to clarify the relationships between land use and surrounding environmental factors, thereby guiding land use allocation through suitability assessment. Meanwhile, the top-down model reveals the interrelationships among land use functions and identifies macro-level constraints imposed by socio-economic development.

2. Materials and Methods

2.1. Methodology Framework

The methodology framework for optimising land use functions is illustrated in Figure 1. The top-down approach ensures that regional land use optimisation fully incorporates policy, social, and cultural influences. The bottom-up approach incorporates the effects of surrounding environmental factors on land use suitability. The first step involves constructing a multi-agent system (MAS) based on the results of land use function assessments, including trade-off and supply–demand relationships among land use functions. By simulating the behaviours and interactions of autonomous agents, the model captures the spatial decision-making processes between humans and land systems, thereby establishing top-down constraints. The MAS model consists of three hierarchical levels: government, departmental, and resident agents. The government agent utilises the results of land use function assessments and regional development plans to determine the dominant functions and transformation directions of each town and assessment unit. The departmental agent is primarily responsible for coordinating different land use functions and reducing trade-off intensity. The resident agent represents the demand of land use functions and provides a reference for improving supply–demand relationships. The second step employs an artificial neural network (ANN) model to evaluate land use suitability for each land unit based on driving factors and pixel neighbourhood rules. Driving factors are selected from both natural and socio-economic dimensions. Neighbourhood rules are applied within a 3×3 grid surrounding each land unit to determine the probability of land use conversion. In the third step, land use conversion probabilities are determined by integrating the land class constraints identified by the MAS model with the suitability indices generated by the ANN model. These probabilities are subsequently incorporated into a cellular automata (CA) model based on the 2021 land use status. The spatial distribution of the optimised land use pattern is generated using GIS, and the effectiveness of the optimisation is ultimately evaluated based on trade-offs among land use functions and the intensity of supply–demand relationships.

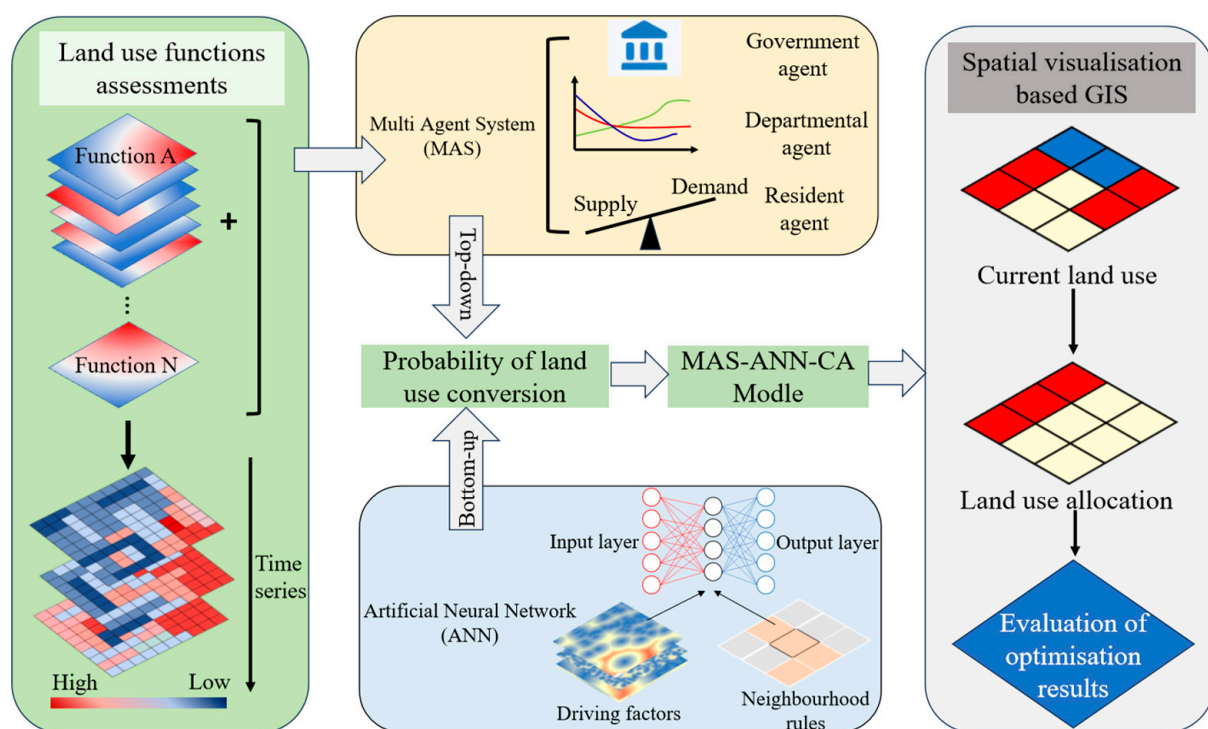


Figure 1. Flowchart for optimal allocation of land use functions.

2.2. Study Area

As shown in Figure 2, Xintai is a county-level city under the jurisdiction of Tai'an City in Shandong Province. Its geographical coordinates are $117^{\circ}14'30''$ – $117^{\circ}59'58''$ E, $35^{\circ}39'00''$ – $36^{\circ}06'40''$ N. It measures 68 km from east to west and 54 km from north to south, covering an area of 1788 km². The city experiences a warm temperate monsoon continental climate with distinct seasons: spring is dry and windy, summer is hot with abundant rainfall, autumn is dry with little rain, and winter is cold with little snow; however, seasonal drought is a significant issue.

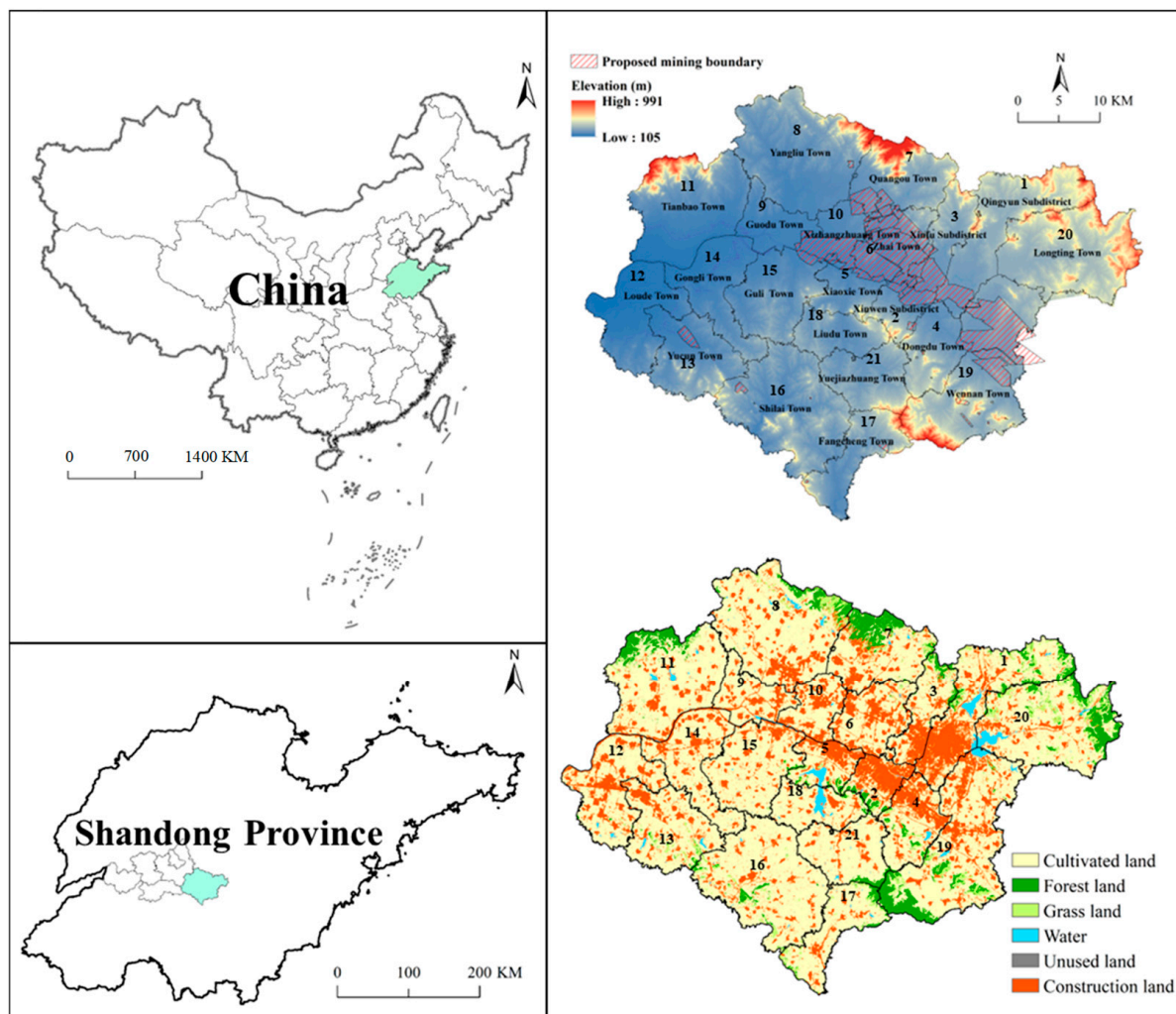


Figure 2. Overview map of the study area.

Xintai City is one of China's key coal-producing regions, with a history of coal mining dating back to the late 19th century. In 2011, it was included in the third batch of nationally designated resource-depleted cities. As resources become depleted, the tensions between industrial development, food production and ecological conservation have become increasingly pronounced; there is significant pressure for regional transformation and development; and there is a lack of key implementation measures for putting macro-level regional development plans into practice.

Xintai comprises 3 subdistricts, 17 towns and 1 township; in response to the depletion of coal resources and the need for urban transformation and development, plans were drawn up in 2010 to establish two urban sub-centres: 'Lou-yu' (Loude Town and Yucun Town) and 'Xi-yang-guo' (Xizhangzhuang Town, Yangliu Town and Guodu Town).

2.3. Source of Data

- (1) Geospatial data: This primarily comprises land use data (2021) sourced from the PIE-Engine Remote Sensing and Geographic Information Cloud Service Platform: <https://engine.piesat.cn> (accessed on 25 June 2023), elevation data, vector data for proposed mining boundaries, and vector boundary and road data for municipal and town areas, sourced from the Shandong Provincial Institute of Urban and Rural Planning and Design.
- (2) Socio-economic data: This section includes data on raw coal production, population statistics, grain production and regional gross domestic product (GDP), primarily sourced from the Xintai City Statistical Yearbook, the Shandong Province Statistical Yearbook and the China Agricultural Product Price Survey Yearbook (2021).

2.4. Land Use Functions Assessment

2.4.1. Development of an Indicator System for the Evaluation of Land Use Functions

As shown in Table 1, an indicator system for evaluating land use functions was developed, comprising 12 element-level variables and three dimensional structural layers, namely production, living, and ecological function [22]. The production function reflects the land system's capacity to generate raw materials and economic products; the living function reflects its capacity to support industrial activities and population development; and the ecological function reflects its capacity to regulate and maintain the regional ecological environment [7,22–24].

