

Hierarchical Optimization Strategy of Landscape Architecture Space Based on Multi-Model Coupling Calculation Method

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Abstract: In the context of ecological protection and regional development, reasonable planning of the spatial hierarchy of landscape architecture can significantly enhance the stability of the ecosystem. To optimize the spatial hierarchy of landscape architecture, this paper selected the A-landscape architecture in southern China as the research object. Subsequently, the multi-model coupling calculation method is employed to construct the ecological network, and a hierarchical optimization strategy based on ecological network evaluation is designed. In the multi-model coupling calculation method, this study uses Morphological Spatial Pattern Analysis (MSPA), Spatial Principal Component Analysis (SPCA), and Minimum Cumulative Resistance (MCR) models to comprehensively analyze ecological source areas, ecological resistance, and ecological corridors. The results demonstrate that 30 potential ecological source areas are identified and divided into 10 primary, 7 secondary, and 5 supplementary (tertiary) ecological corridors. The threshold for selecting ecological source areas is that the patch area is greater than 2 km² and the buffer zone width in key corridors is at least 100 m. After optimization, the ecological network integrity index of different regions of the research object increases, such as from 0.68 to 0.89 in the southern region and from 0.54 to 0.72 in the northern region, and the landscape function index is above 0.80. The optimized biodiversity index shows a maximum increase of 0.32, while the ecosystem service value index remains above 0.75. Through the proposed measures of ecological island restoration, key corridor strengthening, and core area radiation enhancement, this study has achieved hierarchical optimization of landscape space and significantly improved the connectivity of ecological networks and ecosystem service functions. This study can provide quantitative methods and practical references for optimizing landscape space.

Keywords: MSPA; SPCA; MCR; ecological network; optimization strategy.

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1. Introduction

The acceleration of urbanization and industrialization has fragmented ecosystems and weakened their coherence and stability (Cao et al., 2025; Lyu et al., 2023). The degradation of this ecosystem threatens biodiversity and impairs ecosystem services, posing a challenge to the sustainable development of human society. In this context, as an important ecological space, landscape architecture's scientific planning and design are crucial to restoring ecosystem integrity. Additionally, there is a close relationship between optimizing Landscape Architecture Space (LAS) and Constructing Ecological Networks (ENC) (Yan et al., 2025). The optimization of LAS aims to enhance the overall functionality and coherence of ecosystems through rational planning and design, and the ENC is a key means to achieve this goal (Xu and Wang 2024). Therefore, the optimization of LAS needs to be based on the ENC. Currently used construction methods include ENC methods based on niche theory, ecosystem service value assessment methods, network analysis methods based on ecological flow, and Morphological Spatial Pattern Analysis (MSPA) methods (Wang et al., 2025). Meanwhile, many scholars have also conducted research on this issue.

Wang et al. (2025) constructed a 3D assessment system based on ecological networks and ecological security patterns to enhance the ecological resilience of megacities and identify ecological restoration spaces. This study focused on Beijing as the research area. Beijing had 51 Ecological Source Areas (ESAs) and 206 ecological corridors, and its northern and eastern ecosystems exhibited greater resilience. Huang et al. (2025) constructed ecological networks at the provincial, urban

agglomeration, and municipal levels to address ecological fragmentation and vulnerability caused by human interference, and compared the performance of different methods. The consistency of spatial output in the source region at different scales ranged from 50.48% to 97.81%, and the comprehensive method was not applicable to all restoration targets. Zhong et al. (2022) used the Analytic Hierarchy Process, the Entropy Method, and Spatial Principal Component Analysis (SPCA) to generate comprehensive resistance surfaces and construct ecological networks to address habitat fragmentation and biodiversity conservation issues caused by urban expansion. The weight values generated by the three methods differed significantly, but the distributions of high and low values across the three comprehensive resistance surfaces were the same. Li et al. (2025) proposed a comparative analysis to explore the applicability of different methods in ENC, and selected four ecological source identification methods, two comprehensive resistance surface construction methods, and two ecological network generation methods. There were significant differences in the quantity, area, and spatial distribution of ESAs among different methods (Zeng et al., 2024).

Overall, there are currently many studies on the ENC, and the methods used are also quite diverse. However, these methods also have certain shortcomings, such as a lack of quantitative indicators for evaluating the importance of ESAs and the subjectivity of ecosystem service value assessment methods, despite MSPA's ability to identify ESAs. To optimize the LAS hierarchy, this study combines MSPA, SPCA, and Minimum Cumulative Resistance (MCR) models to form a Multi-Model Coupled Computation (MCC) method. The unique contributions of the research are as follows: Unlike existing studies that use the analytic hierarchy process and the entropy method to construct resistance surfaces. This paper derives ecological resistance values from SPCA and objectively weights resistance factors through spatial statistical analysis, thereby reducing subjective judgment errors. At the same time, using this method, a comprehensive analysis of ecological source areas, ecological resistance, and ecological corridors is conducted, and a three-level landscape spatial optimization strategy is designed. The Ecological Network Integrity Index (ENII) and Landscape Functional Index (LFI) serve as core evaluation indicators for assessing optimization effects, forming a quantitative and practical landscape spatial optimization method system. This method aims to provide a quantitative basis for developing the LAS-Hierarchical Optimization Strategy (HOS). The paper aims to comprehensively analyze ESAs, ecological resistance, and ecological corridors, and provide a more comprehensive and scientific quantitative method for LAS optimization. The innovation lies in integrating the advantages of multiple models and overcoming the lack of quantitative indicators in MSPA to achieve multi-level optimization of the ecological network.

