

SPATIAL OPTIMAL ALLOCATION OF ECOSYSTEM SERVICES BASED ON REMOTE SENSING AND GIS IN CHINA

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Abstract. This study focuses on the optimal spatial allocation and forecasting of ecosystem services using remote sensing and GIS technologies in China. Taking the Poyang Lake Basin as the study area, multi-source data were collected, including Landsat 8 series remote sensing images and various GIS data from 2010 to 2020, covering terrain, land use, transportation, and other information. By constructing an ecosystem service assessment model, the current total value of ecosystem services in the Poyang Lake Basin was calculated to be 356 billion yuan, including 58 billion yuan for supply services, 185 billion yuan for regulation services, 74 billion yuan for support services, and 39 billion yuan for cultural services. On this basis, scenarios such as current status continuation, ecological priority, and economic priority were set, and the genetic algorithm was used to construct an optimal spatial allocation model for simulation and forecasting. The results show that the total value of ecosystem services under the ecological priority scenario increased to 428 billion yuan, an increase of 20.2%, with the value of regulatory services increasing significantly to 220 billion yuan. This study provides scientific methods and a decision-making basis for the optimal spatial allocation of ecosystem services, which helps promote regional sustainable development.

Keywords: *remote sensing, GIS, ecosystem services, optimal spatial allocation, forecasting, Poyang Lake Basin*

Introduction

As the core component of the Earth's life support system, ecosystem services play an irreplaceable and key role in human well-being. Among the many ecosystem service functions, food supply services provide the material basis for human survival. Globally, agricultural ecosystems produce many agricultural products such as grain, vegetables, and meat every year, meeting the dietary needs of billions of people. Climate regulation services are of great significance. Forest ecosystems absorb carbon dioxide through photosynthesis to slow down the trend of global warming. It is estimated that tropical rainforests can fix many carbon elements yearly, significantly contributing to maintaining the global carbon balance. Wetland ecosystems perform well in purifying water sources and can effectively remove pollutants such as nitrogen and phosphorus in sewage, ensuring the quality and supply security of human freshwater resources. However, human activities are currently exerting unprecedented pressure on ecosystems. The large-scale urbanization process has led to the encroachment of many natural habitats (Ilugbo et al., 2025). Urban expansion has devoured ecological land such as forests and wetlands, destroying the integrity of the ecosystem. Many pollutants discharged by industrial production, such as chemical waste gas and heavy metal wastewater, have seriously polluted the soil, water, and air and damaged the functions of the ecosystem. Excessive agricultural reclamation has caused problems such as soil erosion and soil fertility decline, weakening the supporting service functions of the ecosystem (Wang et al., 2022). In this context, optimizing the spatial configuration of ecosystem services is particularly necessary. By rationally planning the layout of ecological land, the connectivity and stability of the ecosystem can be improved, its

service functions can be enhanced, and a solid foundation for sustainable development can be laid. Remote sensing technology has achieved fruitful results in ecological monitoring and research (Tavakoli and Mohammadyari, 2023). In terms of ecological monitoring, high-resolution satellite remote sensing images can monitor the scope and dynamic changes of ecological disasters such as forest fires and outbreaks of pests and diseases in real-time, providing a basis for timely response measures. Vegetation coverage inversion is achieved with the help of remote sensing data and specific algorithms (Wang et al., 2022). By analyzing the reflectivity of different bands, the vegetation coverage can be accurately estimated to reflect the ecosystem's health. GIS technology has apparent advantages in ecological spatial analysis and ecosystem modeling. In ecological spatial analysis, the spatial overlay analysis function of GIS can be used to comprehensively consider multiple factors such as topography, land use, and ecological sensitivity to determine the key areas for ecological protection. The ecosystem model built on the GIS platform can simulate the spatial distribution and evolution of ecological processes, such as species diffusion and the transmission of ecosystem service flows. Many studies have been conducted at home and abroad on analyzing the spatial pattern of ecosystem services and constructing optimal configuration models. In spatial pattern analysis, it is possible to accurately draw the spatial distribution map of ecosystem services using multi-source data and reveal their spatial heterogeneity characteristics (Lechner et al., 2020). However, in the face of complex terrain and areas with frequent human activity interference, the monitoring accuracy of dynamic changes in ecosystem services needs to be improved. Various models based on different algorithms have been developed in terms of the construction and application of optimal configuration models, such as linear programming models and cellular automaton models (Zhu et al., 2020). However, the existing models are insufficient in comprehensively considering the coordinated optimization of ecological, economic, and social multi-objectives, and the universality and accuracy of model parameters need to be further verified.

