

## Retraction

# Retracted: Designing Landscape of Urban Gardening Based on Optimized Artificial Intelligence Model

### Journal of Function Spaces

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

- [1] L. Liu, "Designing Landscape of Urban Gardening Based on Optimized Artificial Intelligence Model," *Journal of Function Spaces*, vol. 2022, Article ID 7963173, 12 pages, 2022.

## Research Article

# Designing Landscape of Urban Gardening Based on Optimized Artificial Intelligence Model

Long Liu 

*School of Architectural and Artistic Design, Henan Polytechnic University, Jiaozuo, Henan 454000, China*

Correspondence should be addressed to Long Liu; ll5618@hpu.edu.cn

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The landscape is driven by innovative design, adhering to the concept of “poetic residence, inheritance, and innovation,” which has long served China’s urban and rural development and the construction of ecological civilization and provided high-quality planning and design services for governments at all levels throughout the country; we construct a particle swarm optimization (PSO) landscape pattern spatial optimization model and solution algorithm to optimize the spatial layout of the landscape for economic development, ecological protection, and integrated scenarios in a city in southwest China. The results show that the PSO-based landscape pattern spatial optimization model and algorithm can use particle position to simulate landscape distribution for spatial pattern optimization. In the development of landscape pattern optimization methods, the landscape pattern optimization model with landscape simulation evolution as the core has shown its advantages. In the target year, the dominant landscape of economic development scenario is urban and orchards, and the landscape pattern shows the distribution characteristics of urban, farmland in the western dam area, and orchards in the eastern mountainous area; the dominant landscape of ecological protection scenario is forest, urban, and rural residential and industrial mining; and the landscape pattern shows the distribution characteristics of urban and rural residential and industrial mining, orchards, farmland in the western dam area, and forest in the eastern mountainous area. The landscape pattern shows that the western dam area is dominated by urban and rural residential and industrial, while the eastern mountainous area is dominated by forests and orchards. The integrated scenario has the highest potential for the future, and its economic, ecological, and comprehensive benefits can be optimized, which is the best spatial layout of the landscape pattern in the study area in the target year.

## 1. Introduction

In recent years, the urbanization process of rapid development has focused on the safety and smoothness of traffic, with much emphasis on the vehicular experience of the road, and the consideration of the human living environment is also mostly from the perspective of the driver [1]. However, many factors have led to the fact that most of this year’s urban construction has not only failed to achieve the original purpose of smooth traffic flow but also induced negative emotions such as congestion and anxiety among pedestrians due to various traffic congestions and other “urban diseases.” The American scholar Roger Trancik (2008) proposed the concept of “lost space” in “In Search of Lost Space,” arguing that the misuse of automobiles, private interests overriding

public interests in urban renewal, and land use patterns within cities have created a vacuum. The concept of “lost space” is proposed in “In Search of Lost Spaces” by Roger Trancik (2008), who argues that the misuse of cars, private interests overriding public interests in urban renewal, and land use patterns within cities have created a vacuum in cities. “The “human,” “vernacular,” and “imaginative” positive spaces are increasingly neglected and rejected [2]. The traditional “human,” “vernacular,” and “imaginative” positive spaces are increasingly neglected and rejected [3, 4]. Along with the increasing demand and requirements for the quality of human living environment, the public is increasingly looking forward to public spaces that can bring them pleasant experiences. As one of the important public open spaces in the city, street space is an important direct

carrier for people to recognize and experience urban culture and urban imagery and plays an important role in the daily life of residents, far from being only a simple function of transportation [5].

Urban landscaping landscape design is a landscape pattern that can protect and restore biodiversity and achieve effective control and continuous improvement of ecological and environmental problems [6]. Landscape design is the optimization and adjustment of the landscape quantity structure and spatial layout with the help of GIS technology, scenario analysis, spatial optimization models, and methods to form a landscape spatial configuration scheme with the maximum ecological and economic integrated benefits [7]. The suburban area is an area close to the central area of the city, which is closely related to the central area in economic, social, and cultural aspects and has convenient transportation links with it [8]. In recent years, due to unreasonable land use development and urban sprawl, the structure and function of the ecosystem in periurban areas have been seriously damaged, resulting in dramatic changes in regional climate, hydrological processes, biogeochemical cycles, and biodiversity. Pinto and Maheshwari proposed methods for assessing critical river health in river systems around cities [9]; Zhang et al. studied the relationship between landscape structure of woody plant communities and land use intensification, species diversity, and functional diversity in semiarid regions [10]. Forest reduction and pollution by “three wastes” have appeared. Although some places have improved the local ecological environment through environmental remediation, the overall deterioration trend has not been curbed, mainly because there is no scientific planning of land use in ecological construction, leading to blind and inefficient ecological protection, and the contradiction and ecological protection have been intensified. How to build a reasonable landscape safety pattern and balance the contradiction between economic development and environmental protection spatially has become a practical problem that needs to be solved to implement the national ecological civilization construction strategy [11]. Landscape pattern means to build landscape security pattern and realize regional ecological security, and it is an effective way to ease the conflict between ecological protection and economic development, which has important practical significance.

The innovation of the research lies in that on the grid level of landscape type map, a method of spatial optimization of landscape pattern based on PSO is proposed. It is proved that this method can effectively couple the results of landscape quantity optimization of constrained optimization model with the relevant policy and economic and social factors of spatial optimization. The optimization of landscape pattern based on high-resolution grid map is realized theoretically. The results show that the model and algorithm of landscape pattern spatial optimization based on particle swarm optimization can use particle location to simulate landscape distribution for spatial pattern optimization. In the development of landscape pattern optimization methods, the landscape pattern optimization model with landscape simulation evolution as the core shows its advantages. This

paper provides a reference value for the best spatial layout of the landscape pattern in the target year of the study area.

Section 1 describes the research background of urban gardening landscape design and the main structure of this paper; Section 2 introduces the current status of domestic and international research in related fields and summarizes the research significance of this paper; Section 3 introduces the evaluation of landscape suitability based on logistic regression model and proposes the PSO landscape pattern spatial optimization model and algorithm. Section 4 tests and analyzes the scheme proposed in this paper. Section 5 summarizes the research content of this paper and gives an outlook on future research directions.