2. Methodology

To optimize the LAS hierarchy, the A-landscape garden in southern China is selected as the research object, and multidimensional data, including terrain elevation and slope, are obtained and preprocessed. On this basis, this study adopts the MCC method to construct an ecological network and develops an ecological assessment method to inform subsequent optimization strategies.

2.1. Design of Research Area and Data Acquisition

To optimize the hierarchical structure of LAS, this study begins by establishing the ecological network of landscape architecture, selecting the research object and obtaining data, and then constructing it. Afterward, an ecological network evaluation is conducted, followed by the design of optimization strategies. The core basis of this logic is that the ecological network itself is a centralized carrier of the LAS hierarchical structure and ecological functions. The construction process can directly map relationships among spatial units of different scales, providing precise quantitative support and an operational framework for hierarchical optimization (Tian et al., 2024). Developing the regional ecological network for landscape architecture selects A-landscape architecture in southern China as the research object. The study area is a typical representative of the South China Karst landform and an important transportation hub and economic center. This region belongs to the subtropical monsoon climate zone, with widely distributed karst landforms and distinct four seasons. The annual average temperature ranges from 18 °C to 20 °C. The research area map is shown in Fig. 1.

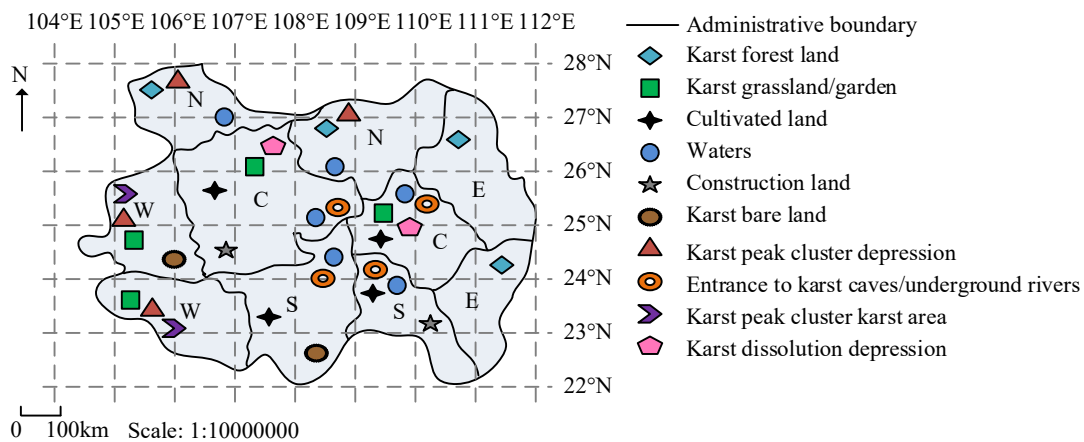


Fig. 1. The map of the study area

In Fig. 1, the study area is located in the core area of South China Karst geomorphology, which clearly outlines the complete geographical boundary of the study area, and is divided into five sub-regions: north (N), south (S), east (E), west (W), and center (C).

(W), and middle (C) according to the natural geographical characteristics and ecological pattern. The map clearly distinguishes the core land use types and karst landform features through different symbols: diamonds represent karst forests, green squares represent karst grasslands/gardens, black four-pointed stars represent cultivated land, blue circles represent water bodies, gray five-pointed stars represent construction land, and brown circles represent karst bare land. These symbols intuitively reflect the land use pattern of "ecological land as the main source and human interference concentrated in the central part" in the study area. At the same time, the red triangle marks the karst peak cluster depression, the orange circle marks the karst cave/underground river entrance, and the pink pentagon marks the karst dissolution depression in the figure. These three clarify the spatial distribution of core karst features, such as the western peak cluster karst area and the central dissolution depression. The map configuration standard includes a north-pointing needle, a 1:10000000-line segment scale (0-100 km), and a latitude and longitude grid (104°-112°E, 22°-28°N) in the WGS1984-UTM_Zone 50°N coordinate system. It accurately defines the spatial geographic attributes of the study area and provides a basic spatial framework for subsequent identification of ecological source areas and construction of ecological corridors. However, the region's ecosystem is fragile and sensitive, thus requiring the ENC to guide the LAS-HOS. The natural landscape simulation map of the area is shown in Fig. 2.