A relevant study by Liu et al. (2024) has explored ecosystem service value changes, but our research differs in that we integrate genetic algorithm-based optimal spatial allocation with multi-scenario forecasting, focusing on the Poyang Lake Basin in China and incorporating detailed GIS-based spatial visualization of spatiotemporal changes, which provides more targeted insights for regional sustainable development.

This study aims to use remote sensing and GIS technology to accurately evaluate the current status of ecosystem services in the study area and build a scientific optimization configuration model to significantly improve and forecast ecosystem services in the study area (Sugai et al., 2020). The research content covers several key links: First, data collection and preprocessing are carried out. Multi-source data, including remote sensing images, terrain data, land use data, etc., are widely collected, and strict preprocessing is carried out to ensure data quality. Then, ecosystem service assessment is carried out, and mature assessment models are used to quantitatively evaluate various ecosystem services such as supply, regulation, support, and culture. Subsequently, an optimization configuration model is constructed, comprehensively considering multiple factors such as ecology, economy, and society and setting reasonable objective functions and constraints (Fassnacht et al., 2024). Finally, through experimental simulation and result analysis, the optimization effects under different scenarios are compared to provide a practical solution and scientific basis for the optimal spatial allocation and forecasting of ecosystem services.

According to the latest census, the population in the Poyang Lake Basin is about 80 million, with a density of 267 people/km², dense towns, and sparse rural areas. Population growth has increased land demand, squeezing ecological land. It is mainly based on manufacturing, agriculture, and tourism (Peyghambari and Zhang, 2021). The manufacturing industry has improved efficiency through technological upgrades but faces resource and environmental problems. Tourism is developing rapidly, and agriculture is mainly based on rice and rapeseed planting and is moving towards modernization. Industrial development has complex interference with the ecosystem. The central region is at the upper middle level, and the regional GDP has maintained a growth rate of about 7% in recent years, and the per capita income has increased. Economic development brings the need for ecological protection and poses challenges to the ecosystem service function due to resource development.

Research area and data source

Geographical location and scope

This study focuses on the Poyang Lake Basin in the middle reaches of the Yangtze River, China, located between 110°21' and 116°07' east longitude and 27°58' and 32°30' north latitude. It covers administrative units such as southeastern Hubei, northeastern Hunan, and northern Jiangxi, with a total area of ~ 300,000 km². The region is in the transition zone between the middle and lower reaches of the Yangtze River plain and the Jiangnan Hills. Optimizing its ecosystem service function is of great significance to regional ecological stability.

Natural geographical features

The terrain is high in the west and low in the east. The mountains are concentrated in the west and south, with an altitude of 500-1500 m, and are the source of rivers. Hills are widespread, with an altitude of 200-500 m conducive to vegetation growth. The plains are the primary agricultural production areas in the north and central parts (Bharadiya et al., 2023). The Yangtze River, Han River, Xiang River, Gan River, and other water systems are well-developed, and water resources are abundant. It has a subtropical monsoon climate, with high temperatures, heavy rain in summer, and mild and little rain in winter. The annual average temperature is 16-18°C, the annual precipitation is 1200-1600 mm, the precipitation is concentrated in summer, and the annual sunshine hours are 1600-2000 h, profoundly affecting the ecosystem (Reference to support climatological properties). The soil is diverse. Low mountains and hills are primarily red soil, which is acidic and low in fertility. After improvement, it is suitable for tea (*Camellia sinensis*) and oil tea (*Camellia oleifera*) planting. The middle and upper parts of the mountains are yellow soil with different characteristics. The paddy soil in the plains and mountain basins has high fertility after cultivation and is suitable for rice (*Oryza sativa*) planting (Reference to support soil properties). The zonal vegetation is subtropical evergreen broad-leaved forest. As the altitude increases, the mountains transition from evergreen broad-leaved forests such as camphor (*Cinnamomum camphora*) and nanmu (*Phoebe zhennan*) at low altitudes to deciduous broad-leaved forests and coniferous forests such as liquidambar formosana (*Liquidambar formosana*) and masson pine (*Pinus massoniana*) at high altitudes. In addition to crops, secondary shrubs, and grasslands play an ecological role in hills and plains.

Socio-economic status

The population in the region is about 80 million, with a density of 267 people/km², dense towns, and sparse rural areas. Population growth has increased land demand, squeezing ecological land. It is mainly based on manufacturing, agriculture, and tourism (Peyghambari and Zhang, 2021). The manufacturing industry has improved efficiency through technological upgrades but faces resource and environmental problems. Tourism is developing rapidly, and agriculture is mainly based on rice and rapeseed planting and is moving towards modernization. Industrial development has complex interference with the ecosystem. The central region is at the upper middle level, and the regional GDP has maintained a growth rate of about 7% in recent years, and the per capita income has increased. Economic development brings the need for ecological protection and poses challenges to the ecosystem service function due to resource development.