## 2. The Related Works

The work of landscaping landscape design generally includes many aspects such as scheduling work, labor and safety management, planning management, financial management, science and technology management, material management, information management, production management, business management, equipment management, infrastructure management, and quality management [12]. Landscape design of greenery and landscaping is still in the development stage and is an important science, and with the development of society, this work is receiving more and more attention. In the development process of greening management information system, 1960s onwards, the United States expounded Taylor, Longwood Chemical, and the University of Tennessee Arboretum began to study the management of plant information under the computer [13]. In the 1990s to the present, with the maturity of computer and information technology, foreign greening applications have become more and more extensive and more refined and in-depth. The National Parks Board of Singapore not only has access to every ornamental plant species, number, and growth status in the country through computer search but also has created a digital information file for all trees in the country. Garden information for each country is an indispensable part of the construction of information technology since the 1960s; the United States led the combination of computer technology and forestry; after nearly half a century of development, the garden information system is not the initial scientific computing tools, but a comprehensive decision-making and information management system; garden research methods and conservation and management techniques have also had a radical change [14].

The methods for optimizing the number of landscape patterns mainly include classical optimization methods such as linear programming, multiobjective programming, and system dynamic models, which are widely used in land use optimization; for example, Kopeva et al. used the land use structure of Montgomery County, Maryland [15]. Hosseinpour et al. developed a multiobjective linear programming model for the Iranian province of Kermanshahan Brimvand watershed land use for optimal allocation [16]. Alkan used SD-MOP model to simulate and optimize the land use structure of western Jilin province in 2020 [17]. With the advancement of computer and GIS technology, a large

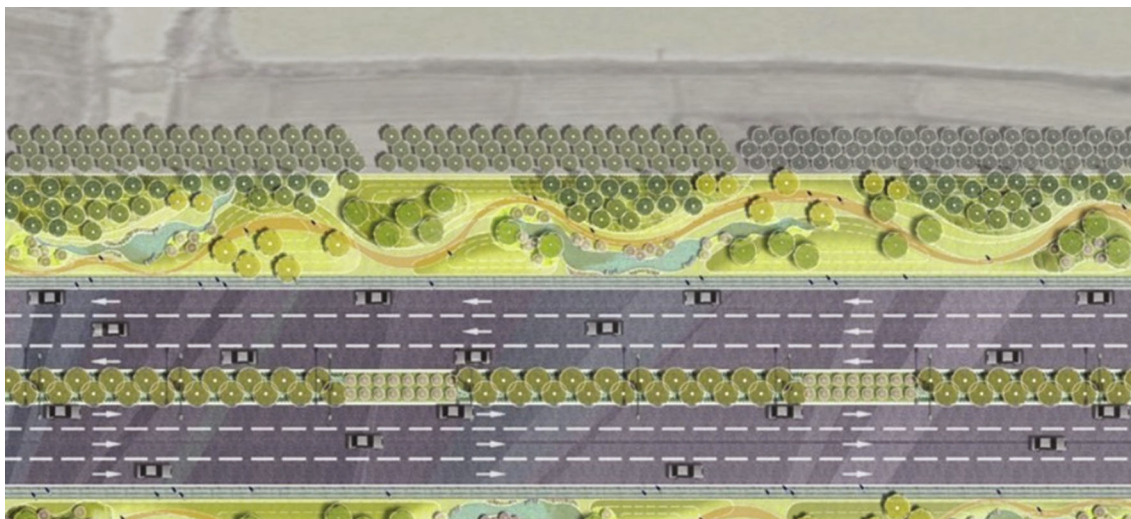


FIGURE 1: Urban green landscape map of A district in a southwestern city.

number of spatial planning decision studies based on meta-cellular automata, scenario analysis method, artificial intelligence optimization method, and integrated optimization method have emerged. For example, Rodrigues et al. used the “ecological location” suitability of metacell to develop probabilistic conversion rules for sustainable land use planning [18]. Padullés et al. applied the Dyna-CLUE model to simulate the spatial distribution of land use for three land demand scenarios in Dianchi watershed [19]. Shan and Sun used a multi-intelligent genetic algorithm to configure the quantitative structure and spatial layout of land use [20]. Alhazzaa applied autologistic and CLUE-S integrated models to simulate the land use pattern of Li River watershed in multiple scenarios [21].

The above research has laid the foundation for the development of green landscape design, but most of the modeling methods used in the research are limited to the unilateral optimization of quantitative structure or spatial layout, lacking the organic coupling of the two; some of the modeling methods also lack the integration of policy and economic and social factors and are cumbersome to operate and poorly applied. Therefore, there is an urgent need for a spatial pattern optimization method that can simulate the quantitative and spatial dynamic processes of landscape patterns and reflect the current socioeconomic conditions and development plans of the region with easy application. PSO is an evolutionary algorithm that can parallelize the multidimensional discontinuous decision space, with simple search speed and easy implementation, and has been successfully applied to shopping mall location, soil layout, land use optimization, and other spatial optimization decisions [22], but its application in landscape pattern optimization is still rare. In order to solve this problem and encourage multidisciplinary research on the interaction between urban people and wildlife, Van Dam et al. proposed the extent to which design and planning actions should be consistent. Define the urban ecological content in the context of compact cities [23]. From the perspective of urban design, Abomohra et al. outline the concept of smart city and high-

light the important entry point of smart city landscape design. This paper introduces the strong principles and relationships of smart city landscape design and the role of urban design [24]. Fekete et al. analyzed the sustainable strategy of local bathing beach transformation and landscape protection. The contents of participatory landscape design and water management are analyzed [25].

In view of this, this paper takes a city in southwest China, Area A, as the study area, and firstly conducts landscape suitability evaluation, then applies the constrained optimization method to optimize the quantitative structure of landscape pattern for each scenario, in order to provide a theoretical basis for land use planning, town planning, and ecological construction planning in this area and also provide a methodological reference for other areas to conduct similar studies. It is expected to provide theoretical basis for ecological construction planning in this area and also provide methodological reference for similar studies in other areas.

### 3. Optimized BP Neural Network Model Based on PSO

*3.1. Landscape Suitability Evaluation Based on Logistic Regression Model.* Based on the basic principles of landscape suitability evaluation and with reference to relevant researches, this paper selects indicators from socioeconomic factors to build an evaluation index system [23]. Landscape suitability evaluation is the evaluation of the suitability of spatial distribution of a certain type of landscape, which is the basis and foundation of landscape pattern optimization. The study area has both flat dams, mountains, and hills. Referring to similar studies, we choose the elevation, slope, slope direction, and topographic relief to characterize the topographic factors affecting the landscape pattern Figure 1.