Table 1. Land use functions calculation index system of Xintai.

Structural Layer	Element Layer	Method of Calculating the Indicator
Production function, PF	Grain supply, GS	The weight of agricultural produce per unit area of cultivated land
	Coal resource supply, RS	Coal production per unit area of land used for mining operations
	Forestry production, FP	Forest product yield per unit area of forest land
	Grass production, GP	Feed cost savings per unit area of grass land for livestock farming
	Water production, WP	Fishery yield per unit area of water
Living function, LF	Industrial development, ID	Economic output per unit area of land used for construction in the secondary and tertiary sectors
	Population bearing, PB	Population density per unit area of developed land
	Livelihood protection, LP	Disposable income per capita
Ecological function, EF	Soil retention, SR	Value of soil conservation ecosystem services per unit area
	Gas regulation, GR	Value of ecosystem services provided by gas regulation per unit area
	Water conservation, WC	Value of ecosystem services provided by water conservation ecosystems per unit area
	Waste explained, WE	The value of ecosystem services related to waste degradation per unit area

2.4.2. Calculation of Land Use Functions at the Element Layer

(1) Grain supply, GS

The primary function of cultivated land is to provide food, measured by the weight of agricultural produce yielded per unit area. Coal mining in Xintai City is carried out via underground mining. This method causes land subsidence, which in turn leads to reduced yields of surface crops. Research indicates that for every tonne of raw coal produced, crop

yields are reduced by approximately 6% [25]. The formula for calculating the grain supply function in non-mining areas is shown in Equation (1), whilst the formula for mining areas is shown as follows:

$$GP_x = \frac{GP_t}{AC_t} \times AC_x \quad (1)$$

$$GP_x = \frac{GP_t}{AC_t} \times AC_x - \frac{GP_t}{AC_t} \times MC_x \times CP_x \times 6\% \quad (2)$$

where GP_x and GP_t represent the grain yields for grid x and town t respectively; AC_t is the cultivated land area of town t ; AC_x is the cultivated land area of grid x ; MC_x is the area of cultivated land within the grid that overlaps with the mining area; CP_x is the coal yield per unit area.

(2) Coal resource supply, RS

Coal resource supply, expressed as coal production per unit area. The calculation formula is shown as follows:

$$RS_x = \frac{RS}{AC1_t} \times AC1_x \quad (3)$$

where RS_x and RS represent the coal production volume in grid x and in 2021, respectively; $AC1_t$ is the total area of land designated for development in the region; $AC1_x$ is the area of land designated for development within grid x .

(3) Forestry production, FP

Forest products primarily consist of economically valuable seedlings produced by forest land, expressed as the economic output per unit area of forest land [26]. The calculation formula is shown as follows:

$$FP_x = \frac{FP_t}{AF_t} \times AF_x \quad (4)$$

where FP_x and FP_t represent the value of forest products for grid x and town t respectively; AF_t is the area of arable land in town t ; and AF_x is the area of forest land within grid x .

(4) Grass production, GP

Grass lands provide food for livestock and, indirectly, products for humans. According to research, approximately 45% of livestock feed comes from grass, and feed costs account for 55% of output value [26]. The formula for calculating the supply of grass land products is shown as follows:

$$GP_x = \frac{GP_t}{AG_t} \times AG_x \times 0.45 \times 0.55 \quad (5)$$

where GP_x and GP_t represent the output value of grass products for grid x and town t respectively; AG_t is the grass land area of town t ; and AG_x is the grass land area of grid x .

(5) Water production, WP

Water can provide humans with a certain amount of fishery products; the supply function of fishery products is expressed as the value of economic output per unit area of water body [26], as shown as follows:

$$WP_x = \frac{WP_t}{AW_t} \times AW_x \quad (6)$$

where WP_x and WP_t represent the value of fishery production for grid x and town t respectively; AW_t is the water body area of town t , and AW_x is the water body area of grid x .

(6) Industrial development, ID

Construction land supports the secondary and tertiary sectors, as measured by the output value of these sectors per unit area of construction land [27]. The calculation formula is shown as follows:

$$ID_x = \frac{ID_t}{AC1_t} \times AC1_x \quad (7)$$

where ID_x and ID_t represent the output value of the secondary and tertiary sectors for grid x and town t respectively; $AC1_t$ is the area of construction land in town t ; and $AC1_x$ is the area of construction land in grid x .

(7) Population bearing, PB

Construction land serves as the physical foundation for human habitation and daily life; its population-carrying capacity is characterised by the number of people per unit area of construction land [28]. The calculation formula is shown as follows:

$$PB_x = \frac{PB_t}{AC1_t} \times AC1_x \quad (8)$$

where PB_x and PB_t represent the population of grid x and town t , respectively; $AC1_t$ is the area of construction land in town t ; and $AC1_x$ is the area of developed land in grid x .

(8) Livelihood protection, LP

The development of the secondary and tertiary industries can provide local residents with employment opportunities and economic benefits, thereby supporting human livelihoods. Therefore, the level of livelihood support function was represented by per capita disposable income, with data obtained from the XinTai statistical yearbook.

(9) Soil retention, SR; Gas regulation, GR; Water conservation, WC; Waste explained, WE

Referring to previous studies on ecosystem service functions, four indicators, namely soil conservation, gas regulation, water conservation, and waste treatment, were selected to characterize the ecological functions of land use. The intensity of ecological functions was calculated using the ecosystem service value (ESV) assessment method [29]. In this study, the equivalent factor method was adopted, as it currently features a well-established and standardized accounting system, intuitive expression, relatively low data requirements, and convenient calculation procedures, demonstrating unique advantages in ESV assessment [30]. Based on the ecosystem service valuation model developed by Costanza and other scholars, Xie Gaodi identified the ecosystem service types in China through expert surveys and gradually improved the value equivalent factor table suitable for China's ecosystems [31], as shown in Table 2.

Table 2. The value of ecosystem services equivalent in China, 2021.

Land Use Type	Types of Ecosystem Services (Unit: RMB/m ²)			
	Soil Retention	Gas Regulation	Water Conservation	Waste Explained
Cultivated land	1.03	0.67	0.02	0.10
Forest land	2.32	1.91	0.30	1.67
Grass land	2.40	1.97	0.31	1.72
Water	0.93	0.77	8.29	5.55
Unused land	0.02	0.02	0	0
Construction land	0	0	0	0

Due to regional differences, the ecosystem service value (ESV) requires correction, and the correction method is shown as follows: The ecosystem service value equivalent factors for different ecosystems in XinTai are presented in Table 3.

$$ESV_{xj} = \sum_{i=1}^n Ec_{ij} \times A_{xi} \quad (9)$$

$$Ec_{ij} = \frac{1}{7} \sum_{i=1}^n \frac{m_i p_i q_i}{M} \quad (10)$$

where ESV_{xj} represents the ecological function j of grid x ; Ec_{ij} denotes the corrected value of the ecological function j for land use type i ; and A_{xi} refers to the value equivalent coefficient of land use type i within grid x . Based on the improved ecosystem service value equivalent table per unit area proposed by Xie Gaodi, the value equivalents were corrected to obtain the corresponding ecosystem service values for each land use type. Among them, m_i , p_i , and q_i represent the four-year average yields of the three major crops in XinTai during the study period, namely wheat, maize, and vegetables, respectively; and M denotes the planting area of the crops [32].

Table 3. The value of ecosystem services equivalent in Xintai, 2021.

Land Use Type	Types of Ecosystem Services (Unit: RMB/m ²)			
	Soil Retention	Gas Regulation	Water Conservation	Waste Explained
Cultivated land	0.26	0.17	0.01	0.03
Forest land	0.59	0.49	0.08	0.43
Grass land	0.61	0.50	0.08	1.42
Water	0.24	0.20	2.11	1.42
Unused land	0.01	0.01	0	0.02
Construction land	0	0	0	0

2.4.3. Calculation of Land Use Functions at the Structural Layer

The element-level land use functions were aggregated according to their attributes to form the structural-level land use functions, while the comprehensive land use function was generated through the interactions and spatial superposition among the structural-level functions. Due to differences in the units and dimensions of each functional element, the functional indices were normalized to ensure comparability among functions, with the results ranging from 0 to 1. The calculation method for the functional factors of each dimension is shown as follows:

$$P_x = \sum_{i=1}^5 p_{ix} \times w_{ix} \quad (11)$$

$$L_x = \sum_{i=1}^2 l_{ix} \times w_{ix} \quad (12)$$

$$E_x = \sum_{i=1}^4 e_{ix} \times w_{ix} \quad (13)$$

$$C_x = P_x + L_x + E_x \quad (14)$$

where P_x , L_x , and E_x represent the production function index, living function index, and ecological function index of grid x , respectively. Since the importance of each functional dimension was considered equal, P_x , L_x , and E_x were calculated by equally weighting

and summing the element-level functional factors within each dimension. w_{ix} denotes the weight of each functional element, while C_x represents the comprehensive land use function index, which was obtained by equally weighting and summing the structural-level land use function indices of the three dimensions.

2.5. Synergy and Trade-Off Assessment of Land Use Functions

Correlation analysis has been widely used to qualitatively examine the trade-off and synergy relationships among various functions within land systems. In this study, the Pearson correlation coefficient was employed to qualitatively analyze the relationships between each pair of land use functions [33]. The calculation formula is shown as follows:

$$P_{ab} = \frac{\sum_{i=1}^n (a_i - \bar{a})^2 (b_i - \bar{b})^2}{\sqrt{\sum_{i=1}^n (a_i - \bar{a})^2} \sqrt{\sum_{i=1}^n (b_i - \bar{b})^2}} \quad (15)$$

where P_{ab} represents the correlation coefficient between two groups of land use functions; n denotes the sample size; and a and b represent the mean values of the two groups of land use function indices, respectively. At the 1% or 10% significance level, a negative correlation coefficient between two groups of land use function indices indicates a trade-off relationship, whereas a positive correlation coefficient indicates a synergistic relationship, implying that the two functions increase or decrease simultaneously [34].

2.6. Supply and Demand Assessment of Land Use Functions

2.6.1. Calculation of Supply and Demand at the Element Layer

Since people's access to resources is an active behavior, this study assumes that resource-product land use functions—such as coal resource supply, forest product supply, grass land product supply, and aquatic product supply—are in a state of supply–demand balance [35]. The following introduces the measurement methods for factor-level land use functions:

(1) Demand for Food Supply

In this study, grain consumption was used to measure the regional population's demand for the food supply function, which can directly reflect the degree of dependence of the regional population on food resources [36]. The calculation formula is shown in Equation (16).

$$gd_x = \frac{GP_t}{P_d} \times P_x \quad (16)$$

where gd_x represents the food demand index of grid x ; GP_t denotes the grain consumption in Shandong Province; P_d represents the population of Shandong Province during the same period; and P_x refers to the population within grid x in XinTai.