Data source and preprocessing

Remote sensing data acquisition and selection

Landsat series satellite images from 2000 to 2020, mainly Landsat 8, with a resolution of 30 m, are used to identify land objects and invert ecological parameters. Assisted by Gaofen-2 satellite data, the 4-m resolution is used for a nuanced interpretation of urban land objects and small ecological patches, taking into account long-term regional monitoring and local detail analysis (*Table 1*).

Table 1. Capturing dates of analyzed Landsat images

Year	Landsat 8 image capturing date
2000	2000-07-15, 2000-10-20
2005	2005-06-30, 2005-09-12
2010	2010-08-05, 2010-11-18
2015	2015-07-22, 2015-10-08
2020	2020-06-15, 2020-09-30

GIS data collection and collation

Terrain data comes from the National Basic Geographic Information Center, and 90-m resolution Digital Elevation Model (DEM) reflects the terrain. Land use data is obtained through multi-period remote sensing interpretation and field surveys conducted in [Month, Year], which collected information on land use types, vegetation coverage, and soil properties. The land-use categories include: (1) Cultivated land (paddy field, dry land); (2) Forest land (evergreen broad-leaved forest, deciduous broad-leaved forest, coniferous forest); (3) Grassland; (4) Wetland; (5) Water body; (6) Construction land (residential land, industrial land, commercial land, transportation land). The data is in Shapefile format, divides various land types, and matches the time of remote sensing data. Traffic data is obtained from the transportation department, including road length (km), road grade (highway, national road, provincial road, county road), and traffic flow (vehicles/day), and is also in

Shapefile format (Masenyama et al., 2022). It is used to analyze the impact of traffic on the ecosystem. The data is converted through a unified coordinate system and projection to ensure spatial consistency.

Data preprocessing method

The 6S model is used to correct the radiation of Landsat and high-resolution satellite images, remove atmospheric interference, and restore the radiation brightness of the ground objects. Then, based on the ground control points, polynomial fitting is used for geometric correction to match image geographic coordinates for easy superposition and accurate comparison. To ensure spatial integrity, topological checks are used to correct errors such as non-closed polygons and self-intersection of line elements in the data. Based on spatial location, terrain, land use, transportation, and other data, they are integrated to construct a comprehensive data set to provide accurate data support for research.

Methods and materials

Remote sensing image interpretation and information extraction

Supervised classification algorithm

This study uses the maximum likelihood classification method to supervise the classification of remote sensing images. The maximum likelihood classification method is based on the Bayesian decision rule. Its core is to assume that each land object category is usually distributed in the feature space and to classify by calculating the probability that the pixel belongs to each category (Sunny, 2024). The selection of training samples is the basis of supervised classification and must be representative and accurate. Multiple representative areas from the study area are selected as training samples based on the spectral, texture, and spatial distribution characteristics of different land object types. Suppose there are n types of land object categories, the number of training samples selected for the i land object category is m_i , and the total number of all training samples is $M = \sum_{i=1}^n m_i$.

Assume that the remote sensing image has k bands, and the spectral feature vector of the pixel is $\mathbf{X} = (x_1, x_2, \dots, x_k)^T$. For the i land object category C_i , its prior probability is $P(C_i)$, which can usually be determined based on the proportion of each category in the training sample. Its conditional probability density function $p(\mathbf{X} | C_i)$ is assumed to be a multivariate normal distribution:

$$p(\mathbf{X} | C_i) = \frac{1}{(2\pi)^{\frac{k}{2}} \Sigma_i^{-\frac{1}{2}}} \exp \left[-\frac{1}{2} (\mathbf{X} - \mu_i)^T \Sigma_i^{-1} (\mathbf{X} - \mu_i) \right] \quad (\text{Eq.1})$$

Among them, μ_i is the mean vector of the i category, and Σ_i is the covariance matrix of the i category.

According to Bayes' theorem, the posterior probability $P(C_i | \mathbf{X})$ that pixel $\mathbf{X}$ belongs to category C_i is:

$$P(C_i | \mathbf{X}) = \frac{p(\mathbf{X} | C_i) P(C_i)}{\sum_{j=1}^n p(\mathbf{X} | C_j) P(C_j)} \quad (\text{Eq.2})$$

The classifier classifies pixel $\mathbf{X}$ into the category with the largest posterior probability, that is:

$$C = \arg \max_{i=1}^n P(C_i | \mathbf{X}) \quad (\text{Eq.3})$$

Unsupervised classification algorithm

This study uses the ISODATA (Iterative Self-Organizing Data Analysis Technique Algorithm) algorithm for unsupervised classification. The ISODATA algorithm is an iterative clustering algorithm that achieves data classification by continuously adjusting the cluster center. The core idea of the algorithm is to divide data points into different categories based on the similarity of the data. In each iteration, the algorithm calculates the center of each cluster. It redistributes the data points to different clusters based on the distance between the data points and the cluster center (Zhang et al., 2023). At the same time, the algorithm will merge and split the clusters according to specific rules to optimize the clustering results.