Climate is the main factor to determine the distribution of landscape, and the spatial variability of temperature and precipitation in the study area is obvious due to the difference, so the multiyear average rainfall and temperature are



selected to characterize the climate factors affecting the distribution of landscape [24]. Soil type distribution will affect the spatial pattern of landscape to a certain extent and is an important basis for soil type classification, so soil organic matter content is chosen to characterize the soil factors affecting, which has been confirmed in similar studies [25].

High buildings in the city, or excessively high, or close to the visual channel, or poor shape, or color incompatible with the surrounding environment, may cause great landscape impact. Urban roads, especially urban trunk roads, determine not only the pattern of the city but also the main visual space and corridor of the city, which plays an important role in the urban landscape. At the same time, the transformation of old urban areas and the construction of new areas have both the landscape impact caused by the planning and layout and the landscape problems of the building itself. Industrial pollution type construction projects discharge air pollutants and reduce atmospheric visibility. It has a significant impact on the urban landscape and residents' comfort. So the nearest distance to the urban center, the nearest distance to the center of the established town, the nearest distance to the main road, and the nearest distance to the main water area are chosen to characterize the neighborhood factors affecting the distribution of the landscape. In the smaller spatial scale, the influence of socioeconomic factors on the landscape pattern is stronger than that of natural factors; the study area is a suburban area of a large city, influenced by the rapid development of urbanization and industrialization; the population continues to gather in towns and cities; and urban-rural distribution is uneven. Choose population density and per capita gross regional product to characterize the influence of landscape. Therefore, population density and gross regional product per capita are chosen to characterize the socioeconomic factors affecting the distribution of the landscape.

Each type of landscape has two states of "existence" and "nonexistence" in a certain spatial range, which is suitable for analysis by logistic regression model, and the expression of the model is

$$p = \frac{\exp(a + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_\theta X_\theta)}{1 + \exp(a + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_\theta X_\theta)}, \quad (1)$$

where  $p$  is the probability value of a certain type of landscape on each raster in the region; the larger the probability value of the raster, the more suitable for the layout of this type of landscape, in other words, the more suitable for the spatial distribution of the landscape, so  $p$  also characterizes the suitability of the spatial distribution of the landscape;  $p \in [0, 1]$ ;  $X_\kappa (\kappa = 1, 2, \dots, \theta)$  is the influence factor of the spatial distribution of the landscape;  $a$  is the constant of the regression equation; and  $\beta_\kappa (\kappa = 1, 2, \dots, \theta)$  is the regression coefficient. In this paper, we first extracted the landscape map of farmland and orchard and assigned the value of "1" to the raster of the landscape map and the value of "0" to the raster of the nonexistent landscape map, then extracted the values of each raster of the landscape map and its corresponding raster of the spatial distribution of

13 evaluation indexes. Then, we extracted the raster values of the landscape map and the raster values of the spatial distribution of the 13 evaluation indexes and introduced them into SPSS 19.0 for binary logistic analysis by stepwise regression method and obtained the spatial pattern impact indexes of the landscape and the regression coefficients of each index; finally, we calculated the probability map of the spatial distribution of each landscape according to equation (1) using Python programming, i.e., the landscape suitability evaluation map.

Combining with the landscape pattern situation in the base year (2014), three scenarios of economic development, ecological protection, and integration were designed, and five types of landscape areas, namely, farmland ( $z_1$ ), orchard ( $z_2$ ), forest ( $z_3$ ), urban and rural habitat and industrial and mining ( $z_4$ ), and water body ( $z_5$ ), were used as decision variables, as constraints to maximize the economic benefits of landscape utilization and maximize ecological safety and comprehensive benefits, respectively. The optimization model of landscape pattern was established with the objectives of maximizing the economic benefits of landscape utilization, maximizing ecological safety and maximizing comprehensive benefits, respectively, and optimizing the landscape area for different scenarios in the target years (2024 and 2034).

The main objective of the economic development scenario is to produce more goods and provide more services by rational use of limited landscape resources, and its objective function is

$$f(z) = \text{Sup} \left\{ \lim_{K \rightarrow \infty} \sum_{k=1}^K c_k z_k \right\}, \quad (2)$$

where  $f(z)$  is the total economic output value of each landscape (million yuan);  $c_k$  is the output value coefficient of the  $k$  type of landscape ((million yuan) /  $\text{hm}^2$ );  $z_k$  is the area of the  $k$  type of landscape; and  $K$  is the number of landscape types. The ratio of the total output value of industry and agriculture, forestry, animal husbandry, service, and fishery to the corresponding landscape area in 2014 is used to express the coefficient of landscape output value; then, the objective function of economic development scenario in the study area is

$$f = 5.48z_1 + 6.31z_2 + 2.04z_3 + 539.36z_4 + 3.85z_5. \quad (3)$$

**3.1.1. Ecological Conservation Scenarios and Objective Functions.** The main objective of the ecological protection scenario is to maximize the regional ecological safety through the rational layout of landscape resources, and its objective function is

$$g(z) = \text{Sup} \left\{ \lim_{K \rightarrow \infty} \sum_{k=1}^K a_k z_k \right\}, \quad (4)$$

where  $g(z)$  is the ecological safety index of each landscape and  $a_k$  is the ecological safety index per unit area of the  $k$

type of landscape. According to the results of spatial evaluation of ecological safety in the study area, the ecological protection scenario objective function is

$$g = 4.68z_1 + 5.03z_2 + 5.35z_3 + 4.46z_4 + 4.96z_5. \quad (5)$$

**3.1.2. Integrating Scenarios and Objective Functions.** The main objective of the integrated scenario is to maximize the comprehensive benefits of the regional landscape through the integrated arrangement of various landscape resources, and its objective function is

$$F(z) = \text{Sup} \left\{ \omega_1 \lim_{K \rightarrow \infty} \sum_{k=1}^K v_k z_k + \omega_2 \lim_{K \rightarrow \infty} \sum_{k=1}^K v'_k z_k \right\}, \quad (6)$$

where  $F(z)$  is the comprehensive benefits generated by each landscape in the region;  $\omega_1, \omega_2$  is the objective function weight, respectively; and  $v_k, v'_k$  is the standardized  $k$  type of landscape production value coefficient and ecological safety index per unit area, respectively.

The total area constraint is

$$\lim_{K \rightarrow \infty} \sum_{k=1}^K z_k = A, \quad (7)$$

where  $A$  is the total area of the regional landscape, taken from 55569  $\text{hm}^2$ .