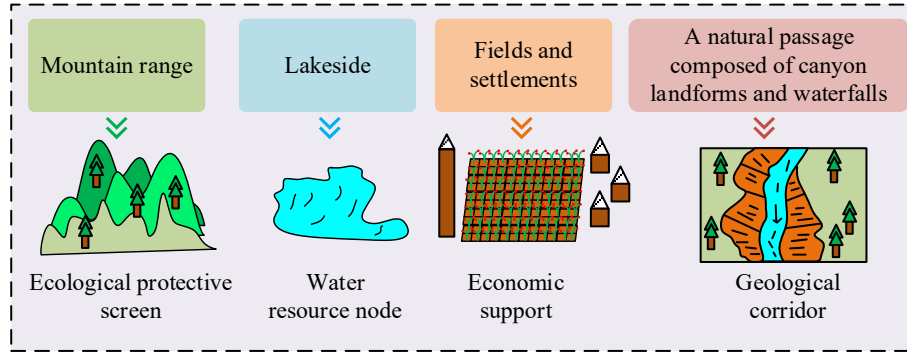


Fig. 2. Simulation diagram of natural landscape

Table 1. Data sources and related information

Data category	Data sources	Time	Data type	Resolution
Terrain elevation data	Geospatial data cloud	2023	Raster data	30m*30m
Terrain slope data	Arc Geographic Information System (ArcGIS) spatial analysis	2023	Raster data	30m*30m
Landscape road data	National Geographic Information Resource Catalog Service System	2023	Vector data	/
Vegetation remote sensing data	European space agency Copernicus data center	2023	Raster data	10m*10m
Site boundary data	National Geographic Information Resource Catalog Service System	2023	Vector data	/
Protected data	Local garden bureau/cultural relics bureau archives	2023	Vector data	/
Land use data (site and surroundings)	Resources and environment science data center of Chinese academy of sciences	2023	Raster data	30m*30m
Landscape point of interest data	Gaode map open platform	2023	Vector data	/
Built environment data	Urban planning database/remote sensing image interpretation	2023	Vector data	/
Meteorological data	China Meteorological Data Network	2023	Raster data	1 km*1km

In Fig. 2, the area's natural landscape includes ecological barriers, water resource nodes, economic support, and geological corridors. Among them, the ecological barriers in the research area are mainly plateau mountains, while water resource nodes are mainly mountain lakes, streams, and karst cave water systems. In addition, economic support is mainly reflected in cultivated land in mountain basins and settlements in river valleys, while geological corridors are mainly composed of canyons and rivers. To construct an ecological network, it is necessary to first obtain imagery of the study area. The specific data sources and related information are listed in Table 1.

In Table 1, the required data categories are quite diverse, covering terrain elevation, slope, landscape roads, vegetation remote sensing, and other categories. Among them, the terrain elevation and slope data are obtained from the geographic spatial data cloud and ArcGIS spatial analysis, and both are raster data with a resolution of 30m*30m. These multidimensional data provide comprehensive support for the ENC. After obtaining the data, it needs to be preprocessed. Firstly, this study uses ArcGIS software to obtain slope data and to classify land-use conditions. Secondly, this study conducts radiometric calibration and geometric correction on remote sensing data. Among them, radiometric calibration is used to convert digital quantification values from remote sensing images into true surface reflectance or radiance, thereby

eliminating the influence of factors such as the sensor and atmosphere. The expression for converting digital quantization values to radiance is given by Eq. (1).

$$A = B \times CD + E \quad (1)$$

In Eq. (1), A is the radiance and B is the gain. CD is the numerical value of the image pixel, and E is the bias. B and E can be obtained from the metadata of remote sensing images. The expression of surface reflectance ρ is shown in Eq. (2).

$$\rho = \frac{\pi \times A \times G^2}{H_0 \times \cos I_j} \quad (2)$$

In Eq. (2), G represents the distance between the sun and the earth, H_0 is the solar irradiance at the top of the atmosphere, and I_j is the zenith angle of the sun. The model commonly used for geometric calibration is shown in Eq. (3) (Tian et al., 2024).

$$\begin{cases} X = a_0 + a_1x + a_2y + a_3xy + a_4x^2 + a_5y^2 \\ Y = b_0 + b_1x + b_2y + b_3xy + b_4x^2 + b_5y^2 \end{cases} \quad (3)$$

In Eq. (3), (x, y) and (X, Y) are the coordinates of the original image and the corrected pixels. $a_0 \sim a_5$ and $b_0 \sim b_5$ are polynomial coefficients and are calculated by fitting the coordinates of ground control points.