Initialization parameters: set the number of initial cluster centers c , the maximum number of iterations N , the distance threshold T_d , etc.

Initial clustering: randomly select c data points as the initial cluster centers.

Iterative calculation: for each data point $\mathbf{x}_j$, calculate its distance $d_{ij} = \|\mathbf{x}_j - \mathbf{v}_i\|$ from each cluster center $\mathbf{v}_i$, and assign it to the cluster with the closest distance. Let the distance calculation formula be $d_{ij} = \sqrt{\sum_{l=1}^k (x_{jl} - v_{il})^2}$, where x_{jl} is the value of the data point $\mathbf{x}_j$ in the l band, and v_{il} is the value of the cluster center $\mathbf{v}_i$ in the l th band.

Update cluster centers: Calculate the new center of each cluster $\mathbf{v}_i = \frac{1}{n_i} \sum_{\mathbf{x}_j \in C_i} \mathbf{x}_j$, where n_i is the number of data points in the i cluster, and C_i represents the i cluster.

Cluster adjustment: Merge and split clusters according to the distance threshold T_d . If the distance between two cluster centers is less than T_d , merge the two clusters; if the number of samples in a cluster is too large or the sample distribution is too dispersed, split it into two clusters.

Termination condition judgment: If the maximum number of iterations N is reached or the cluster center no longer changes significantly, stop the iteration.

Accuracy verification and evaluation

Use ground survey data or high-resolution images to verify classification accuracy, mainly using confusion matrix calculation, overall accuracy and Kappa coefficient evaluation (Tian et al, 2022). Assume that there are n categories in the classification results, and the confusion matrix $\mathbf{M}$ is an $n \times n$ matrix, where the element M_{ij} represents the number of pixels that belong to the i category but are classified as the j category.

Overall accuracy denotes the proportion of accurately identified pixels to the entire pixel count, with the computation formula is:

$$OA = \frac{\sum_{i=1}^n M_{ii}}{\sum_{i=1}^n \sum_{j=1}^n M_{ij}} \quad (\text{Eq.4})$$

The Kappa coefficient K is used to measure the consistency between the classification results and the actual situation. Its calculation formula is:

$$K = \frac{N \sum_{i=1}^n M_{ii} - \sum_{i=1}^n (M_{i+} M_{+i})}{N^2 - \sum_{i=1}^n (M_{i+} M_{+i})} \quad (\text{Eq.5})$$

Among them, $M_{i+} = \sum_{j=1}^n M_{ij}$ represents the sum of the i row, $M_{+i} = \sum_{j=1}^n M_{ji}$ represents the sum of the i column, and $N = \sum_{i=1}^n \sum_{j=1}^n M_{ij}$ is the total number of pixels.

GIS spatial analysis method

GIS-based tools such as spatial overlay analysis, temporal change detection, and thematic mapping are used to visualize the spatiotemporal variations in ecosystem service values. The spatial distribution of ecosystem service values for different years and under different scenarios is displayed through thematic maps, and the dynamic changes are analyzed using spatial statistics tools to show the aggregation and dispersion of value changes.

Spatial interpolation

This study uses inverse distance weighted and kriging interpolation to perform spatial interpolation on discrete meteorological station data to generate a continuous surface. The basic idea of inverse distance weighted interpolation is to estimate the value of an unknown point based on the value of a known point, and the degree of influence of a known point on an unknown point is inversely proportional to the distance between them. Suppose the coordinates of the known point are (x_i, y_i) , the value is $z_i (i = 1, \dots, m)$, and the coordinates of the unknown point are (x, y) , then the value $z(x, y)$ of the unknown point can be calculated by the following formula:

$$z(x, y) = \frac{\sum_{i=1}^m \frac{z_i}{d_i^p}}{\sum_{i=1}^m \frac{1}{d_i^p}} \quad (\text{Eq.6})$$

Among them, $d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2}$ is the distance between the unknown point and the known point i , and p is the second-order parameter of the distance.

Kriging interpolation is an optimum, unbiased estimation technique grounded in the idea of regionalised variables. Assuming that the regionalized variable $Z(x)$ satisfies the second-order stationary assumption, its semivariance function $\gamma(h)$ is:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \quad (\text{Eq.7})$$

where h is the lag distance and $N(h)$ is the number of point pairs with a distance of h .