(2) Demand for Industry development

People's demand for industrial development is largely shaped by the economic development level of surrounding cities or the province during the same period, which serves as an important reference for forming expectations and demands regarding regional industrial development [9]. Therefore, in this study, the output value of the secondary and tertiary industries in Shandong Province during the same period was used to measure the demand for economic development in XinTai. The calculation formula is shown as follows:

$$id_x = \frac{EP_d}{AC_d} \times AC_x \quad (17)$$

where id_x represents the economic supply demand index of grid x ; EP_d denotes the output value of the secondary and tertiary industries in Shandong Province during the same period; AC_d represents the construction land area in Shandong Province during the same period; and AC_x refers to the construction land area within grid x in XinTai.

(3) Demand for Population Carrying Capacity

A strong population carrying function indicates that more people can be accommodated within the same area of construction land, which not only directly reflects population distribution and agglomeration, but also demonstrates the intensive utilization and efficient allocation of regional construction land. Such intensiveness is reflected in the effective management and optimized layout of construction land, whereby the maximization of land resource utilization is achieved through increasing land use intensity and optimizing land use structure [37]. In this study, the population carrying level of Shandong Province during the same period was used to measure the demand level, and the calculation formula is shown as follows:

$$pd_x = \frac{P_d}{AC_d} \times AC_x \quad (18)$$

In the equation, pd_x represents the population carrying demand index of grid x ; P_d denotes the population of Shandong Province during the same period; AC_d represents the construction land area in Shandong Province during the same period; and AC_x refers to the construction land area within grid x in XinTai.

(4) Demand for Livelihood Protection

People's perception of the level of demand for livelihood security is shaped through comparisons with the income levels of other regions during the same period, which further generates expectations and demands for living standards. Therefore, the livelihood security demand index was represented by the per capita disposable income of Shandong Province during the same period.

(5) Demand for Soil Conservation, Gas Regulation, Water Conservation, and Waste Treatment

The ecological services provided by land systems are jointly influenced by social development, population cognition, land development intensity, and economic level. Among them, land use development intensity refers to the proportion of construction land area to the total regional land area. A larger proportion of construction land indicates a higher degree of land development and utilization, implying greater human consumption intensity of the ecosystem [36]. Population density reflects the degree of demand for ecological functions, with higher population density corresponding to greater overall demand for ecosystem services. Gross domestic product, GDP, reflects the level of regional economic and social development and can indirectly represent human awareness and cognition of ecological functions. Regions with higher GDP are expected to have stronger demands for ecological functions. Due to the significant differences in population density and GDP among a few highly developed regions, these two indicators exhibit substantial fluctuations. Therefore, a logarithmic transformation method commonly used in statistics was adopted to weaken local extreme fluctuations without affecting the overall distribution trend, thereby facilitating subsequent analysis [30]. The calculation formula for the ecological function of each element layer is shown as follows:

$$ecd_{xi} = EF_{xi} \times \ln(A_1) \times \ln(A_2) \times \ln(A_3) \quad (19)$$

where ecd_{xi} represents the demand index of the ecological function i in grid x ; EF_{xi} denotes the land use function index of the ecological function i ; A_1 represents land development intensity; A_2 denotes population density; and A_3 represents the GDP level.

2.6.2. Calculation of Supply and Demand at the Structural Layer

The calculation method for the demand of structural-level land use functions was derived from the comprehensive evaluation approach and was obtained through the weighted summation of element-level functional demands. The calculation formulas are shown as follows:

$$PD_x = \sum_{i=1}^n PD_{ix} \times W_i \quad (20)$$

$$LD_x = \sum_{i=1}^n LD_{ix} \times W_i \quad (21)$$

$$ED_x = \sum_{i=1}^n ED_{ix} \times W_i \quad (22)$$

$$CD_x = PD_x \times W_{ip} + LD_x \times W_{il} + ED_x \times W_{ie} \quad (23)$$

where PD_x represents the demand index of the production function i in grid x ; PD_{ix} denotes the land use function index of the production element function in grid x ; and W_i represents the weight of the corresponding element function. LD_x represents the demand index of the living function in grid x ; LD_{ix} denotes the land use function index of the living element function i in grid x ; and W_i represents the weight of the corresponding element function. ED_x represents the demand index of the ecological function in grid x ; ED_{ix} denotes the land use function index of the ecological element function i in grid x ; and W_i represents the weight of the corresponding element function. CD_x represents the demand index of the comprehensive function in grid x ; PD_x denotes the land use function index of the production function in grid x ; W_{ip} represents the weight of the production function; LD_x denotes the land use function index of the living function in grid x ; W_{il} represents the weight of the living function; ED_x denotes the land use function index of the ecological function in grid x ; and W_{ie} represents the weight of the ecological function. In this study, equal weights were assigned to all the structural-level functions.

2.7. Improvement of Land Use Functions

2.7.1. Construction of Multi-Agent Models (MAS)

According to the hierarchical structure of regional development and the allocation of land use stakeholders, a three-level decision-making agent system consisting of government agents, departmental agents, and resident agents was established. The primary role of government agents is to formulate regional development objectives and provide references for regional land use policies. Departmental agents are mainly responsible for implementing land use policies, which means translating land use policies into specific spatial behaviors and subsequently allocating these policies spatially. Resident agents, as the demand side of land use functions, guide the allocation of various land use types according to their demands for land use functions.

(1) Government Agents

Government agents determine the strategic direction of regional development and formulate land use control indicators based on regional planning objectives, thereby achieving the decomposition of land use indicators and structural balance across the entire region according to local conditions. In this study, towns were used as the basic units, and the development orientation of each town was classified with reference to regional planning.

The development orientations of towns in XinTai were divided into four categories: agricultural type, industrial type, ecological tourism type, and comprehensive service type. The spatial distribution of these development types is shown in Figure 3.

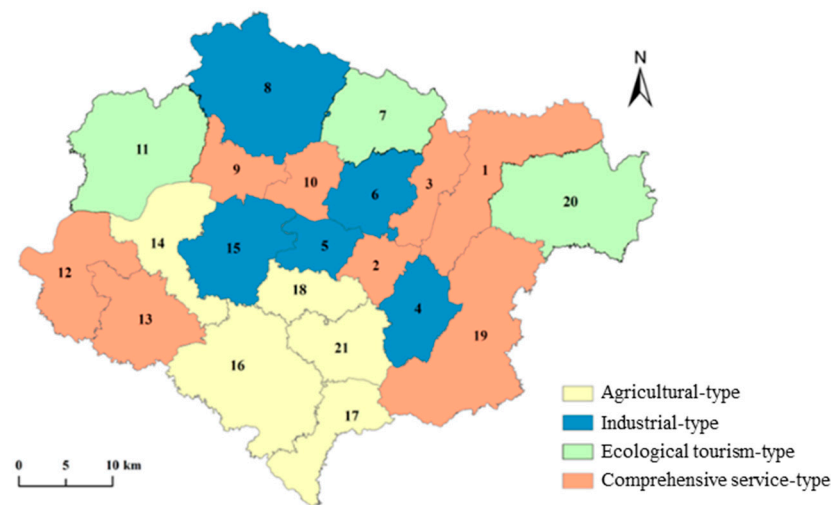


Figure 3. Spatial distribution of township development types in Xintai.

Agricultural-type towns are mainly distributed in southern XinTai, including Fangcheng Town, Shilai Town, Liudu Town, Yuejiazhuang Township, and Gongli Town. Benefiting from flat terrain and contiguous cultivated land, this region exhibits strong production functions and is suitable for agricultural production activities.

Industrial-type towns are mainly distributed around mining areas, including Zhai Town, Yangliu Town, Guli Town, Xiaoxie Town, and Dongdu Town. Relying on the existing coal mining and mining equipment manufacturing industries, these towns possess a relatively strong industrial foundation. Industrial-type towns should optimize the spatial layout of industries, guide the intensive deployment of construction land, accelerate the establishment of industrial systems that meet the requirements of a circular economy, promote industrial clustering, and increase the proportion of the population employed in industrial sectors.

Ecological tourism-type towns are mainly distributed in northern XinTai, including Tianbao Town, Quangou Town, and Longting Town. These towns possess favorable ecological conditions and certain tourism resources.

Comprehensive service-type towns are mainly distributed in the central urban area of XinTai and the two urban sub-centers of Loude and Xiyangguo. These include Qingyun Subdistrict, Xinfu Subdistrict, Xinwen Subdistrict, Loude Town, Yucun Town, Guodu Town, Xizhangzhuang Town, and Wennan Town, totaling eight towns and subdistrict communities. Supported by the planning of the central urban area and urban sub-centers, these towns serve as the primary carriers of living functions, featuring high population density and a tertiary industry-oriented economic structure.

(2) Departmental Agents

Departmental agents are responsible for organizing and implementing regional land use development, improving trade-off relationships among land use functions, and maximizing interdepartmental benefits. At the same time, land development and planning conducted by departmental agents should be consistent with the development directions determined by the government. Departmental agents can be divided into three categories: production departments, living departments, and ecological departments. The task of the production department is to coordinate conflicts among cultivated land, grass land, forest

land, and construction land, while also managing the conversion among these land use types. The living department is mainly responsible for the development of construction land, serving the development of the secondary and tertiary industries as well as supporting human living needs. It should avoid the disorderly expansion of construction land and identify suitable areas for construction land allocation. The ecological department is committed to protecting the ecological environment and improving ecological conditions.

The improvement of land use functions should follow the principles of functional maximization and functional synergy [38]. In essence, land use function optimization is a multi-objective optimization problem. Pareto optimal solutions are commonly used to compare the achievement of multiple objectives under different decision-making schemes and to identify decision schemes capable of achieving optimal multi-objective outcomes [23]. The multi-objective programming used in this study can be described as follows:

$$\forall_i \in \{1, 2\}, LUF_i(R) \geq LUF_j(R') \quad (24)$$

$$\exists_i \in \{1, 2\}, LUF_i(R) \geq LUF_j(R') \quad (25)$$

where LUF_i and LUF_j represent the objective functions of objectives i and j , respectively; R denotes the optimal decision-making scheme for achieving these objectives; and R' represents alternative decision-making schemes. A Pareto optimal solution should satisfy the following condition: under a given land use function A, the land use function B of a grid is greater than or equal to that under all the other schemes [8].

As shown in Figure 4, land use function A was used as the horizontal axis and land use function B as the vertical axis. Curve fitting was performed for the Pareto-efficient selection points of two groups of land use functions across different grids, after which the inflection points of the first derivative, synergy potential, and trade-off intensity were calculated. For the first derivative of the fitted curve, the horizontal axis represents land use function B, while the vertical axis indicates the reduction in land use function A corresponding to each unit increase in land use function B, namely the opportunity cost measured by land use function A. The inflection point of the first derivative is regarded as a relatively stable region between the two land use functions, where function A can maintain a relatively high value despite changes in function B near the inflection point. Synergy potential reflects the possibility of achieving a higher-level “win-win” situation between two land use functions under specific conditions. The points on the fitted curve correspond to the most efficient combinations for jointly providing the two land use functions. In the coordinate system, the farther a point is from the origin, the higher the total theoretical land use function value that the grid can provide, and thus the greater the synergy potential.