All spatial data in the study are uniformly projected and registered using the WGS1984-UTM_Zone 50°N geographic coordinate reference system. For raster data of different resolutions, bilinear interpolation is used to resample vegetation remote sensing data from 10 m to 30 m, consistent with the resolutions of raster data such as terrain and land use, thereby preserving spatial features during resampling. At the same time, based on the characteristics of karst landforms and the spatial attributes of landscape architecture in the research area, a two-level classification scheme for land use is formulated, which is divided into seven categories: forest land, grassland, cultivated land, water area, construction land, karst bare land, and garden land. Ecological resistance values are set based on the category resistance theory, with the following criteria: Forest land and water area have good ecological foundations and the lowest resistance values (10 and 15, respectively). Grassland and garden are semi-natural ecological spaces with moderate resistance values (30 and 40, respectively). The cultivated land is mildly disturbed by human activities, with a resistance value of 60. The ecological foundation of karst bare land is fragile, with a resistance value of 80. The construction land has the highest human interference and the worst ecological connectivity, with a resistance value of 200.

2.2. Design of ENC Evaluation and Optimization Strategies Considering MCC

To perform LAS hierarchical optimization, the MCC method is first used to construct the ecological network, and then various indices are used to evaluate it. Finally, based on the principle of landscape connectivity, optimization strategies are designed. The structure of the MCC method is shown in Fig. 3.

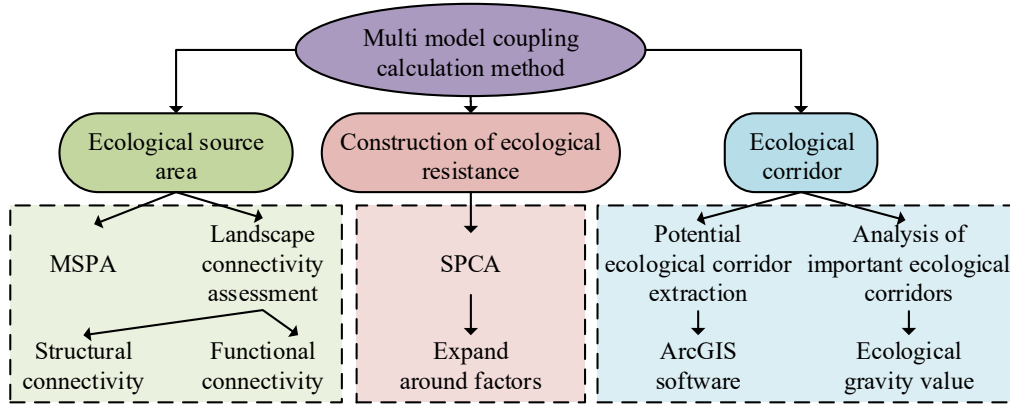


Fig. 3. The structure of MCC method

In Fig. 3 of the ESA, this study uses MSPA and a landscape connectivity assessment. The construction of ecological resistance adopts the SPCA. The ecological corridor adopts the MCR model. MSPA is a spatial analysis method based on the principles of digital morphology that can clearly reveal the internal structure of spatial data and offers good compatibility and strong operability, providing a structural basis for ecological source identification (Mao et al., 2023; Zheng et al., 2025). When using MSPA, it is necessary to first set the foreground and background, convert the raster image to binary, and specify the edge width and pixel size. MSPA is a spatial analysis method based on the principles of digital morphology that clearly reveals the internal structure of spatial data, is highly compatible and highly operable, and provides a structural basis for identifying ecological source areas. When conducting MSPA in this study, forest land, water bodies, and grasslands are selected as foreground categories, while other land use types are selected as background categories. The edge width is set to 3 pixels (corresponding to a field depth of 90 m, and the MSPA analysis pixel size in the study area is 30m × 30m). Seven landscape types are identified in the MSPA: core area, patch area, edge area, connecting area, bridging area, ring area, and pore area. The core area is selected as a candidate ecological source area. As the core ecological space of the landscape, the

core area has strong ecological connectivity and stability, serving as the primary carrier of the regional ecological source. On this basis, the introduction of the Landscape Connectivity Index (LCI) calculation clarifies the importance level of ecological source areas. LCI is a quantitative indicator that measures the degree of connectivity among patches in a landscape, typically divided into structural and functional connectivity, and offers advantages such as strong quantifiability and guidance (Sun et al., 2024; Liang et al., 2024). The expression of structural connectivity F is shown in Eq. (4).

$$F = \frac{\sum_{m=1}^k \sum_{n=1}^k L_m L_n P_{mn}}{Q^2}, (0 < F < 1) \quad (4)$$

In Eq. (4), F is the total area of the landscape, k is the total amount of patches, and m and n are both patch numbers. L_m and L_n are the areas of plaques m and n . P_{mn} is the maximum probability that the plaque is connected between m and n . The solution for the overall connectivity index is shown in Eq. (5).

$$R = \frac{1}{Q_l^2} \sum_{m=1}^k \sum_{n=1}^k \frac{L_m L_n}{1 + k S_{mn}}, (0 < R < 1) \quad (5)$$