The farmland area constraint is

$$A_L \leq z_1 < A, \quad (8)$$

where  $A_L$  is the minimum area of farmland required in the target year. The minimum area of farmland per capita in Area A of a city in southwest China from 1988 to 2014 is 0.0106  $\text{hm}^2$ . Using the population data from 1978 to 2014 in Area A of a city in southwest China, a first-order linear regression model was developed to predict the household population of 680,200 and 742,800 in 2024 and 2034, respectively, and the minimum demand for farmland in 2024 and 2034 was calculated to be 7235  $\text{hm}^2$  and 7901  $\text{hm}^2$ , respectively.

The orchard area is bounded by

$$A_G \leq z_2 < A. \quad (9)$$

The minimum area of orchard is determined according to the principle of guaranteeing the basic demand of fruit for regional residents. The average production of orchard in A district of a city in southwest China from 2000 to 2012 is 12994  $\text{kg}/\text{hm}^2$ , and the fruit demand in 2024 and 2034 is 62068250  $\text{kg}$  and 67780500  $\text{kg}$ , respectively, according to the fruit consumption level of urban and rural residents of 0.25  $\text{kg}/\text{person}/\text{day}$ , so the minimum area of orchard in 2024 and 2034 is projected to be 4777  $\text{hm}^2$  and 5216  $\text{hm}^2$ , respectively.

The forest area is bounded by

$$A_S \leq z_3 < A, \quad (10)$$

where  $A_S$  is the minimum forest demand area in the target year ( $\text{hm}^2$ ). In order to consolidate the achievement of creating a national ecological zone in Area A of a city in southwest China, the forest planning area in 2024 and 2034 should be no less than the current area 5167  $\text{hm}^2$ .

The urban and rural habitat and industrial and mining area constraints are

$$A_C \leq z_4 < m_1 p_1 + m_2 p_2 + \varphi + \delta. \quad (11)$$

The area of the water body is bounded by

$$A_W \leq z_5 < A, \quad (12)$$

where  $A_W$  is the minimum demand area of water bodies in the target year. In order to ensure the regional water security, the planned area of water bodies in 2024 and 2034 should be no less than the current area 1610  $\text{hm}^2$ .

Ecological service value constraints are calculated as

$$\xi_{\min} \leq \lim_{K \rightarrow \infty} \sum_{k=1}^K \varepsilon_k z_k < \xi_{\max}. \quad (13)$$

The minimum and maximum ecological service values in 2024 were estimated to be RMB 669.72 million and RMB 1008.107 million, and in 2034 were RMB 691.80 million and RMB 10086.88 million, respectively, based on the area constraints of each landscape.

Chemical oxygen demand ( $\text{COD}_{\text{cr}}$ ) annual load constraint are calculated as

$$\text{COD}_{\min} \leq 10^4 \lim_{K \rightarrow \infty} \sum_{k=1}^K u_k h \text{LC}_k z_k < \text{COD}_{\max}, \quad (14)$$

where  $\text{COD}_{\min}$  and  $\text{COD}_{\max}$  are the minimum and maximum annual load of chemical oxygen demand for the target year, respectively ( $\text{kg}$ );  $u_k$  is the runoff coefficient for the  $k$  category of landscape;  $h$  is the multiyear average rainfall ( $\text{m}$ ); and  $\text{LC}_k$  is the surface runoff for the  $k$  category of landscape  $\text{COD}_{\text{cr}}$  concentration ( $\text{kg}/\text{m}^3$ ).

Total nitrogen (TN) annual load constraint is calculated as

$$\text{TN}_{\min} \leq 10^4 \lim_{K \rightarrow \infty} \sum_{k=1}^K u_k h \text{LN}_k z_k < \text{TN}_{\max}. \quad (15)$$

Total phosphorus (TP) annual load constraint is calculated as

$$\text{TP}_{\min} \leq 10^4 \lim_{K \rightarrow \infty} \sum_{k=1}^K u_k h \text{LP}_k z_k < \text{TP}_{\max}, \quad (16)$$

where  $TP_{\min}$  and  $TP_{\max}$  are the minimum and maximum annual load of total phosphorus in the target year, respectively (kg);  $LP_k$  is the TP concentration of surface runoff from the  $k$  type of landscape (kg/m<sup>3</sup>). Based COD<sub>cr</sub> on the rainfall monitoring data and fertilizer application survey data of major fruits and crops in the study area, the annual load per hectare of farmland, orchard, forest, urban and rural habitat, industrial and mining, and water body landscapes were estimated to be 87.89 kg, 23.12 kg, 16.41 kg, 528.84 kg, and 6.63 kg and TN and TP for 35.08 kg, 22.59 kg, 2.57 kg, 18.70 kg, 2.64 kg, 3.03 kg, 2.66 kg, 0.19 kg, 6.30 kg, and 0.34 kg, respectively. The minimum and maximum annual COD loads in 2024 are 9412702 kg and 17895612 kg and in 2034 are 9481387 kg and 18864542 kg. The minimum and maximum annual TN loads in 2024 are 682316 kg and 3863575 kg and in 2034 are 715596 kg and 3897836 kg. The minimum and maximum annual TP loads in 2024 are 138262 kg and 470088 kg, and in 2034 are 141448 kg and 481631 kg.

Industrial structure constraints are calculated as

$$\zeta_{\min} \leq \frac{a_4 z_4}{a_1 z_1 + a_2 z_2 + a_3 z_3 + a_5 z_5} \leq \zeta_{\max}, \quad (17)$$

where  $\zeta_{\min}, \zeta_{\max}$  is the minimum and maximum value of the ratio of the output value of secondary industry to the output value of primary and tertiary industry in the target year. Combining with the macroeconomic situation and the industrial development of a city in southwest A, the growth rates of primary, secondary, and tertiary industries are expected to be 2%, 12%, and 8%, respectively, and then, the values of  $\zeta_{\min}$  and  $\zeta_{\max}$  can be projected to be 33.76 and 62.61 in 2024 and 33.76 and 116.98 in 2034, respectively, according to the industrial development statistics of a city in southwest A.

**3.2. PSO Landscape Pattern Spatial Optimization Model and Algorithm.** The essence of spatial pattern optimization based on landscape type rasterized data is to adjust the image element position around the optimization target, so the key to apply PSO for landscape pattern spatial optimization is to use particle position to simulate the spatial distribution of landscape type raster image elements. The raster map can be regarded as a real number matrix, the raster image elements correspond to the elements in the matrix, and the image element position and attribute value (landscape type code) correspond to the element row number and value, respectively, so the processing of the raster image element position and attribute value is equivalent to the processing of the matrix element row number and value. The matrix is abstracted as a particle; the matrix element value and row number are abstracted as the particle element and position, according to the principle of particle swarm algorithm; no matter how the spatial position of the particle element changes, the particle element itself, that is, the landscape type code, remains unchanged; i.e., the value of several elements composing the matrix is eternally unchanged. The element rank can be optimized by PSO algorithm. When the new matrix corresponds to the landscape spatial pattern,

certain optimization objectives can be made. To achieve the maximum spatial optimization of the landscape pattern under the target. The basic idea of model optimization is shown in Figure 2.