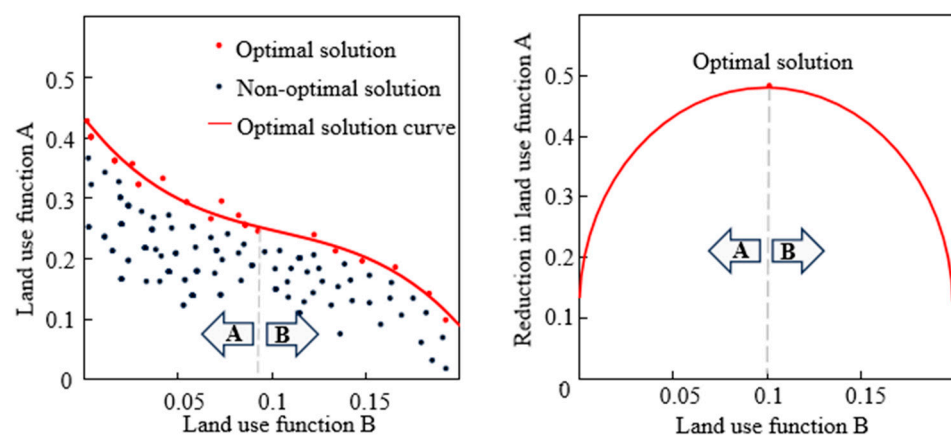


Figure 4. Schematic diagram of the Pareto optimal solution.

By calculating the area enclosed by the reciprocal of the first derivative of the fitted curve and the coordinate axes, the synergistic provision capacity of the two land use functions can be measured. The calculation formula is as follows:

$$S = \int_0^Z f(x)dx \quad (26)$$

where S represents the envelope area under the first derivative of the fitted curve; $f(x)$ denotes the fitting function of the curve; and Z represents the intersection point between the fitted curve and the horizontal axis. A larger S value indicates greater synergy potential of land use functions across the entire study area.

In practical applications, first, identify the most significant land-use trade-offs faced by towns with different development types—specifically, which two land-use functions present the greatest trade-offs. Then, using the Pareto optimality method, determine which land-use function needs to be enhanced, thereby constraining the probability of conversion between land-use types.

(3) Resident Agents

Resident agents refer to collectives or individuals who actually use the land. They serve as the carriers for measuring the supply–demand relationships of regional land use functions and are also the target beneficiaries for improving regional supply–demand relationships. Land use functions are the result of human transformation and utilization of nature. Meanwhile, with social development and changes in human demands, land use optimization has continuously evolved through activities such as returning cultivated land to forest and relocating rural residential areas. Accordingly, resident agents in each grid accept the land use optimization decisions generated by the model and further adjust their behaviors based on the supply–demand conditions of land use functions within the corresponding grid. The process of land development and utilization by resident agents must also comply with the regional development plans formulated by the government and must not conflict with the plans of departmental agents. During the optimization process, the model generates resident agents corresponding to different land use types on land parcels that satisfy the constraint conditions.

2.7.2. Suitability of Land Use Type Conversion Based on Artificial Neural Networks (ANN))

Land use and conversion patterns are jointly influenced by multiple surrounding factors related to location as well as adjacent land use types. Therefore, the comprehensive suitability of land use conversion includes both land suitability and neighborhood suitability, obtained by multiplying the two together [34].

(1) Land Use Suitability

Referring to previous studies, nine driving factors were selected from the perspectives of the natural environment and socioeconomic conditions, as shown in Figure 5, including altitude, slope, aspect, geological conditions, hydrological conditions, distance to roads, distance to railways, distance to towns, and density of commercial and service industries [39]. These driving factors jointly determine the suitability of different locations for various land use types. In general, higher elevation is associated with greater surface relief and steeper slopes, making the land less suitable for cultivated land and construction land allocation, while providing better ecological environmental conditions that are more suitable for forest land and grass land. Mountain aspect affects the duration of sunlight exposure and solar radiation intensity received by vegetation and crops. In the Northern Hemisphere, solar radiation is greatest on south-facing slopes, followed by southeast and

southwest-facing slopes, then east, west, northeast, and northwest-facing slopes, while north-facing slopes receive the least solar radiation [40]. The geological conditions of XinTai are affected by coal mining activities, which have created underground goaf areas that may lead to land subsidence. Therefore, such areas are unsuitable for the allocation of construction land. Water systems can provide irrigation water for crops as well as domestic and industrial water for human activities, making areas near water systems more favorable for the allocation of cultivated land and construction land. Industrial development also depends on transportation conditions, while residential settlements are generally distributed around towns and areas with dense commercial and service industries [24]. Therefore, the expansion of construction land exhibits characteristics of agglomeration and distribution along transportation corridors. Accordingly, distance to major roads, distance to railways, distance to towns, and density of commercial and service industries were selected to guide the suitability assessment of construction land.

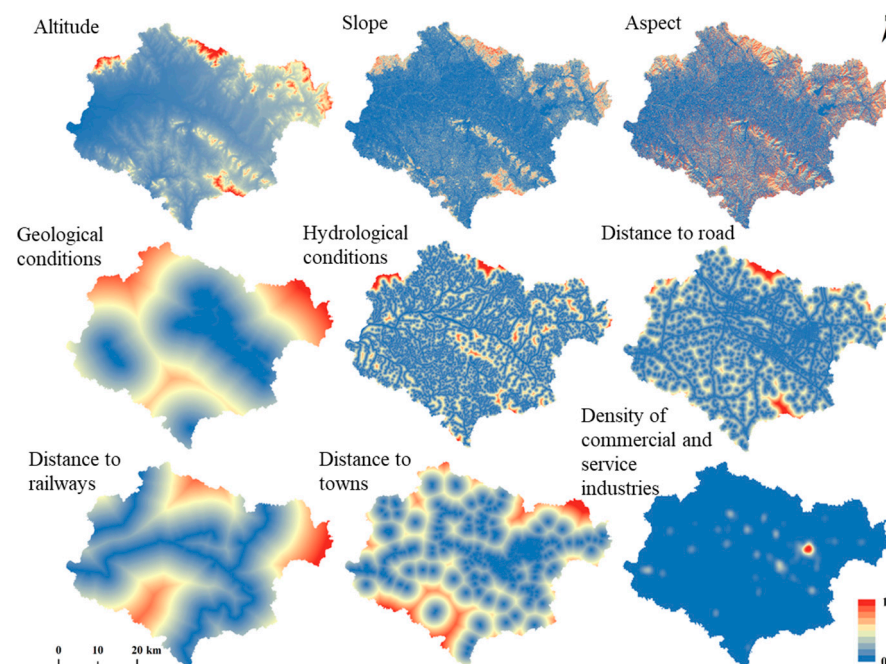


Figure 5. Spatial distribution of land use driving factors.

(2) Neighborhood Suitability

Land use conversion is also influenced by neighborhood suitability, which, in simple terms, refers to the composition of land use types surrounding the target land use type. Considering neighborhood characteristics in land use is conducive to maintaining the agglomeration of land landscapes and reducing fragmentation [21]. As shown in Figure 6, for example, a 3×3 grid was used to search the surrounding land use types of land use type X.

$$N_x = \sum_{i,j=1}^9 N_{ijl} \quad (27)$$

where if the surrounding land use type belongs to the target land use category, a value of 1 is assigned; otherwise, a value of 0 is assigned. The comprehensive neighborhood suitability of the optimization target is then calculated accordingly. The calculation formula is as follows. N_x represents the neighborhood suitability of land use type x ; i and j denote the column and row indices of the grid, respectively; and l represents the land use type.

0	0	0
0	X	1
0	0	1

Figure 6. Neighbourhood suitability diagram.

Finally, the suitability of land use type conversion was calculated using an artificial neural network (ANN) model. The ANN model possesses strong nonlinear processing capabilities and operates through the in-depth analysis and simulation of the behavioral characteristics of neural networks. The main workflow of the ANN model is illustrated in Figure 7, and the primary calculation steps are as follows; this process is implemented using the Geosos1.2.1 software.

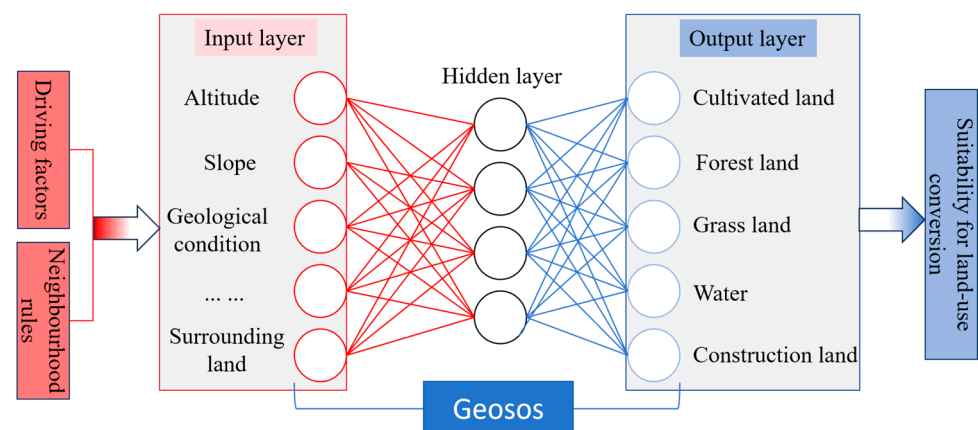


Figure 7. Artificial neural network structure diagram.

Determination of the Input Layer of the Neural Network: The simulation units corresponding to neurons possess different attributes, and differences in these attributes determine the conversion probability of each simulation unit at time t . The expression is as follows:

$$X_i(k, t) = [x_1(k, t), x_2(k, t), x_3(k, t), \dots, x_n(k, t)]^T \quad (28)$$

where $X_i(k, t)$ represents the i th variable of simulation unit k at simulation time t ; and T denotes matrix transposition.

Data Normalization: The processed data values were normalized to the range of (0,1). The normalization formula is as follows:

$$X_i(k, t) = \frac{[X_i(k, t) - Min]}{Max - Min} \quad (29)$$

where Max represents the maximum value and Min represents the minimum value.

Determination of the Output Layer of the Neural Network: After the input layer receives the normalized data, the data are transmitted to the hidden layer. The signal received by the neuron j in the hidden layer is expressed as follows:

$$Net_j(k, t) = \sum_i (w_{ij})x_j(k, t) \quad (30)$$

where $Net_j(k, t)$ represents the signal received by the j th neuron in the hidden layer; and $w_{i,j}$ denotes the parameters between the input layer and the hidden layer. The hidden layer responds to these signals and then outputs the processed information to the next layer, namely the output layer.