In Eq. (5), Q_l represents the total area of the study area, and S_{mn} is the number of connections between patches m and n . The calculation of importance T is shown in Eq. (6).

$$T = \frac{100\% \times (F - F')}{F} \quad (6)$$

In Eq. (6), F' is the overall connectivity index of the landscape after removing a certain patch. SPCA is a method that combines spatial information and statistical analysis to reveal the main directions of variation and spatial structures in the data by extracting principal components from spatial data. It offers good dimensionality reduction and strong interpretability (Ji et al., 2023; Postiglione et al., 2023). The calculation of SPCA involves the PCA formula. The core formula of PCA is shown in Eq. (7) (Ziar et al., 2023).

$$U = V \cdot W \quad (7)$$

In Eq. (7), V is the raw data matrix, W is the load matrix, and U is the principal component score matrix. The process of constructing ecological resistance is shown in Fig. 4.

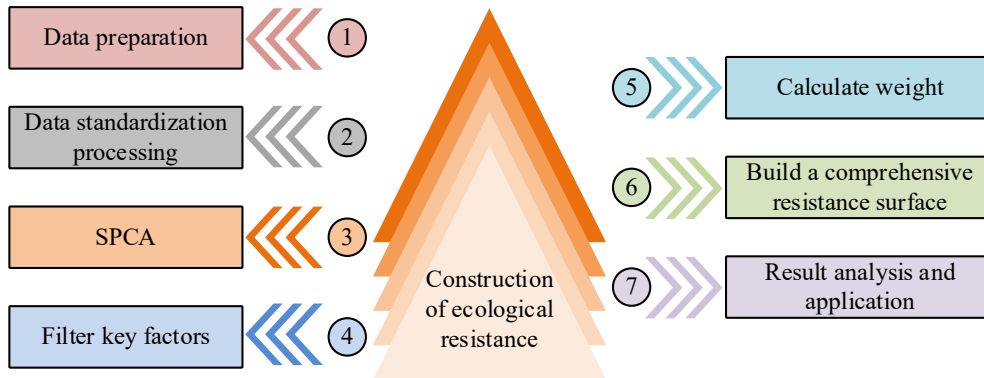


Fig. 4. The process of constructing ecological resistance

In Fig. 4, the construction of ecological resistance mainly includes data preparation, data standardization, SPCA, screening key factors, calculating weights, constructing a comprehensive resistance surface, and analyzing and applying the results. Data preparation includes three aspects: terrain and landform factors, habitat type factors, and human interference factors. Due to significant differences in the dimensions and numerical ranges of different factors, standardization is required. The standardized formula is given by Eq. (8).

$$Z_{cd} = \frac{f_{cd} - \mu_d}{\sigma_d} \quad (8)$$

In Eq. (8), Z_{cd} represents the standardized value. f_{cd} is the value of the d -th factor of the c -th sample in the original data matrix. μ_d and σ_d are the mean and standard deviation of the d -th factor. Afterward, this study will input the standardized single-factor data for SPCA. Next, when selecting key factors, use the Cumulative Contribution Rate (CCR) as the basis. The formula of the CCR z is given by Eq. (9).

$$z = \sum_{u=1}^g \frac{\lambda_u}{\sum_{v=1}^{\beta} \lambda_v} \quad (9)$$

In Eq. (9), λ_u and λ_v are the eigenvalues of the u -th and v -th principal components. β and g are the total and selected number of principal components. The next step is to calculate the weights of different factors, as shown in Eq. (10).

$$w_v = \frac{\lambda_v}{\sum_{u=1}^g \lambda_u} \quad (10)$$

In Eq. (10), w_v is the weight of the v -th factor. Subsequently, each individual factor is weighed and summed according to the calculated weights to obtain the comprehensive resistance surface. The calculation of the comprehensive resistance surface is shown in Eq. (11).

$$\delta_u = \sum_{v=1}^{\varphi} (Z_{cd} \times w_v) \quad (11)$$

In Eq. (11), δ represents the comprehensive resistance value, and φ is the number of key factors selected. Afterward, based on the spatial distribution characteristics of the comprehensive resistance surface, this study can identify areas with low and high resistance values and provide a scientific basis for ENC and ecological corridor planning. The MCR model is a path analysis method based on resistance surfaces that determines the optimal path and ecological corridor by calculating MCR values from the source point to other points. It offers high computational speed and broad applicability (Du et al., 2023; Yu et al., 2024). In specific applications, it is necessary to approach the problem from two perspectives: identifying potential ecological corridors and analyzing important ecological corridors. On the former, this study needs to first prepare comprehensive resistance evaluation data and ArcGIS software, and then generate ecological corridors through MCR. The latter requires solving the ecological gravity value to screen the ecological corridor. Subsequently, an ecological corridor classification map is constructed. Based on the above analysis and the acquisition of key ecological nodes, an ecological network is constructed.