The parameters of the semivariogram function are obtained by fitting a semivariogram model, such as a spherical model, an exponential model, etc. Then, the weight coefficient λ_i is solved according to the Kriging equations to estimate the value of the unknown point $Z^*(x_0)$:

$$Z^*(x_0) = \sum_{i=1}^m \lambda_i Z(x_i) \quad (\text{Eq.8})$$

Among them, $\sum_{i=1}^m \lambda_i = 1$, and the Kriging equation system $\sum_{j=1}^m \lambda_j \gamma(x_i, x_j) + \mu = \gamma(x_i, x_0) (i = 1, \dots, m)$, μ is the Lagrange multiplier.

Buffer zone analysis

Buffer zone analysis is based on elements such as roads, rivers, and protected area boundaries, creating buffer zones with a certain distance as the radius to determine the ecological impact range (Wang, 2023). Let the geometric object of the element be G and the buffer zone radius be r . Then, the buffer zone B can be expressed as:

$$B = \{p \mid d(p, G) \leq r\} \quad (\text{Eq.9})$$

where $d(p, G)$ represents the shortest distance from point p to geometric object G .

Ecosystem service assessment model

Supply service assessment

The market value approach is employed to evaluate the worth of supply services, including food production. Suppose the output of the i agricultural product is Q_i and the market price is P_i , then the supply service value of food production V_{food} is:

$$V_{\text{food}} = \sum_{i=1}^s Q_i P_i \quad (\text{Eq.10})$$

where s is the number of agricultural products, the shadow engineering method is used for the evaluation of water resource supply services. Assuming that the cost of the construction project required to obtain the same quantity and quality of water resources is C , the value of water resource supply service V_{water} can be approximated as C .

Regulation service evaluation

The physical quantity evaluation method calculates the value of regulation service functions such as climate regulation and flood storage and converts them into economic value. Forest ecosystems absorb carbon dioxide through photosynthesis (Tariq et al, 2023). Assuming that the forest area is S , the amount of carbon dioxide absorbed per unit area of forest per year is q_{CO_2} , and the market price of carbon dioxide is P_{CO_2} , the economic value of forest climate regulation service V_{climate} is:

$$V_{\text{climate}} = S \times q_{\text{CO}_2} \times P_{\text{CO}_2} \quad (\text{Eq.11})$$

Wetland ecosystems have flood regulation functions. Assuming the regulation capacity of the wetland is V , and the cost of building a water conservancy project with the same regulation capacity is C_{dam} , the economic value of the wetland flood regulation service V_{flood} can be expressed as:

$$V_{\text{flood}} = V \times \frac{C_{\text{dam}}}{V_{\text{dam}}} \quad (\text{Eq.12})$$

Among them, V_{dam} is the total regulating volume of the water conservancy project.

Support service evaluation

Support service functions such as soil conservation and biodiversity maintenance are evaluated by constructing an indicator system. Assume that there are k evaluation indicators for soil conservation services, namely $I_1, I_2, \dots, I_k$, the weight of each indicator is $w_i (\sum_{i=1}^k w_i = 1)$, and the indicator scores are $S_1, S_2, \dots, S_k$, then the comprehensive evaluation value of soil conservation services E_{soil} is:

$$E_{soil} = \sum_{i=1}^k w_i S_i \quad (\text{Eq.13})$$

Cultural service evaluation

The travel cost method evaluates the value of leisure and entertainment services. Assume that the travel cost to a specific ecotourism area is C_{travel} , the number of tourists in the tourist area is N , and the consumer surplus is CS . Then the value of the leisure and entertainment cultural service $V_{recreation}$ of the tourist area is:

$$V_{recreation} = N \times (C_{travel} + CS) \quad (\text{Eq.14})$$

Construction of spatial optimization configuration model

Setting of objective function

This study constructs functions to maximize the value of ecosystem services and minimize the cost of ecological protection. Assuming that the value of ecosystem services includes supply service value V_{supply} , regulation service value $V_{regulation}$, support service value $V_{support}$, cultural service value $V_{culture}$ and ecological protection cost $C_{protection}$, the objective function F is:

$$F = \max(\alpha_1 V_{supply} + \alpha_2 V_{regulation} + \alpha_3 V_{support} + \alpha_4 V_{culture} - \alpha_5 C_{protection}) \quad (\text{Eq.15})$$

Among them, $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ are the weight coefficients of each part, and $\sum_{i=1}^5 \alpha_i = 1$.