Calculation of land use suitability is shown as follows:

$$P(k, t, l) = \sum_i W_{ij} \frac{1}{1 + e^{-Net_j(k, t)}} \quad (31)$$

where $P(k, t, l)$ represents the suitability of unit k for conversion from the current land use type to land use type l at calculation time t ; and W_{ij} denotes the parameters between the hidden layer and the output layer.

2.7.3. Constraints on Land Use Conversion

(1) Government Agent Constraints

The government determines development objectives according to the characteristics of each town, and these regional development objectives provide important guidance for land use development. Land use development is constrained through the land use compatibility values between different land use types and regional development objectives, thereby influencing the optimization decision-making process and further ensuring the rationality of the MAS land policies under regional development constraints within the algorithm. For example, the higher the compatibility value of a certain land use type with a region, the more suitable that land use type is for the regional development strategy, and vice versa. The land use compatibility coefficients are shown in Table 4.

Table 4. Land use compatibility factor.

Land Use Type	Town Development Types			
	Agricultural	Industrial	Ecological Tourism	Comprehensive Service
Cultivated land	1.00	0.34	0.59	0.36
Forest land	0.81	0.36	1.00	0.54
Grass land	0.78	0.31	0.86	0.32
Water	0.90	0.68	1.00	0.76
Unused land	0.21	0.21	0.31	0.11
Construction land	0.54	1.00	0.68	1.00

(2) Departmental Agent Constraints

In the actual process of land development and utilization, the cost of land use type conversion must be considered to ensure the economic efficiency and feasibility of the scheme. In this model, conversion costs include direct costs and implicit costs, which constitute another constraint condition for land use conversion. Direct costs refer to the costs associated with land use type conversion and represent the difficulty or cost of converting the current land use type into the target type. For example, the conversion cost from construction land to grass land is relatively high, whereas the conversion cost from cultivated land to construction land is relatively low. Implicit costs refer to the degree of synergy between the functions generated after conversion to the target land use type and the regional development objectives. For instance, in industrial-type towns, if grass land can be converted into either cultivated land or construction land, the economic output generated by conversion into cultivated land is much lower than that of conversion into construction land and is also inconsistent with the regional development objectives. The

conversion cost coefficient ranges from 0 to 1. A higher coefficient value indicates a lower conversion cost and, consequently, a higher probability of conversion to the corresponding land use type. The results are shown in Table 5.

Table 5. Land use conversion cost constraint factor.

Agricultural Type						
Land Use Type	Cultivated Land	Forest Land	Grass Land	Water	Unused Land	Construction Land
Cultivated land	0.00	0.34	0.59	0.36	0.00	0.12
Forest land	0.61	0.00	0.20	0.34	0.00	0.31
Grass land	0.78	0.31	0.00	0.00	0.00	0.61
Water	0.41	0.68	0.31	0.00	0.00	0.19
Unused land	0.21	0.21	0.31	0.11	0.00	0.53
Construction land	0.24	0.10	0.08	1.00	0.00	0.00
Industrial Type						
Land Use Type	Cultivated Land	Forest Land	Grass Land	Water	Unused Land	Construction Land
Cultivated land	0.00	0.34	0.29	0.41	0.00	0.87
Forest land	0.71	0.00	0.31	0.51	0.00	0.71
Grass land	0.78	0.31	0.00	0.56	0.00	0.91
Water	0.9	0.68	0.27	0.00	0.00	0.31
Unused land	0.21	0.21	0.31	0.41	0.00	0.97
Construction land	0.54	0.00	0.01	0.08	0.00	0.00
Ecological Tourism Type						
Land Use Type	Cultivated Land	Forest Land	Grass Land	Water	Unused Land	Construction Land
Cultivated land	0.00	0.74	0.29	0.36	0.00	0.78
Forest land	0.02	0.00	0.41	0.34	0.00	0.01
Grass land	0.02	0.31	0.00	0.42	0.00	0.21
Water	0.02	0.68	0.30	0.00	0.00	0.15
Unused land	0.79	0.91	0.81	0.51	0.00	0.87
Construction land	0.49	0.40	0.38	0.09	0.00	0.00
Comprehensive Service Type						
Land Use Type	Cultivated Land	Forest Land	Grass Land	Water	Unused Land	Construction Land
Cultivated land	0.00	0.21	0.19	0.31	0.00	0.88
Forest land	0.71	0.00	0.21	0.41	0.00	0.79
Grass land	0.88	0.71	0.00	0.46	0.00	0.91
Water	0.41	0.68	0.27	0.00	0.00	0.31
Unused land	0.61	0.21	0.31	0.41	0.00	0.77
Construction land	0.09	0.08	0.01	0.10	0.00	0.00

(3) Constraints on Resident Agent Conversion Relationships

The resident agent level represents the demand side of land use functions, and local residents' demands for land use functions are aimed at improving the current supply–demand relationships of land use functions. Based on the degree to which changes in land use types affect the supply–demand relationships of land use functions, constraint relationships at the resident agent level for land use conversion are established, as shown in Table 6.

Table 6. Resident agent land use conversion relationship constraint coefficients.

Demand for Production Functions						
Land Use Type	Cultivated Land	Forest Land	Grass Land	Water	Unused Land	Construction Land
Cultivated land	0.00	0.34	0.59	0.36	0.00	0.12
Forest land	0.61	0.00	0.20	0.34	0.00	0.31
Grass land	0.78	0.31	0.00	0.00	0.00	0.61
Water	0.41	0.68	0.31	0.00	0.00	0.19
Unused land	0.21	0.21	0.31	0.11	0.00	0.53
Construction land	0.24	0.10	0.08	1.00	0.00	0.00
Demand for Living Functions						
Land Use Type	Cultivated Land	Forest Land	Grass Land	Water	Unused Land	Construction Land
Cultivated land	0.00	0.34	0.29	0.41	0.00	0.87
Forest land	0.71	0.00	0.31	0.51	0.00	0.71
Grass land	0.78	0.31	0.00	0.56	0.00	0.91
Water	0.9	0.68	0.27	0.00	0.00	0.31
Unused land	0.21	0.21	0.31	0.41	0.00	0.97
Construction land	0.54	0.00	0.01	0.08	0.00	0.00
Demand for Ecological Functions						
Land Use Type	Cultivated Land	Forest Land	Grass Land	Water	Unused Land	Construction Land
Cultivated land	0.00	0.74	0.29	0.36	0.00	0.78
Forest land	0.02	0.00	0.41	0.34	0.00	0.01
Grass land	0.02	0.31	0.00	0.42	0.00	0.21
Water	0.02	0.68	0.30	0.00	0.00	0.15
Unused land	0.79	0.91	0.81	0.51	0.00	0.87
Construction land	0.49	0.40	0.38	0.09	0.00	0.00

2.7.4. Model Accuracy Validation and Parameter Optimization

To identify the optimal operating parameters of the cellular automata model and improve model accuracy, this study conducted nine groups of experiments under different neighborhood scales and iteration numbers. Experiments were performed from the perspectives of cell scale, neighborhood scale, and iteration number, and the model performance was evaluated using three indicators: the kappa coefficient, overall accuracy (OA), and figure of merit (FOM).

(1) Kappa coefficient

The Kappa coefficient is a commonly used measure of agreement between data sets, frequently employed to verify the accuracy of results in remote sensing image classification and land-use modelling. In this paper, the Kappa coefficient is used to assess the accuracy of the land-use simulation results obtained using cellular automata. A confusion matrix is constructed by comparing the simulated land-use data with the actual land-use data, where the rows of the matrix represent the simulated land-use data and the columns represent the actual land-use data. The formula for calculating the Kappa coefficient is shown below:

$$Kappa = \frac{(P_0 - P_e)}{(1 - P_e)} \quad (32)$$

In the formula: P_0 represents the consistency ratio between the current land-use data and the simulation results; P_e represents the expected proportion of the correct simulation results under random conditions.

The Kappa coefficient ranges from 0 to 1; the higher the value, the greater the consistency between the simulation results and the current land-use data, indicating higher simulation accuracy. According to existing research, when the Kappa coefficient exceeds 0.62, the simulation results can be considered to meet the accuracy requirements [41].

(2) Overall accuracy (OA)

OA is a parameter used to assess the proportion of pixels correctly classified as a particular land-use category out of the total number of pixels in that category; the higher the value of overall accuracy, the greater the consistency between the classification results and the ground-truth data. The formula for calculating overall accuracy is as follows:

$$OA = \frac{\sum_{i=1}^n x_{ii}}{M} \quad (33)$$

In the formula: x_{ii} represents the elements on the diagonal of the confusion matrix; M represents the total number of elements in the matrix.

OA ranges from 0 to 1; it is generally accepted that classification results are considered valid when the OA value exceeds 0.8. OA provides a good measure of classification accuracy and complements the Kappa coefficient, which assesses accuracy in pixel-type classification [41].

(3) Figure of merit (FOM)

The FOM was proposed by the scholar Pontius; it is primarily used to assess the variability in land-use simulation and classification results, that is, to evaluate the accuracy of the dynamic changes in simulation outcomes. The formula for calculating the FOM is as follows:

$$FOM = \frac{b}{a + b + c + d} \quad (34)$$

In the formula: a is the number of pixels where the observed state has changed but the simulation result remains unchanged; b is the number of pixels where the observed state has changed and the simulation result has also changed; c is the number of pixels where the observed state has changed, the simulation result has also changed, but the type of change is incorrect; d is the number of pixels where the observed state remains unchanged but the simulation result has changed.

The range of values for the FOM is (0, 1); the higher the value, the greater the accuracy of the simulated changes in the cellular automaton model. When the FOM exceeds 0.21, the model is deemed to meet the simulation accuracy requirement [41].

The experimental results are shown in Table 7. The accuracy validation indicators demonstrate that the simulation accuracy of the cellular automata model gradually decreases as the neighborhood scale increases [11]. Meanwhile, with the increase in iteration number, the accuracy first increases and then decreases. Ultimately, land use optimization was conducted at a spatial resolution of 30 m using a 3×3 neighborhood scale and 500 iterations. In this study, the 2011 land use data were used to predict the land use pattern in 2021, and the simulated results were then compared with the actual land use data of 2021 to identify the optimal model parameters between suitability and land use.

Table 7. Comparison of model-scale experimental accuracy.

Neighborhood Scale	Number of Iterations	Kappa	OA	FOM
3 × 3	200	0.84	0.76	0.27
3 × 3	500	0.87	0.81	0.32
3 × 3	1000	0.86	0.77	0.28
5 × 5	200	0.82	0.80	0.27
5 × 5	500	0.80	0.77	0.29
5 × 5	1000	0.84	0.75	0.23
7 × 7	200	0.81	0.72	0.29
7 × 7	500	0.82	0.74	0.29
7 × 7	1000	0.80	0.77	0.27

2.7.5. Implementation of Land Use Optimization

Through experiments using land use data at different scales, the performance of the model under different scales was evaluated based on the kappa coefficient, overall accuracy (OA), and figure of merit (FOM), thereby identifying the optimal scale for land use optimization. Under the optimal scale, each pixel forms an independent information unit and calculation unit, incorporating constraint parameters derived from the multi-agent system as well as land use suitability. Among the three hierarchical levels of the multi-agent system, the priority order is government agents > departmental agents > resident agents [9]. In other words, when conflicts occur among conversion objectives, the decisions of government agents take precedence. The parameters generated by the multi-agent system (MAS) and the artificial neural network (ANN) were integrated into the cellular automata (CA) model to ultimately achieve the spatial allocation optimization of land use [9]. All of the above operations were implemented using GeoSOS software.