MATLAB is a high-level programming language with matrix as the basic programming unit, which has powerful matrix operations and image processing functions. Therefore, the following key technologies are mainly involved in the design of PSO algorithm for landscape pattern space optimization using MATLAB:

- (1) Let  $B$  be a valid element (i.e., the raster value is the element of landscape type code, excluding the value of null -9999 or the element outside the value range of landscape type code) in the matrix  $A_{m \times n}$  corresponding to the base year landscape type map, and store the value of vector  $(\alpha_1, \alpha_2, \dots, \alpha_N)$ , which represents a particle, corresponding to a spatial layout scheme of landscape pattern;  $\alpha_j \in B$  is a valid element value, which represents a particle element, and its row number represents the particle element position, then the model optimization process
- (2) Model optimization objectives and constraints. The spatial optimization of landscape pattern is a multiobjective optimization problem; this paper constructs the objective function (fitness function) from two aspects: the maximum suitability of landscape and the maximum spatial compactness, where the suitability of landscape is characterized by the product of various landscape weights and their corresponding suitability, and the spatial compactness is expressed by the landscape patch shape index. The constraints include area, type, and conversion rules. The expressions of model objective function and constraints are

$$\max F(A) = w_1 \sum_{k=1}^K \sum_{l=1}^Q \lambda_k p_{kl} + w_2 \sum_{k=1}^K \sum_{r=1}^R \frac{c_{kr}}{\sqrt{s_{kr}}} \quad (18)$$

$$\text{s.t.} \begin{cases} d_k(A) = D_k^*, \sum_{k=1}^K d_k(A) = \sum_{k=1}^K D_k^* \\ \alpha_j \in [1, 2, \dots, K] \\ 0 \leq T_j(k \rightarrow k') \leq 1 \end{cases} \quad (19)$$

The  $\lambda_k$  weights of farmland, orchard, forest, urban and rural habitat, industrial and mining, and water body in the economic development scenario are 0.1378, 0.2107, 0.0606, 0.5514, and 0.0395, respectively, and the weights in the ecological protection scenario are 0.0706, 0.1366, 0.5071, 0.0350, and 0.2507, respectively, and the weights in the integrated scenario are 0.0930, 0.1613, 0.3582, 0.2072, and 0.1803;  $p_{kl}$  is for the suitability value of  $l$  image element of  $k$ ;  $c_{kr}, s_{kr}$  is for the perimeter and area of  $k$  landscape patches of  $r$ ;  $w_1, w_2$  is for the weights of landscape suitability and

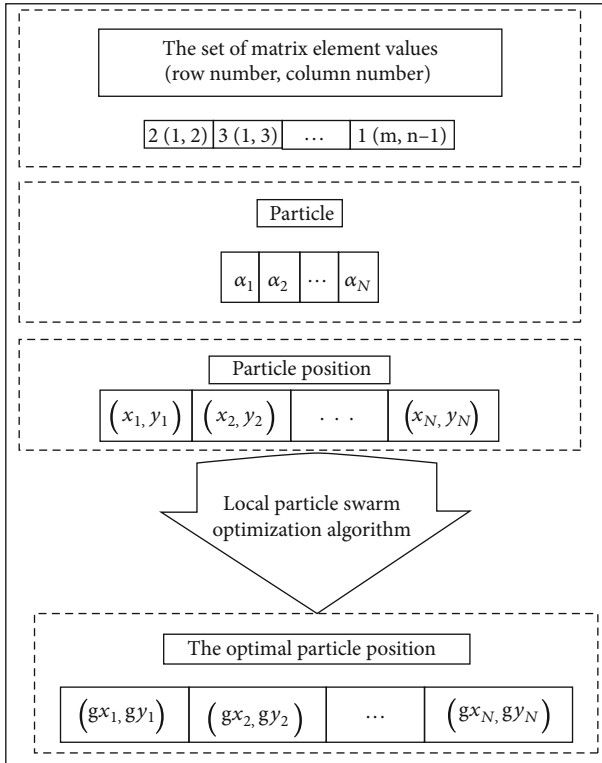


FIGURE 2: Schematic diagram of the PSO landscape pattern spatial optimization model.

spatial compactness in the objective function;  $k$ ,  $l$ , and  $r$  for the landscape type, image element, and patch number, respectively;  $k$ ,  $Q$ , and  $R$  for the landscape type, a landscape raster, and the number of patches, respectively;  $d_k(A)$  is for the landscape pattern;  $D_k^* = z_k^*/e^2$  is the number of  $k$ -type landscape pixels in the optimization scheme  $A$ ;  $D_k^*$  is the number of pixels obtained from the optimization of the number of  $k$ -type landscape in a certain scenario ( $z_k^*$  is the optimal area of  $k$ -type landscape;  $e$  is the size of pixels);  $\alpha_j \in [1, 2, \dots, K] (j = 1, 2, \dots, N)$  is the coding value domain of the corresponding landscape type for pixels;  $T_j(k \rightarrow k')$  is the possibility of successful transformation of the corresponding landscape for pixels  $\alpha_j$ . Combining with the characteristics of landscape pattern change in the study area, the rules and possibilities of landscape conversion are defined as follows: the interconversion between urban and rural human settlements and industrial and mining and farmland and orchards is completely possible, the interconversion between watershed and farmland is completely possible, the interconversion between forest and farmland and orchards is completely possible, and the interconversion between farmland and orchards is completely possible.

- (3) Initialization of the spatial layout scheme (particles) of the landscape pattern

In order to generate the initial particles with the same number of image elements of each landscape, the spatial allocation of the number of image elements of each land-

scape is carried out based on the landscape type conversion rule and landscape suitability based on the landscape type map of the base period year. The structure of  $V$  (see Equation (19)) is an array of cells storing the row and column values of effective elements of each landscape and their corresponding landscape suitability values,  $\Delta d_k = |d_k(A) - D_k^*|$  is the absolute difference between the number of base year images of  $k$  types of landscapes  $d_k(A)$  and the number of optimized images of a scenario,  $\text{sort}(\text{Val})$ ,  $\text{sort}'(\text{Val})$  is the ascending and descending order of the variable  $\text{Val}$ , and  $A(x, y) = \alpha$  is the transformation of a landscape image with row number  $x$  and  $y$  in  $A$  into a landscape image with the code  $\alpha$ .