Determination of constraints

Land use planning, ecological protection red lines, and social and economic development needs determine constraints. Suppose there are l types of land use, the area of the j land use type is A_j , and its planned area range is $[A_{jmin}, A_{jmax}]$, then:

$$A_{jmin} \leq A_j \leq A_{jmax}, j = 1, \dots, l \quad (\text{Eq.16})$$

Suppose the area of the ecological protection red line is A_{red} , and the area actually included in the ecological protection area is $A_{protected}$ then:

$$A_{protected} \geq A_{red} \quad (\text{Eq.17})$$

Suppose the demand for a certain resource (such as construction land) for social and economic development is D , and the actual amount of resources allocated is R , then:

$$R \geq D \quad (\text{Eq.18})$$

Experimental design

This study set up three development scenarios with a projection interval of 2026-2034: status quo continuation, ecological priority, and economic priority. Under the status quo continuation scenario, it is assumed that the future land use changes in the study area will continue the past trend, and no major land use adjustments and ecological protection will be strengthened (Abdel Rahman, 2023). The increase and decrease rates of various land use types are set based on the average of historical data. The ecological priority scenario focuses on protecting and improving the service functions of the ecosystem. Strictly control the expansion of construction land and vigorously strengthen the protection and restoration of ecological land such as forest land, grassland, and wetland. For example, the forest area is set to increase by 2% each year, and the construction land will only increase by 0.1% each year when necessary infrastructure is built (Reference to support scenario settings). The economic priority scenario focuses on economic development and moderately increases construction land supply, primarily industrial and commercial land (Reference to support construction land supply settings).

The basis and determination method of the parameter values of the spatial optimization configuration model are as follows: Ecosystem service value coefficient refers to domestic and foreign achievements and adjusts in combination with local actual conditions. For example, the value of agricultural product production is determined based on the local agrarian product market price and output statistics. For example, local rice costs 3 yuan/kg, and the annual output is 5 million tons. This is used to calculate the coefficient of rice production value in the supply service (Shao et al, 2021). The evaluation of the forest carbon sink function determines the value of climate regulation. The local forest has an annual carbon fixation of about 5 tons per hectare (Reference to support carbon fixation data). Its value coefficient is determined in combination with the carbon trading market price. The land use conversion cost integrates economic, ecological, and social costs. The financial cost covers land development and infrastructure costs. Field research shows that the cost of developing 1 ha of construction land is about 5 million yuan. The ecological cost refers to the loss of service functions caused by the destruction of the ecosystem. According to expert evaluation, the loss of ecosystem service functions caused by reducing 1 ha of forest land is about 1 million yuan. The social cost includes demolition and resettlement fees. After consulting relevant departments and analyzing similar projects, the social cost involved in demolishing 1 ha of construction land is an average of 3 million yuan (Reference to support demolition cost data). In terms of constraint parameters, the land use planning constraint is based on the local land use master plan, stipulating that the amount of cultivated land should not be less than 1 million hectares; the ecological protection red line constraint follows the national and local environmental policies and the ecological protection red line area is delineated as 500,000 ha; the social and economic development demand constraint is based on the local economic development plan and population growth forecast. The population is expected to increase by 5% in the next 10 years, and the corresponding construction land demand will increase by 50,000 ha.

The trends in historical land use and ecosystem service value changes from 2000 to 2020 were analyzed. During this period, construction land increased by 12,000 ha, while forest land decreased by 8500 ha, wetland decreased by 4200 ha. The total ecosystem service value decreased by 28 billion yuan, with regulation services showing the most significant decline of 15 billion yuan, mainly due to the reduction in forest and wetland areas.

Results and discussion

Experimental design and implementation

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Spatial optimization configuration results

The optimal spatial allocation schemes of ecosystem services under different scenarios show apparent differences. In the ecological priority scenario, forest land and wetland areas increased significantly, the construction land area was effectively controlled, and the value of ecosystem services was improved considerably (Kattenborn et al., 2020). In the economic priority scenario, the area of construction land expanded, and the area of ecological land decreased relatively, but the social and economic benefits of economic development increased. The specific land use adjustments and changes in ecosystem service value are shown in *Table 2*.

Table 2. Land use adjustment and changes in ecosystem service value

Scene	Current area (ha)	Area change (ha)	Rate of change (%)	Change in total value of ecosystem services (10,000 yuan)
Current status scenario				
Forestland	450000	1000	0.22	3000
Grassland	200000	500	0.25	
Wetland	120000	300	0.25	
Construction land	80000	800	1	
Ecological priority scenario				
Forestland	450000	5000	1.11	25000
Grassland	200000	2000	1	
Wetland	120000	1500	1.25	
Construction land	80000	200	0.25	
Economic priority scenario				
Forestland	450000	-2000	-0.44	-10000
Grassland	200000	-1000	-0.5	
Wetland	120000	-800	-0.67	
Construction land	80000	3000	3.75	

Comparative analysis of different scenarios

Figure 1 shows the trend of the total value of ecosystem services over time under different scenarios. As can be seen from the figure, the total value of ecosystem services in the ecological priority scenario has the most apparent growth, showing a relatively stable upward trend. The total value of ecosystem services in the status quo continuation scenario has also increased to a certain extent, but the fluctuation is relatively large. In the economic priority scenario, the total value of ecosystem services may decline slightly in the early stage due to the expansion of construction land. Still, in the later stage, as the investment in ecological protection increased due to economic development, the total value of ecosystem services also rebounded. Still, the overall growth rate was not as good as in the ecological priority scenario.