3. Results

3.1. Changes in Optimized Land Use Structure

The area statistics comparing the optimized land use results with the current land use pattern are shown in Table 8. After optimization, cultivated land exhibited the largest area change, decreasing by 2650.81 hm², followed by construction land, which increased by 2234.83 hm². The areas of forest land and grass land decreased slightly, while the water area increased slightly.

Table 8. Statistics on land use structure before and after optimization.

Land Use Type	Current Land Area (hm ²)	Proportion (%)	Optimized Land Area (hm ²)	Proportion (%)	Area Change (hm ²)
Cultivated land	134,782.26	69.67%	132,870.85	68.88%	2650.81
Forest land	10,738.79	5.55%	9705.06	5.03%	1033.73
Grass land	6245.34	3.23%	7023.65	3.64%	778.31
Water	2670.52	1.38%	2804.22	1.45%	133.70
Unused land	1.71	0.00%	0	0.00%	1.71
Construction land	39,016.66	20.17%	41,251.50	21.38%	2234.83

By constructing a land use transition matrix, the types and areas of land use conversion inflows and outflows can be analyzed. The results are shown in Table 9. Regarding land use conversion, approximately 54.5% (14,849.95 hm²) of land pixels were reallocated during the optimization process. In terms of inflow, the largest converted area was construction land, totaling 6586.79 hm², of which 6420.42 hm² was converted from cultivated land, followed by 123.99 hm² converted from grass land. A total of 5702.44 hm² was converted

into cultivated land, among which 3946.27 hm² originated from construction land. This was mainly achieved through land consolidation of scattered residential settlements and subsequent reclamation into cultivated land. At the same time, through the implementation of the policy of “returning forest and grass land to cultivated land,” forest land and grass land suitable for cultivation were converted into cultivated land. A total of 2151.44 hm² of grass land was converted into other land use types, among which 1290.86 hm² originated from cultivated land. In terms of outflow, cultivated land experienced the largest conversion-out area, reaching 8094.50 hm², mainly converted into construction land. Construction land ranked second, with 4003.11 hm² converted out, primarily into cultivated land. Meanwhile, all the unused land within XinTai was fully utilized, thereby avoiding the waste of land resources. The area statistics indicate that cultivated land, construction land, forest land, grass land, and Water underwent mutual conversions rather than unilateral conversion into a single land use type, demonstrating the intelligence and controllability of the optimization model.

Table 9. Land use transfer matrix before and after optimization.

Land Use Type	Cultivated Land	Forest Land	Grass Land	Water	Unused Land	Construction Land	Total Transferred-Out Area (hm ²)
Cultivated land	-	165.15	1290.86	218.07	0	6420.42	8094.50
Forest land	386.82	-	821.07	1.53	0	0.17	1209.59
Grass land	1311.75	5.85	-	0	0	123.99	1441.59
Water	57.24	0	0.09	-	0	42.12	99.45
Unused land	0.36	0	1.26	0	-	0.09	1.71
Construction land	3946.27	5.13	38.16	13.55	0	-	4003.11
Total Inflow Area (hm ²)	5702.44	176.13	2151.44	233.15	0	6586.79	14,849.95

3.2. Optimized Spatial Distribution of Land Use

The spatial distribution of the optimized land use results is shown in Figure 8b. By comparing it with the current land use spatial distribution shown in Figure 8a, it can be observed that the newly developed land use areas originated from the conversion of existing land use types. The overlay analysis of the optimized land use pattern and the current land use pattern is presented in Figure 9. The results indicate that forest land and grass land increased to a certain extent in the mountainous and hilly areas of northern, central, and southern XinTai. Construction land expanded moderately in the central urban area as well as in the two urban sub-centers of “Louyu” and “Xiyangguo,” with the increase in construction land being relatively concentrated in these urban sub-centers.

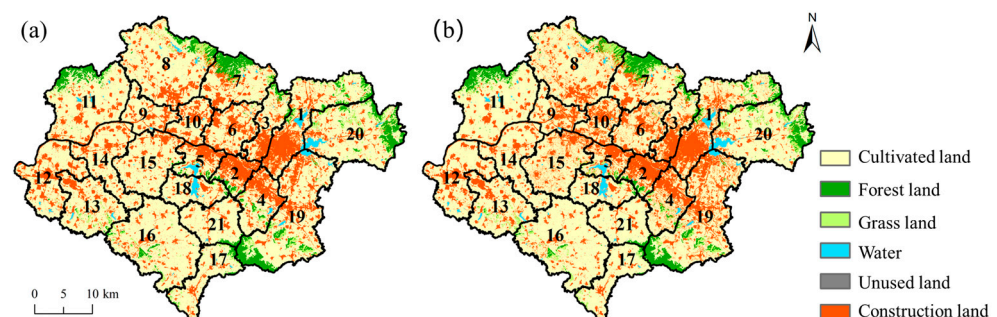


Figure 8. Spatial distribution of land use before and after optimization. (a) Before optimization, the spatial distribution of land use in Xintai City; (b) Optimized spatial distribution of land use in Xintai City.

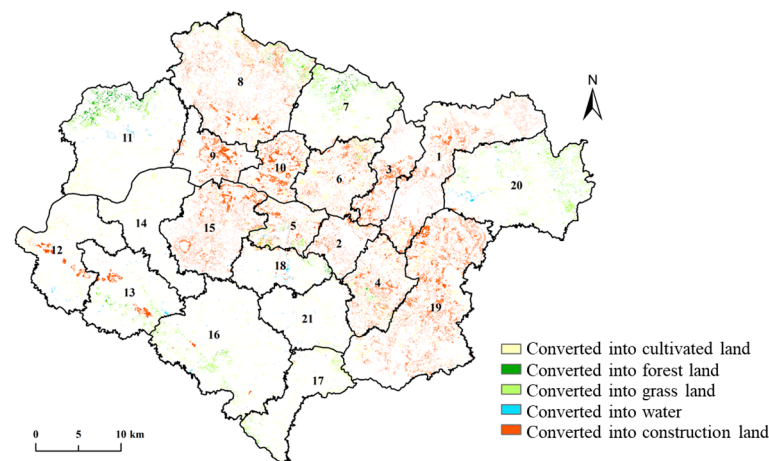


Figure 9. Spatial distribution of land use change after land use optimization.

The land use optimization effects for different development types are shown in Figure 10. The results indicate that, in agricultural-type towns and villages, the areas of forest land, grass land, and construction land were reduced to some extent and converted into cultivated land. In industrial-type towns and villages, construction land further expanded around the existing built-up areas. In ecological tourism-type towns and villages, the areas of cultivated land and construction land were appropriately reduced and converted into ecological land uses such as forest land and grass land. Comprehensive service-type towns, villages, and communities experienced moderate expansion around existing construction land.

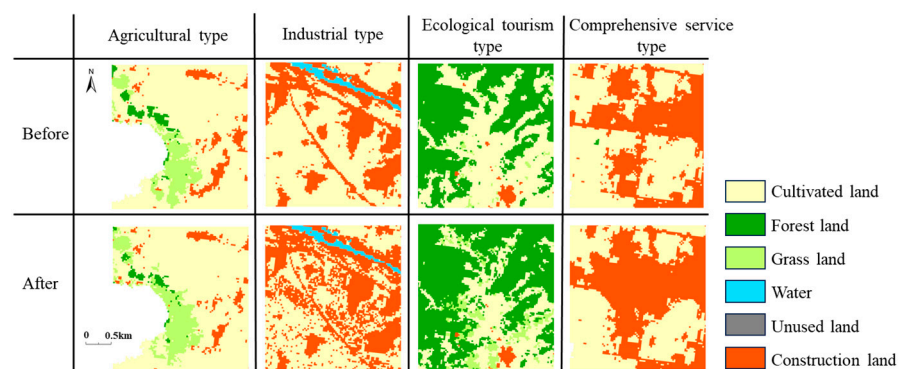


Figure 10. Optimizing effects of land use by development types.

3.3. Changes in Land Use Functions After Optimization

The spatial distribution of the optimized land use functions is shown in Figure 11. Areas with increased production functions are mainly concentrated in the western plain region as well as in Quanguo Town and Longting Town. In contrast, areas with decreased production functions are mainly distributed in the northern mountainous and hilly regions, where part of the cultivated land was reduced through the implementation of the “returning cultivated land to forest” policy. In addition, production functions decreased slightly in industrial-type and comprehensive service-type towns and villages. Areas with increased living functions are mainly concentrated in Qingyun Subdistrict and Xinfu Subdistrict, with additional increases observed in the two urban sub-centers. In Tianbao Town, Quanguo Town, and the mining-area towns of Xiaoxie, Zhai, Dongdu, and Wennan, living functions showed a certain degree of decline. Areas with increased ecological functions are mainly concentrated in the mountainous and hilly regions of northern, central, and southern XinTai. In these areas, the areas of forest land and grass land increased through measures such as

returning cultivated land to forest and relocating certain residential settlements. Ecological functions in the central urban area and the two urban sub-centers decreased slightly because urban expansion encroached upon portions of cultivated land and ecological land.

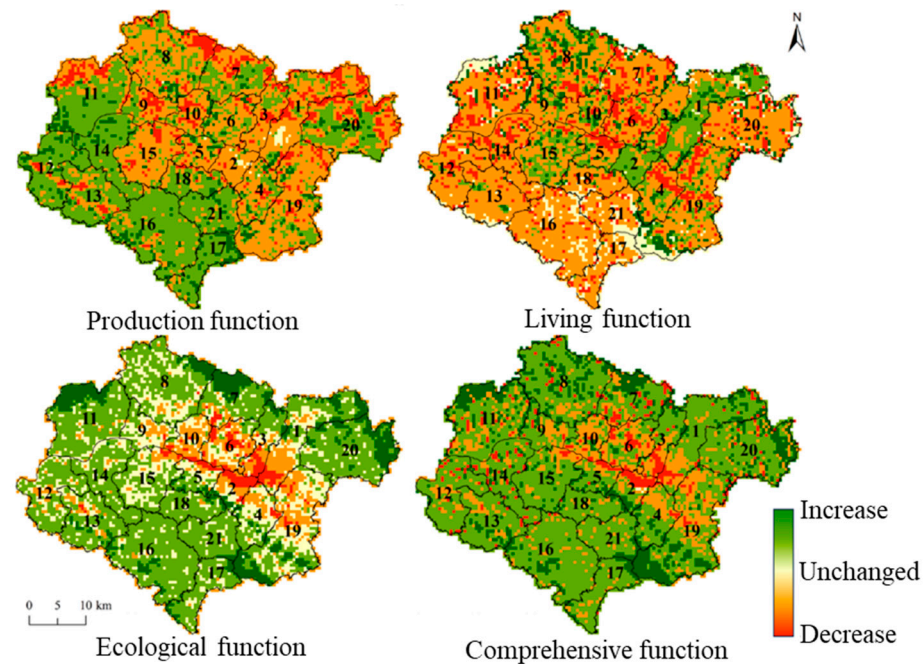


Figure 11. Spatial distribution of functional changes in land use before and after optimization.