#### 4. Analysis of Simulation Results

Combining the regional land use/cover status, the landscape types were classified into five major categories: agricultural land (paddy field, dry land, and watered land), orchard, forest (forested land, shrubland, barren hills, and slopes), urban and rural habitat and industrial and mining (towns, rural settlements, industrial and mining land, special land, and transportation land), and water bodies (rivers, reservoirs, ponds, and ditches), with the study area August 13, 2014, Landsat OLI imagery and ASTERGDEM V2 digital elevation model as the base data, the 2009 1:10,000 land use status map, and the results of the landscape field survey in October–November 2014 as auxiliary data, and the QUEST decision tree classification method was applied to classify the landscape and extract the landscape type map of the areas not involved in landscape pattern optimization.

As shown in Figure 3, the correct prediction rates of the logistic models for each landscape show that the correct prediction rates of the modeled and validated data for farmland are 85.1% and 85.3%, respectively; for orchards, both are 65.6%; for forests, 90.1% and 89.5%, respectively; for urban and rural habitats, 82.7% and 81.7%, respectively; and for water bodies, 97.2% and 97.6%, respectively, indicating that the logistic model has high prediction accuracy for each landscape, and the prediction results have strong credibility.

At the same time, as shown in Figure 4, the ROC values of each logistic model are greater than 0.7. This indicates that the evaluation indicators entering into the regression equation have a better explanation effect on the spatial pattern of each landscape, and these indicators can be used to evaluate the suitability of this type of landscape.

The MATLAB constrained optimization problem solving function  $f \min \text{con}()$  was used to solve the landscape pattern quantity optimization model to obtain the optimized area of economic development, ecological protection, integrated scenario farmland, orchard, forest, urban and rural habitat and industrial and mining, and water bodies landscape in 2024 and 2034. The results are shown in Figures 5 and 6.

As can be seen from Figures 5 and 6, compared to the 2014 landscape area, in the economic development scenario, the urban and rural habitat and industrial and mining and agricultural land area increased in the target year, the



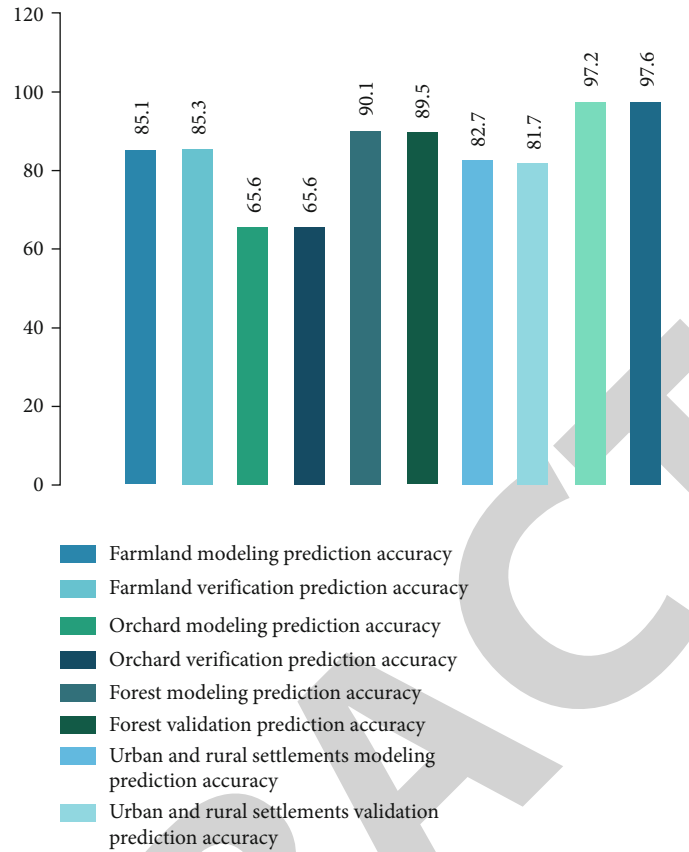


FIGURE 3: Correct prediction rate of the logistic model for each landscape.

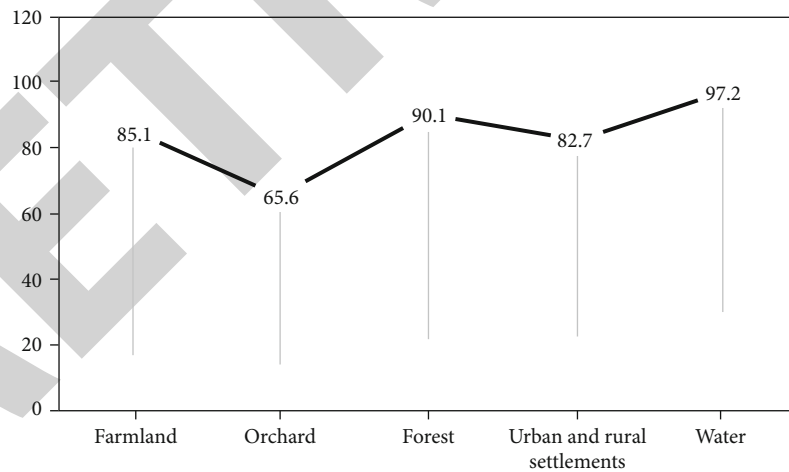


FIGURE 4: ROC values for each logistic model.

orchard area decreased, and the forest and water body area remained unchanged. Urban and rural habitat and industrial and mining increased the most, and orchards decreased the most in both phases of the plan. This is mainly due to the fact that the economic benefits of urban and rural residential and industrial mines are greater than those of orchards, so there is significant increase in urban and rural residential and industrial mines and the significant decrease. The most significant increase is in forests and the most significant

decrease is in orchards in both phases of the plan. This is mainly because the ecological safety level of forests is higher than that of orchards, so the adjustment of large orchards to forests to maximize ecological safety is in line with the actual ecological protection scenario. In the integrated scenario, the area of forests, urban and rural habitats, industrial and mining areas, and agricultural land increased in the target year, while the area of orchards decreased and the area of water bodies remained unchanged. In the two phases of the plan,