In evaluating ecological networks, based on existing research, NCI, connectivity index, and connectivity rate are selected. Based on the results of the ecological evaluation, the LAS-HOS design is implemented, and the optimization process is shown in Fig. 5.

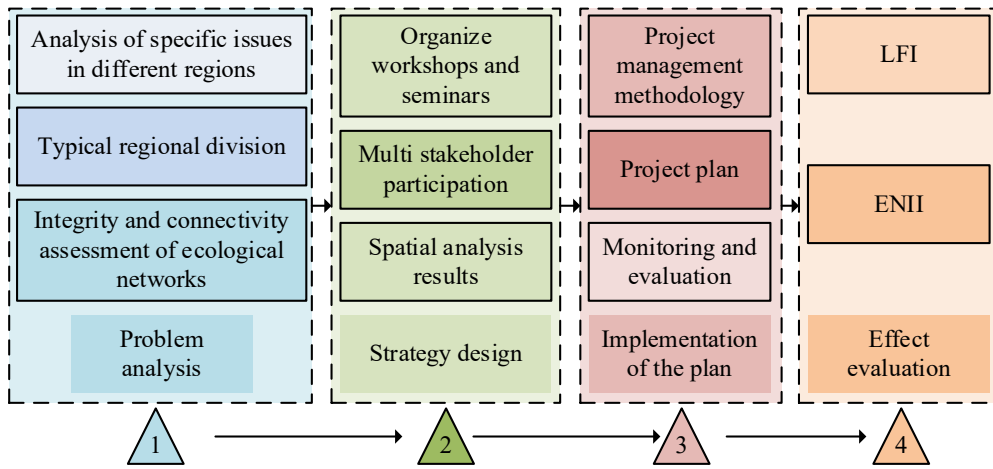


Fig. 5. Hierarchical optimization process of LAS

In Fig. 5, the LAS-HOS process includes problem analysis, strategy design, scheme implementation, and effectiveness evaluation. The problem analysis mainly includes assessing the integrity and connectivity of the ecological network, dividing typical regions and analyzing specific problems in different regions. In terms of strategy design, in addition to integrating spatial analysis results, it is also possible to invite multiple stakeholders to participate and organize workshops and seminars to enhance the strategy's scientific rigor. In implementing the plan, a project management methodology can be adopted. The effect evaluation adopts the ENII and LFI.

3. Results

To evaluate the A-landscape ecological network in southern China and optimize spatial hierarchy, this study identified 30 potential ESAs and proposed a three-level optimization strategy based on the ecological network evaluation results. To evaluate the effectiveness of the optimization strategy, various indicators, such as ENII and LFI, were compared before and after optimization.

3.1. Ecological Network Evaluation Results

To evaluate the ecological network of the research area for LAS hierarchical optimization, this study used a Windows 10 system and an Intel Core i5-13600K central processing unit (with a maximum turbo frequency of 5.1 GHz and support for up to 128 GB of memory). Firstly, the potential ESAs in the study area were annotated, namely habitat patches with an area greater than 2 km², and then ranked according to their importance level. Afterward, a comprehensive landscape resistance surface was constructed, including the CCRs and the weight results for different factors. The acquisition of ecological corridors is considered the value of ecological gravity. In addition to the primary and secondary ecological corridors, supplementary corridors have also been considered to connect them. Finally, an ecological network was constructed and evaluated using NCI, connectivity index, and connectivity rate. In the multi-model coupling calculation, the core operating parameter values of MSPA, SPCA, and MCR models were uniformly set as follows, and all parameters were optimized based on the 30 m grid resolution and karst landform features in the study area: the segmentation threshold of MSPA is 0.5, the morphological operation type is eight neighborhood operation, and the foreground connectivity is eight connectivity. The threshold for principal component extraction in SPCA was $CCR \geq 85\%$, the data standardization method was Z-score standardization, and the rotation method was maximum variance rotation. The basic resolution of the MCR

resistance surface was $30\text{m} \times 30\text{m}$, and the source diffusion type was isotropic. The cumulative resistance calculation coefficients were $\alpha=1$ and $\beta=2$, and the corridor extraction threshold was 1.2 times the MCR value. The potential ESAs and their ranking results are shown in Fig. 6.