Table 10 shows the statistical results of the average values of current land use functions and optimized land use functions for XinTai and different development-type towns and villages. The results indicate that agricultural-type towns and villages experienced significant improvements in production functions and ecological functions, increasing by 9.55% and 19.80%, respectively, while the comprehensive function increased by 12.68%. In contrast, living functions decreased by 11.38%. This outcome is consistent with the development objectives of agricultural-type towns and villages. At the same time, these areas are facing serious issues such as population outflow and housing vacancy, resulting in the waste of land resources, and the optimization results therefore align well with the current socioeconomic context. In industrial-type towns and villages, living functions increased by 11.16%, while production and ecological functions decreased slightly. The comprehensive function increased by 10.78%. In ecological tourism-type towns and villages, ecological functions increased substantially by 68.50%, whereas production and living functions declined to some extent. The comprehensive function increased by 14.09%. In comprehensive service-type towns and villages, living functions improved by 5.34%, while production and ecological functions decreased by 7.94% and 0.88%, respectively. From the perspective of the entire XinTai region, ecological functions exhibited the largest increase, reaching 24.11%, while living and production functions declined slightly. Overall, the comprehensive land use function increased by 9.32%.

3.4. Changes in Trade-Off Relationships of Land Use Functions

Through the overlay analysis of land use function trade-off relationships before and after optimization, the spatial distribution results are shown in Figure 12. From the perspective of production and living functions, the areas with weakened trade-off intensity are mainly concentrated in the agricultural-type towns and villages of Shilai Town, Fangcheng Town, and Liudu Town in southern XinTai. This was primarily achieved by reducing scattered rural residential settlements and implementing the policy of “returning forest land

and grass land to cultivated land,” thereby increasing the amount of cultivated land. At the same time, weakened trade-off intensity was also observed in comprehensive service-type towns and subdistricts such as Qingyun Subdistrict, Xinfu Subdistrict, and Wennan Town. These areas are mainly oriented toward the development of commercial and service industries. Economic growth and population agglomeration inevitably lead to the conversion of cultivated land into construction land, thereby enhancing living functions. However, in the remaining industrial-type and comprehensive service-type towns and villages, the trade-off intensity increased slightly, indicating that in regions characterized by mixed industrial development, conflicts between construction land expansion and cultivated land still persist before construction land reaches a certain scale.

Table 10. Land use functional index statistics before and after optimization.

Town Development Types	Land Use Function Types	Current	After Optimization	Change Rate (%)
Agricultural	Production function	0.16	0.17	9.55%
	Living function	0.17	0.15	−11.38%
	Ecological function	0.10	0.12	19.80%
	Comprehensive function	0.14	0.16	12.68%
Industrial	Production function	0.14	0.13	−8.45%
	Living function	0.25	0.28	11.16%
	Ecological function	0.11	0.09	−14.68%
	Comprehensive function	0.17	0.19	10.78%
Ecological Tourism	Production function	0.13	0.13	−5.97%
	Living function	0.19	0.17	−10.16%
	Ecological function	0.13	0.21	68.50%
	Comprehensive function	0.15	0.17	14.09%
Comprehensive Service	Production function	0.13	0.11	−7.94%
	Living function	0.28	0.30	5.34%
	Ecological function	0.11	0.11	−0.88%
	Comprehensive function	0.17	0.18	6.36%

From the perspective of production and ecological functions, areas with weakened trade-off relationships are mainly concentrated in the mountainous and hilly regions of northern, central, and southern XinTai. In these areas, the area of ecological land increased through the implementation of the policy of “returning cultivated land to forest and grass land,” thereby enhancing ecological functions. In the agricultural-type towns and villages of the western plain area, trade-off intensity also weakened slightly. These areas improved the synergy between production and ecological functions by increasing the area of cultivated land. In contrast, industrial-type and comprehensive service-type towns and villages exhibited an increasing trend in trade-off intensity. Due to the expansion of construction land, portions of ecological land and a small amount of cultivated land were occupied, leading to stronger trade-offs between production and ecological functions.

From the perspective of living and ecological functions, areas with weakened trade-off intensity are mainly distributed in the mountainous and hilly regions of northern, central, and southern XinTai, as well as in industrial-type and comprehensive service-type towns and villages surrounding the central urban area. On the one hand, the mountainous and hilly regions possess favorable ecological baseline conditions, and ecological functions were enhanced through the relocation of residential settlements and the restoration of ecological land, thereby weakening the trade-off between living and ecological functions. On the other hand, in industrial-type and comprehensive service-type towns and villages,

the expansion of construction land improved living functions and reduced the trade-off intensity between the two functions.

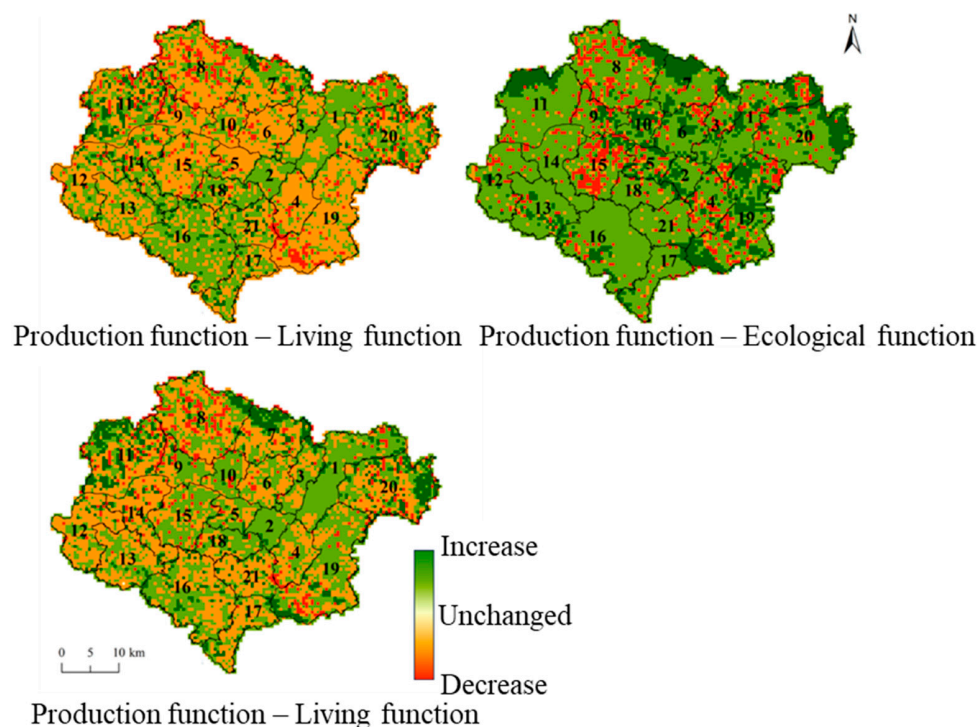


Figure 12. Spatial distribution of changes in the intensity of land use function trade-offs before and after optimization.

Table 11 presents the zonal statistics of changes in land use function trade-off relationships after land use optimization for different development-type towns and villages as well as the entire Xintai region. The results indicate that the trade-off relationship between production and living functions in Xintai increased slightly, mainly due to the encroachment of cultivated land by construction land driven by economic development.

Table 11. Statistics on changes in land use function trade-offs before and after optimization.

Town Development Types	Land Use Function Trade-Offs Types	Current	After Optimization	Change Rate (%)
Agricultural	Production function–Living function	−0.093	−0.086	−7.53%
	Production function–Ecological function	−0.006	−0.004	−28.33%
	Living function–Ecological function	−0.268	−0.242	−9.70%
Industrial	Production function–Living function	−0.376	−0.282	−25.00%
	Production function–Ecological function	−0.005	−0.002	−60.00%
	Living function–Ecological function	−0.132	−0.151	14.39%
Ecological Tourism	Production function–Living function	0.094	0.097	3.19%
	Production function–Ecological function	−0.251	−0.413	64.54%
	Living function–Ecological function	−0.179	−0.169	−5.59%
Comprehensive Service	Production function–Living function	−0.146	−0.156	6.85%
	Production function–Ecological function	−0.039	−0.033	−15.38%
	Living function–Ecological function	−0.102	−0.096	−5.88%
Xintai City	Production function–Living function	−0.179	−0.182	1.68%
	Production function–Ecological function	−0.094	−0.067	−28.72%
	Living function–Ecological function	−0.133	−0.099	−25.56%

In contrast, the trade-off intensity between production and ecological functions, as well as between living and ecological functions, decreased substantially.

Among the different development-type towns and villages, agricultural-type towns and villages exhibited the greatest reduction in the trade-off intensity between production and ecological functions, reaching 28.33%. This was mainly achieved by reducing conflicts between ecological land and cultivated land through the implementation of the policy of “returning forest land and grass land to cultivated land.” In industrial-type towns and villages, the trade-off intensity between production and living functions and between production and ecological functions weakened, whereas the trade-off intensity between living and ecological functions increased. This was mainly because the expansion of construction land occupied ecological land and portions of cultivated land. In ecological tourism-type towns and villages, the synergy between production and living functions increased by 3.19%, while the trade-off intensity between production and ecological functions decreased by 15.14%, and the trade-off intensity between living and ecological functions decreased by 5.59%. These changes were mainly attributable to the implementation of policies such as “returning cultivated land to forest and grass land” and the relocation of residential settlements, which enhanced ecological functions within the region. In comprehensive service-type towns and villages, the trade-off degree between production and living functions increased by 6.85%, whereas the trade-off intensity between production and ecological functions decreased by 15.38%, and the trade-off intensity between living and ecological functions decreased by 5.88%.