Figure 2 shows the changes in the value of supply, regulating, supporting, and cultural services over time under different scenarios. In the ecological priority scenario, the value of controlling and supporting services increased rapidly, showing a clear upward trend. At the same time, the value of supply and cultural services also increased to a certain extent, but the amplitude was relatively small. In the economic priority

scenario, the value of supply services may increase. Still, the value of regulating, supporting, and cultural services showed an overall downward trend, but there was a certain degree of recovery later. In the status quo continuation scenario, the value of various ecosystem services changed relatively steadily, but the growth rate was not as good as that in the ecological priority scenario.

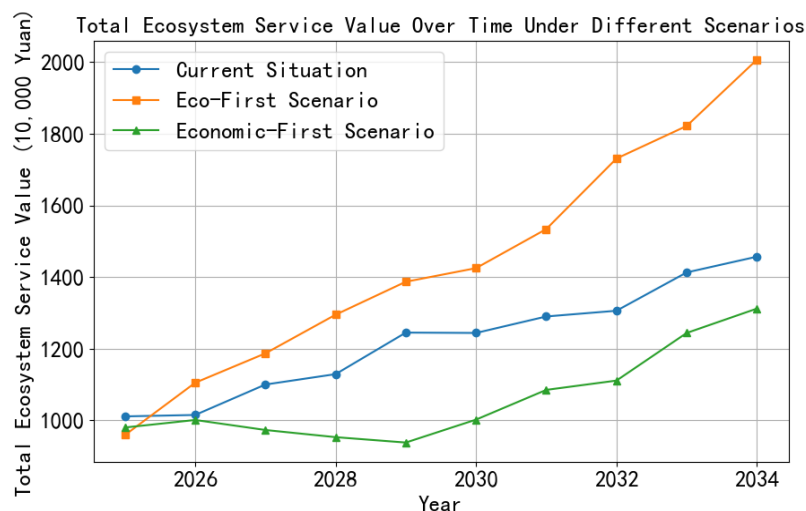


Figure 1. Line chart of the total value of ecosystem services over time under different scenarios

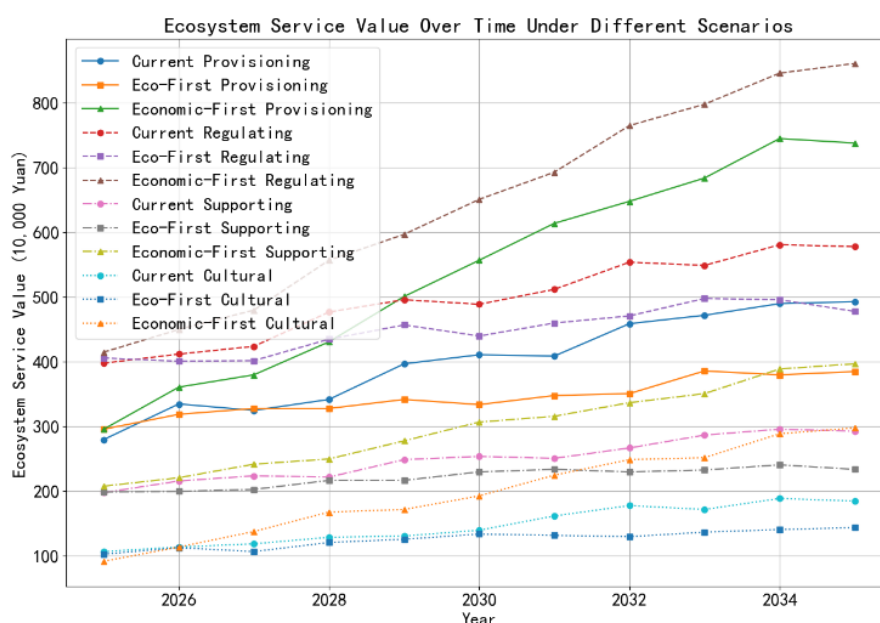


Figure 2. Line chart of the change in the value of ecosystem services over time under different scenarios

Figure 3 shows the changing trend of forest land, grassland, wetland, and construction land area over time under different scenarios. In the ecological priority scenario, the forest land and wetland area continued to increase, the grassland area also increased to a certain extent, and the construction land area was effectively controlled, showing a slow upward

trend. In the economic priority scenario, the construction land area increased significantly, and the forest land, grassland, and wetland decreased relatively. Still, there was a certain degree of stability in the later period. In the status quo continuation scenario, the changes in the area of various land uses were relatively stable. Still, the growth rate was not as good as in the ecological priority scenario. The construction land area continued to increase, and the forest land, grassland, and wetland area increased slowly.