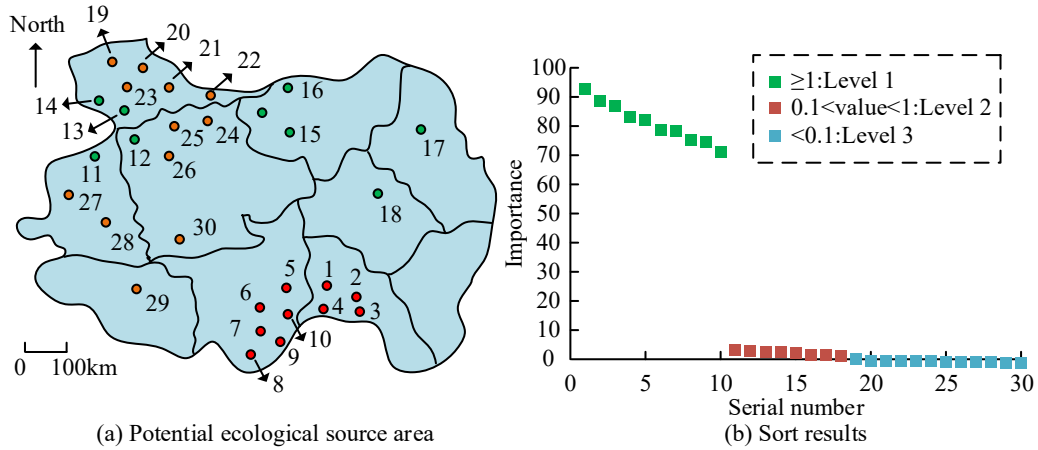


Fig. 6. Potential ecological source areas and their ranking results

In Fig. 6(a), there were a total of 30 potential ESAs in the study area, mainly distributed in the northwest and south of the study area. In Fig. 6(b), out of 30 potential ESAs, a total of 10 ESAs had an importance level greater than or equal to 1, and were mainly distributed in the southern part. This study categorized these ESAs into one level. In addition, there were 8 ESAs with importance levels within the range of (0.1, 1), and 12 ESAs with importance levels less than 0.1, which were classified as level 2 and level 3. This mismatch between hierarchy and space reflected the problem of the ecological pattern being "strong in the south and weak in the north, with dispersed cores". Table 2 presents the CCRs and weights for the different factors.

Table 2. CCRs and weight results of different factors

Principal component	Eigenvalue	Contribution rate	CCR	Evaluation	
				Land-use type	Slope
1	4.05	29.67%	29.67%	-0.080	0.350
2	2.75	20.36%	50.03%	-0.015	0.100
3	1.89	14.21%	64.24%	-0.030	0.640
4	1.70	12.73%	76.97%	0.010	0.570
5	1.25	9.36%	86.33%	-0.100	0.240
6	0.78	5.85%	92.18%	0.010	0.060
7	0.40	2.97%	95.15%	0.980	0.050
Weight				0.2050	0.2450
Principal component	Evaluation				
	Distance from major built-up areas	Distance from major transportation arteries	Vegetation coverage	Elevation	Distance from nature reserves
1	-0.450	-0.520	0.580	-0.230	-0.030
2	0.290	0.620	0.640	-0.210	-0.040
3	-0.470	0.440	-0.390	-0.110	0.010
4	0.690	-0.330	-0.180	-0.140	-0.060
5	0.020	0.010	0.190	0.920	-0.100
6	0.030	-0.010	0.040	0.060	0.970
7	-0.060	-0.020	0.050	0.060	-0.020
Weight	0.1350	0.2600	0.1050	\	\

In Table 2, the CCR of the top 5 of the top 7 principal components is 86.33%. The contribution rate of the first principal component, terrain, was the highest at 29.67%, while the second principal component, human interference, was second at 20.36%. This indicated that terrain conditions and human activities were the two dominant factors affecting ecological resistance. In addition, the weight analysis found that the negative weight of "distance from major built-up areas" was 0.26, while the positive weight of "vegetation coverage" was 0.58. This also reflected the clear antagonistic relationship between urbanization and ecological protection. In the optimization process of LAS, the focus should be on controlling the urban expansion boundary and strengthening vegetation restoration projects. The ecological gravity values among different ecological sources are shown in Fig. 7.

In Fig. 7(a), on important ecological corridors, the ecological gravity values between ESAs 7-8 and 5-6 were as high as 3501.17 and 2438.69, significantly higher than those in other situations. This reflected the formation of a strong interaction network between the primary ecological sources in the southern core area of the research region. In Fig. 7(b), along the secondary ecological corridor, the ecological gravity values were generally below 190.00. The ecological gravity values between ESAs 4-6 and 1-3 were 180.17 and 150.33, respectively, indicating a significant distance-attenuation effect. In Fig. 7(c), on the supplementary ecological corridor, the range of ecological gravity values was (20, 60), and the overall value was relatively small. The ecological network in the research area presented a binary pattern of "core resilience and edge fragility". The ecological network and its evaluation results are shown in Fig. 8.

In Fig. 8(a) of the overall ecological network, the study primarily selected the primary source areas in the southern region. These source areas and ecological corridors together formed a network structure covering the study area. In Fig. 8(b), the Network Closure Index (NCI) from the ecological network evaluation was 0.31, indicating that the ecological network's structural stability is relatively low. The connectivity index was 1.42, indicating that the ecological network has some connectivity, but the overall structure still appears loose. Finally, the connectivity rate was 0.25, indicating that the actual number of corridor connections in the ecological network is only about a quarter of the theoretically maximum, highlighting a substantial gap in the network's connectivity.