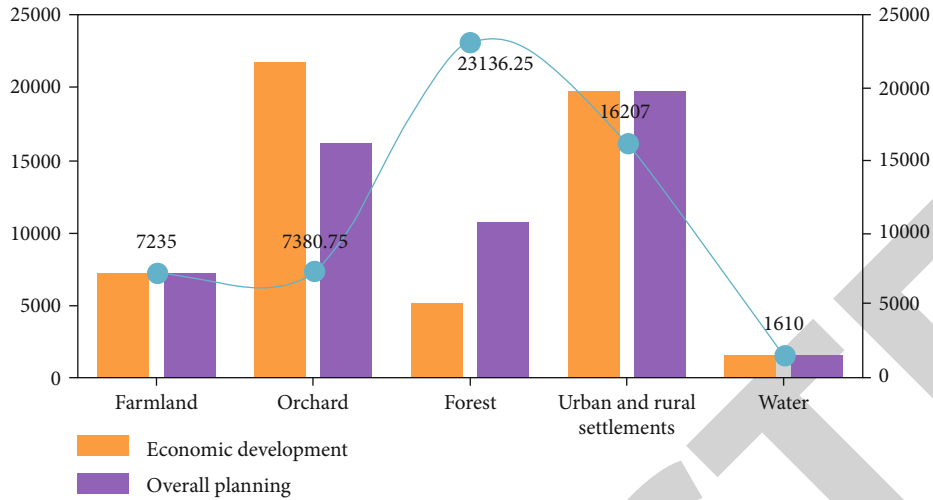


FIGURE 5: Results of landscape area optimization for each scenario in 2024.

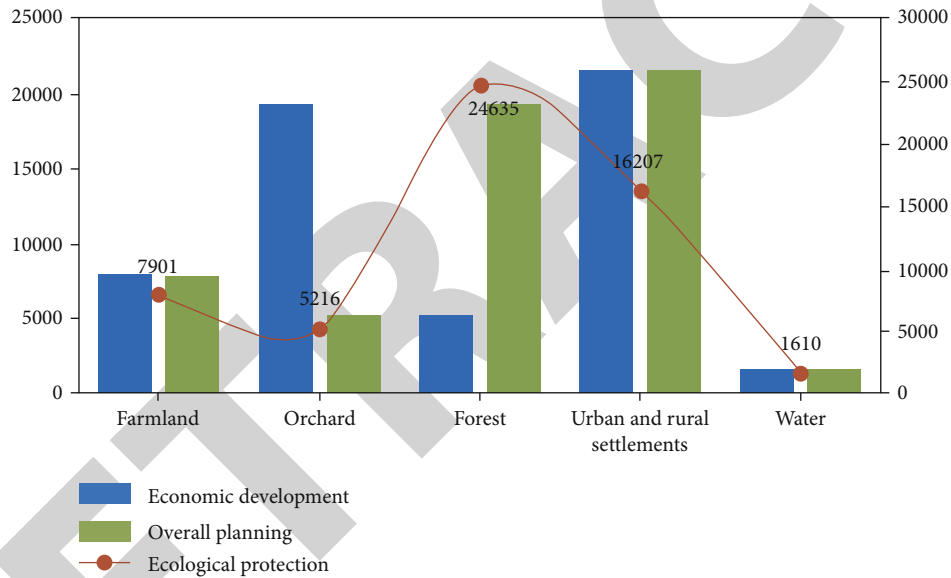


FIGURE 6: Optimization results of landscape area by scenario in 2034.

forests increase the most, urban and rural settlements and industrial and mining areas are relatively second, while orchards decrease the most. This is mainly due to the fact that the ecological safety levels of forests, urban and rural habitats, and industrial and mining economic benefits are greater than orchards, so the adjustment of large orchards to forests and urban and rural habitats in order to increase the comprehensive ecological and economic benefits of the region has resulted in a significant reduction, which is in line with the actual integrated scenario.

The results are shown in Figures 7–9. 2034 economic development scenario has the largest spatial optimization error of 3.47% for forest area and the smallest error of 0.08% for urban and rural habitat and industrial and mining, which indicates that the solution result of PSO landscape pattern spatial optimization model does not fully satisfy

the equation constraint. This is because some particle elements collide in flight; i.e., when a certain type of landscape particle element arrives at an optimized location, another type of landscape particle element arrives at the same optimized location to replace it, resulting in a decrease of the former type of landscape and an increase of the latter type of landscape, resulting in the solution results not fully satisfying the equation constraint. According to the PSO landscape pattern space optimization algorithm, the first particles are initialized and fully satisfy the equation constraint; the reason for breaking the equation constraint is that the corresponding objective function value of the particles breaking the equation constraint is greater than the corresponding objective function value of the first particles; in essence, this makes the landscape pattern space layout further optimized, and a certain error range of the

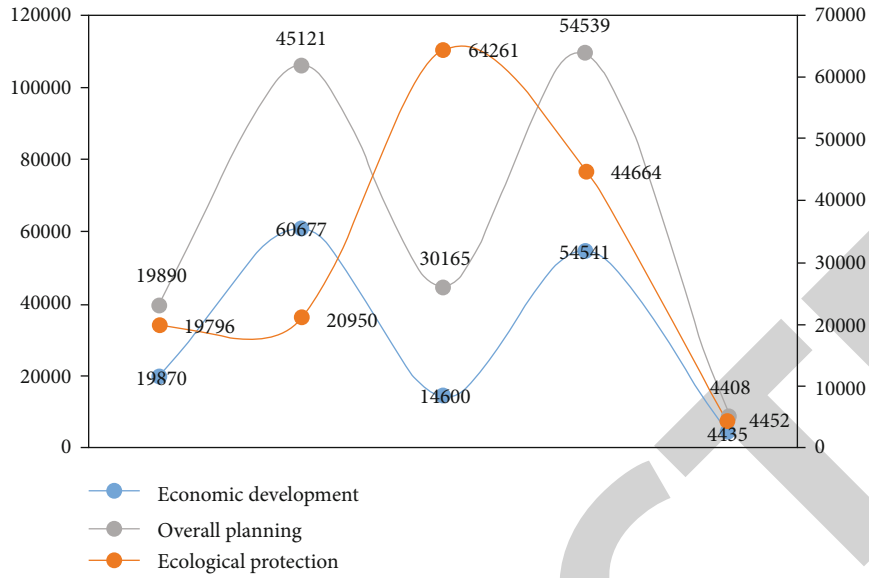


FIGURE 7: Results of the spatial optimization model for PSO landscape pattern in 2024 for each scenario.