3.5. Changes in the Supply–Demand Relationship of Land Use Functions

The optimization of land use function supply–demand relationships is mainly reflected by improvements in supply capacity and reductions in deficit conditions. As shown in Figure 13, by comparing the supply–demand relationships of land use functions before and after land use optimization and conducting an overlay analysis of the spatial changes in supply–demand ratios, the following results were obtained. In terms of the supply–demand relationship of production functions, the supply–demand ratio improved in the western plain region and Longting Town in eastern XinTai. These areas enhanced the supply of production functions through the expansion of cultivated land. Regarding the supply–demand relationship of living functions, improvements were observed in the northern mountainous and hilly regions as well as in the industrial-type towns of Wennan, Dongdu, and Guli. On the one hand, the mountainous and hilly regions reduced the demand for living functions through the relocation of residential settlements. On the other hand, industrial-type towns increased the supply of living functions by expanding construction land. For the supply–demand relationship of ecological functions, the areas with improved supply–demand conditions were mainly concentrated around mining areas and in the western plain region, including the central industrial-type towns, Dongdu Town, Xinwen Subdistrict, and Xinfu Subdistrict. In these areas, the expansion of construction land occupied ecological land, thereby reducing regional demand for ecological functions. In agricultural-type towns such as Shilai Town and Gongli Town, reductions in construction land and increases in cultivated land led to a decrease in demand for ecological functions. In terms of comprehensive functions, the areas showing improvement were mainly concentrated in the western plain region and around mining areas. In the plain region, reductions in certain construction land areas enhanced the supply of production and ecological functions, while around the mining areas, the expansion of construction land strengthened the supply of living functions, thereby improving the supply–demand relationships of land use functions.

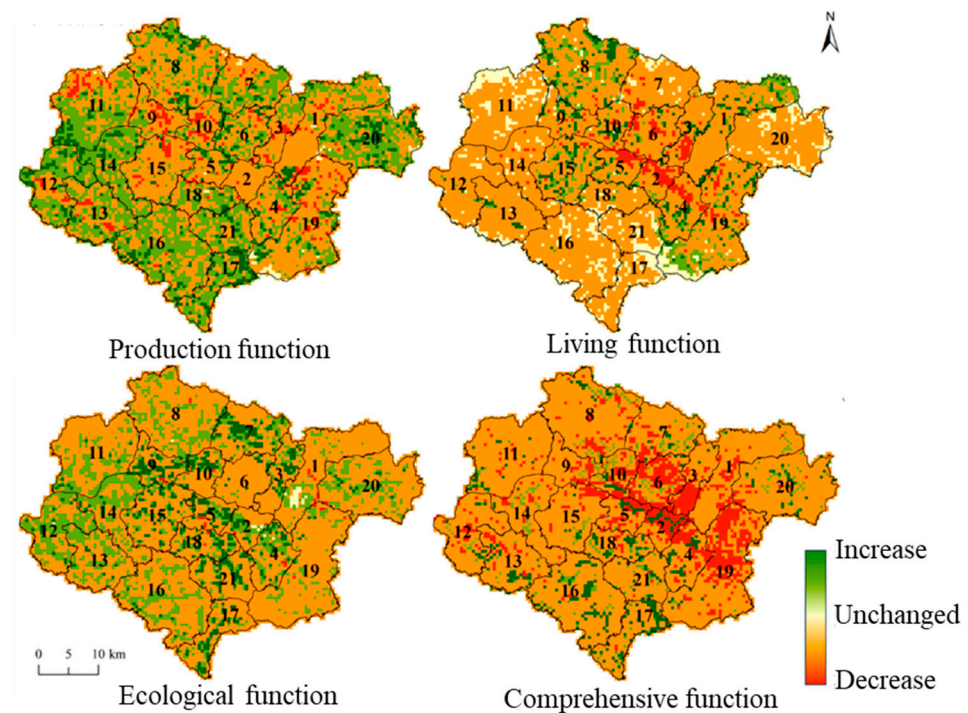


Figure 13. Spatial distribution of changes in supply–demand relationship of land use function before and after optimization.

Table 12 presents the changes in the optimized supply–demand relationships of land use functions in XinTai and different development-type towns and villages. The results indicate that, for the entire XinTai region, the surplus level of the production function supply–demand relationship decreased by 13.46%, while the surplus level of the living function supply–demand relationship increased by 16.67%. The deficit condition of the ecological function supply–demand relationship improved by 33.33%, and the surplus level of the comprehensive function increased by 23.53%. In agricultural-type towns and villages, the surplus level of the production function supply–demand relationship increased by 65.31%, the deficit level of the living function supply–demand relationship improved by 20.00%, the surplus level of the ecological function supply–demand relationship increased by 30.00%, and the surplus level of the comprehensive function increased by 23.53%. In industrial-type towns and villages, the surplus level of the production function supply–demand relationship decreased by 26.67%, while the surplus level of the living function supply–demand relationship increased by 42.86%. The deficit level of the ecological function supply–demand relationship increased by 16.67%, whereas the surplus level of the comprehensive function increased by 38.46%. In ecological tourism-type towns and villages, the surplus level of the production function supply–demand relationship decreased by 30.30%, the deficit level of the living function supply–demand relationship increased by 14.29%, the surplus level of the ecological function supply–demand relationship increased by 66.67%, and the surplus level of the comprehensive function increased by 9.52%. In comprehensive service-type towns and villages, the surplus level of the production function supply–demand relationship decreased by 27.27%, while the surplus level of the living function supply–demand relationship increased by 16.25%. The deficit level of the ecological function supply–demand relationship increased by 38.00%, whereas the surplus level of the comprehensive function increased by 15.56%.

Table 12. Statistics on changes in supply–demand of land use function before and after optimization.

Town Development Types	Land Use Function Supply and Demand Types	Current	After Optimization	Change Rate (%)
Agricultural	Production function	0.098	0.162	65.31%
	Living function	−0.015	−0.018	20.00%
	Ecological function	0.001	0.002	30.00%
	Comprehensive function	0.028	0.031	10.71%
Industrial	Production function	0.045	0.033	26.67%
	Living function	0.007	0.010	42.86%
	Ecological function	−0.012	−0.010	−16.67%
	Comprehensive function	0.013	0.018	38.46%
Ecological Tourism	Production function	0.066	0.046	−30.30%
	Living function	−0.007	−0.008	14.29%
	Ecological function	0.003	0.005	66.67%
	Comprehensive function	0.021	0.023	9.52%
Comprehensive Service	Production function	0.022	0.016	−27.27%
	Living function	0.016	0.019	16.25%
	Ecological function	−0.010	−0.006	−38.00%
	Comprehensive function	0.009	0.010	15.56%
Xintai City	Production function	0.052	0.045	−13.46%
	Living function	0.003	0.004	16.67%
	Ecological function	−0.006	−0.008	33.33%
	Comprehensive function	0.017	0.021	23.53%

4. Discussion

Land use functions constitute the interface between human society and land systems, and enhancing these functions is the primary objective of land-use allocation optimisation. Enhancing land-use functions involves not only improving overall functional performance but also aligning land allocation with regional development characteristics while balancing trade-offs among multiple land use functions and meeting societal demands. Accordingly, this study proposes a methodological framework for enhancing land-use functions. The framework aims to align land allocation with regional development plans, minimise trade-offs among land use functions, and improve the balance between functional supply and demand. These objectives are integrated with land suitability assessment to optimise regional land zoning, classification, and spatial allocation. This study provides an effective decision-support framework for land-use management during the sustainable transformation of resource-depleted cities.

Previous studies have primarily employed CA–ANN models to simulate land-use expansion under rapid urbanisation, with an emphasis on improving the accuracy of land-use change prediction and characterising spatial expansion patterns [42,43]. In contrast, this study focuses on resource-depleted cities undergoing simultaneous industrial transformation, population decline, and ecological conservation. The proposed framework extends the application of CA–ANN models from land-use change prediction and simulation to land-use functional optimisation and spatial restructuring by integrating top-down policy constraints with bottom-up land suitability assessment. This extension broadens the applicability of CA–ANN models.

Following the study results, distinct spatial adjustment patterns emerged across different types of towns and villages. Agricultural towns and villages experienced the conversion of forest, grassland, and built-up land into cultivated land, whereas industrial towns and villages expanded around their existing built-up areas. Eco-tourism towns and villages

prioritised the conversion of cultivated and built-up land into ecological land, including forests and grasslands, while comprehensive service towns, villages, and communities underwent moderate outward expansion. These spatial adjustment patterns are consistent with the optimisation strategies proposed for resource-based cities during critical transition periods, which emphasise ecological conservation while simultaneously safeguarding industrial development, food security, and ecological security [41,43].

The results indicate that the proposed methodological framework effectively mitigates trade-offs among land-use functions and optimises functional supply–demand relationships while providing differentiated guidance for land-use planning across different town types. Although the model does not fully reproduce the evolution of land use, it remains effective for optimising land-use allocation because it captures the dominant mechanisms governing land-system dynamics and the interactions between regional development factors and land resources.

Despite these contributions, this study has several limitations. The indicator system was developed based on regional characteristics; however, the relatively small study area, limited data availability, and restricted indicator selection may constrain its broader applicability. Future applications should adapt the indicator system, ecosystem service value equivalence coefficients, and land conversion probabilities to local environmental characteristics and regional development strategies. Furthermore, estimating land-use functions solely on the basis of land area limits the spatial resolution to the township level and cannot capture functional heterogeneity within the same land-use category. Future studies could integrate NDVI/EVI, night-time light imagery, POI data, and field surveys to improve the spatial representation of agricultural, industrial, and residential functions. Future research could further improve optimisation efficiency and simulation accuracy by integrating emerging artificial intelligence techniques with CA models, such as Monte Carlo uncertainty analysis, deep learning algorithms, or advanced simulation frameworks including the PLUS model.

5. Conclusions

In response to the land use function conditions of XinTai in 2021, this study adopted a combined top-down and bottom-up framework to conduct land use optimization aimed at improving land use functions. At the bottom-up level, an artificial neural network (ANN) model was employed to emphasize land use suitability of different land use types. At the top-down level, a multi-agent system (MAS) model was adopted to reflect decision-making processes within human social systems. These two models were further integrated into a cellular automata (CA) model to achieve the spatial allocation optimization of land use. In addition, the model coupled land use function trade-off relationships and supply–demand relationships into the process of land use spatial optimization.

The optimization results show that approximately 54.5% (14,849.95 hm²) of land pixels were reallocated during the optimization process. After optimization, cultivated land exhibited the largest area change, decreasing by 2650.81 hm², followed by construction land, which increased by 2234.83 hm². Forest land and grass land decreased slightly, while water areas increased slightly. The largest conversion area was into construction land, totaling 6586.79 hm², among which 6420.42 hm² originated from cultivated land. Meanwhile, 5702.44 hm² of land was converted into cultivated land, including 3946.27 hm² converted from construction land. The optimization results of land use functions indicate that, compared with the land use function conditions in 2021, ecological functions showed the greatest improvement, increasing by 24.11%, while living functions and production functions decreased slightly by 4.35% and 0.87%, respectively. Overall, the comprehensive land use function increased by 9.32%. Regarding land use function trade-off relationships,

the trade-off intensity between production and living functions in XinTai increased by 1.68%, whereas the trade-off intensity between production and ecological functions and between living and ecological functions weakened, decreasing by 28.72% and 25.56%, respectively. In terms of land use function supply–demand relationships, the surplus level of the production function supply–demand relationship decreased by 13.46%, while the surplus level of the living function supply–demand relationship increased by 16.67%. The ecological function supply–demand deficit improved by 33.33%, and the surplus level of the comprehensive function increased by 23.53%.

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