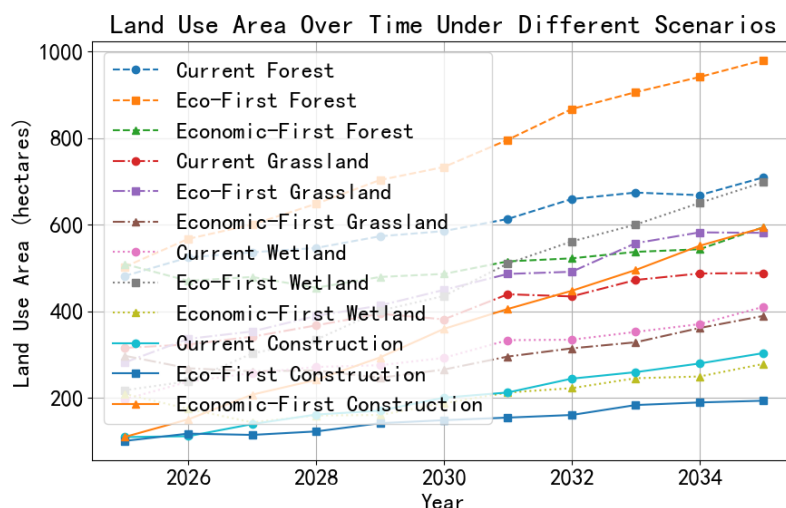


Figure 3. Line chart of land use area change over time under different scenarios

Figure 4 shows the change in social and economic benefits (taking GDP as an example) over time under different scenarios. In the economic priority scenario, the social and economic benefits grow faster, showing a clear upward trend, and GDP has increased significantly in a short period. In the ecological priority scenario, certain indirect economic benefits can also be brought about in the long term by improving ecosystem services. Still, the growth rate is relatively small, showing a relatively stable upward trend. In the status quo continuation scenario, social and economic benefits growth is relatively slow, and the overall change trend is not as good as the economic priority scenario.

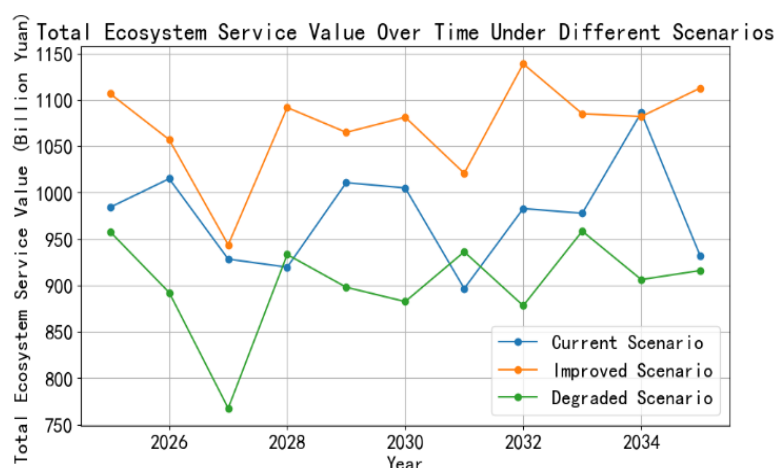


Figure 4. Line chart of social and economic benefits under different scenarios

Conclusion

This study successfully used remote sensing and GIS technology to comprehensively assess and optimize ecosystem services in the Poyang Lake Basin. The current status of ecosystem services is presented through precise data processing, model construction, and each service type's value distribution. In terms of spatial optimization configuration, a multi-scenario analysis is innovatively set, and the simulation shows that the ecosystem service improvement effect is best under the ecological priority scenario. The innovation of the study lies in the fusion application of multiple technologies and multi-scenario optimization analysis, which provides new ideas for environmental research. However, the research has certain limitations, such as the difficulty in obtaining some high-precision land use change data, which affects the accuracy of the model, and the scenario setting is challenging to cover all complex fundamental factors, such as the short-term and drastic impact of sudden natural disasters on the ecosystem. Future research can expand data sources, such as introducing high-resolution drone image data, improving dynamic models, considering seasonal changes and emergencies, and refining scenario settings. In-depth further enhances the scientificity and practicality of the research on spatial optimization of ecosystem services and provides more substantial support for ecological protection and regional sustainable development.

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Data availability. The data that support the findings of this study are available upon reasonable request from the author.

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