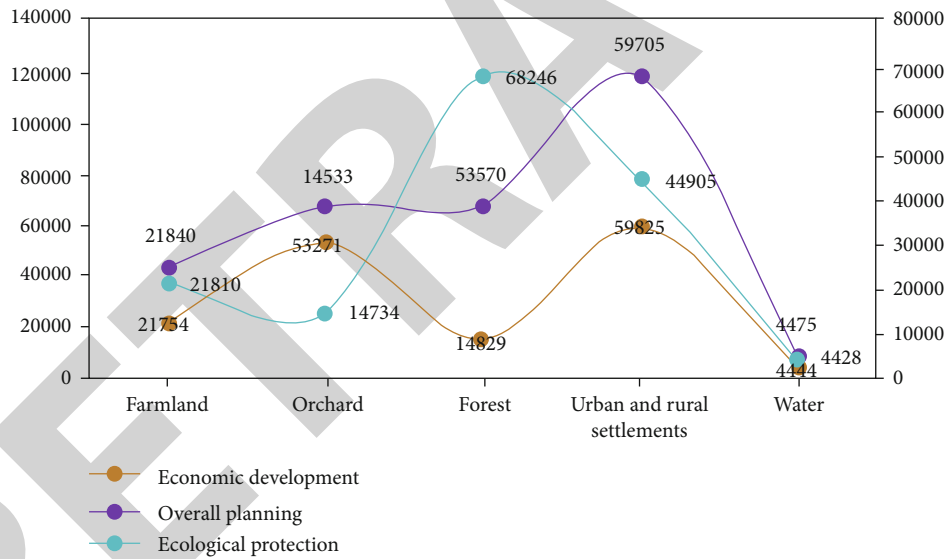


FIGURE 8: Results of the spatial optimization model for PSO landscape pattern in 2034 for each scenario.

equation constraint breakthrough may also be a solution to the number and space optimization objective function coupling problem. Therefore, the model can be applied to optimize the spatial layout of the landscape pattern.

Figure 9 analyzes the landscape pattern distribution characteristic index of PSO landscape pattern spatial optimization results in each scenario from the landscape level, such as overall economic ecology, economic ecology, overall development, protection planning, and other indexes. It provides necessary conditions for further study on the changes of ecological processes and their interactions in the whole region. The index of landscape level is suitable for comparative analysis of landscape pattern and feature changes in

different phases or regions. Since there is only one scene of remote sensing data in this study, this table only reflects the overall landscape pattern features of the study area.

Through the calculation of various landscape indexes in the study area, a comprehensive description of the landscape structure characteristics of the study area is very important for the real-time analysis of the urban landscape pattern structure. The integrated application of the overall optimization method of landscape pattern and the analysis of ecological sensitivity and suitability takes into account the vertical matching and horizontal correlation of landscape units. On this basis, the ecological regulation of the overall spatial pattern provides a more feasible spatial approach for the

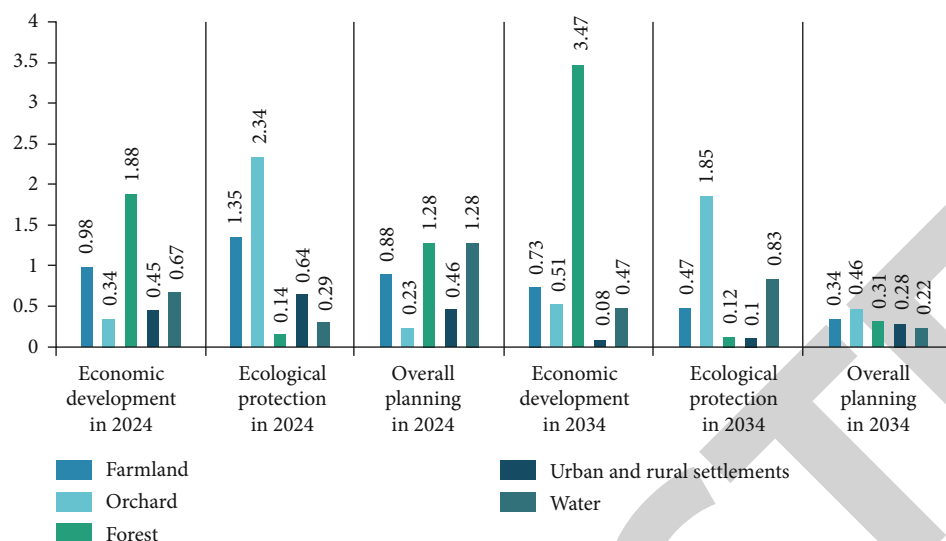


FIGURE 9: Relative errors of spatial optimization results and quantitative optimization results of PSO landscape pattern for 2024 and 2034 for each scenario.

ecological regulation of urban areas and provides support for urban landscape ecological planning.

## 5. Summary and Outlook

In this study, a model and algorithm of spatial optimization of landscape pattern based on PSO are designed, and the optimization of spatial layout of landscape pattern under three scenarios is realized. The results show that the dominant landscape under the economic development scenario is orchard, and the distribution pattern is farmland in the western dam area and orchard in the eastern mountain area. For the dominant landscape under the ecological protection scenario, the western dam area is composed of urban and rural settlements, industrial and mining areas, orchards, and farmland, and the eastern mountain area is composed of forests. The main landscapes in the integrated scene are forests, urban and rural residential areas, industrial mining areas, orchards, and farmland. The landscape types are forests, industrial mines, and orchards. The distribution pattern is mainly urban and rural settlements, industrial mines, and farmland in the western dam area and forests and orchards in the eastern mountain area. Among them, the economic, ecological, and comprehensive benefits of the comprehensive scenario can be optimized, with the greatest potential in the future. It is the most ideal spatial layout of the landscape pattern in the target year of the study area. In this paper, a method of spatial optimization of landscape pattern based on PSO is proposed on the grid level of landscape type map. It is proved that this method can effectively couple the results of landscape quantity optimization of the constrained optimization model with the relevant policy and economic and social factors of spatial optimization. The optimization of landscape pattern based on high-resolution grid map is realized theoretically, but in application.

However, with the improvement of the grid map resolution or the expansion of the research scope, the amount of

calculation and the running time of the program increase exponentially. This not only puts forward new requirements for computer hardware support but also is the focus of further improvement of this method. Therefore, when making spatial optimization decisions, we should select the appropriate grid map resolution according to the research scope and scale. In addition, considering the coupling between the number of landscape patterns and the objective function of spatial optimization and the efficiency of the algorithm, the particle collision constraint is not added separately, and the relative error of the calculation results is less than 4%, which is a certain limitation for the macroplanning of landscape security pattern at the regional level.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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