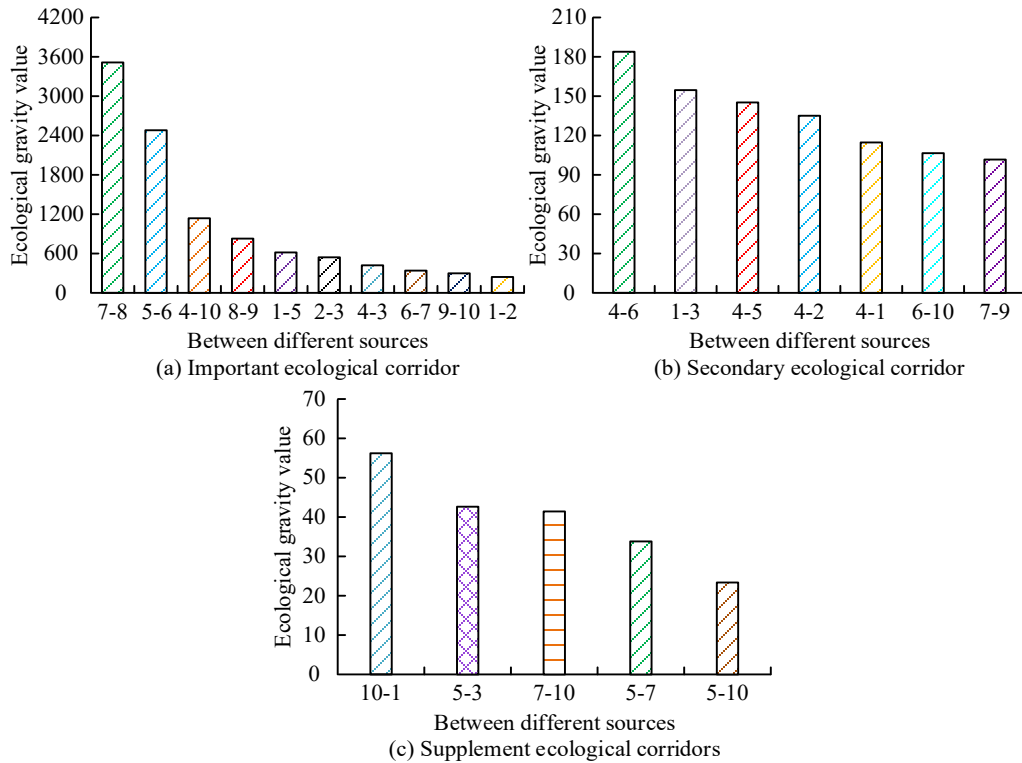


Fig. 7. Ecological gravity values between different ecological sources

3.2. Optimization Strategy and its Application Effect

Based on the evaluation results of the ecological network, this study proposed a three-level LAS-HOS: 1. The restoration of ecological islands in the northwest involves adding 8 ecological steppingstones (with an area of $\geq 0.5 \text{ km}^2$) between 12 tertiary source areas, and improving the connectivity probability between patches through vegetation restoration projects. 2. Key corridor reinforcement refers to the construction of ecological buffer zones with a width of $\geq 100 \text{ m}$ for the secondary corridors of faults. 3. The radiation in the southern core area is enhanced, which means extending three cross-regional corridors from the primary source area to the northwest. The comparison of ENII and LFI before and after optimization is shown in Fig. 9.

In Fig. 9(a), on ENII, the values of 0.58, 0.61, 0.68, 0.54, and 0.64 in the eastern, western, southern, northern, and central regions before optimization were increased to 0.65, 0.76, 0.89, 0.72, and 0.75 after optimization. The southern region has seen the most significant improvement due to the radiation enhancement strategy in the core area, while the northern region has seen a significant increase in the use of ecological island restoration strategies. In Fig. 9(b) for LFI, the values for each region before optimization ranged from 0.65 to 0.75, while after optimization, they were all above 0.80, with the southern region ranking first at 0.86. LAS-HOS effectively enhanced the integrity of ecological networks and landscape functions, and the synergistic effect between core-area leadership and edge-area restoration was significant.

The biodiversity index studied was calculated using the Shannon Wiener diversity index, and the model formula was $H' = -\sum (P_i \times \ln P_i)$ (P_i is the proportion of the area of the landscape type i). At the same time, based on the karst characteristics of the research area, three indicators of species richness, evenness, and dominance were selected to construct a comprehensive evaluation system for biodiversity, with weights of 0.4, 0.3, and 0.3, respectively. The comprehensive

biodiversity index was obtained by weighted summation. The calculation of ecosystem service value adopted the equivalent factor method, combined with the "China Ecosystem Service Value Equivalent Factor Table", and modified the equivalent factors based on the karst landform characteristics of the study area. Seven indicators were selected, including supply services (food production, raw material production), regulation services (climate regulation, hydrological regulation, soil conservation), support services (biological habitat), and cultural services (leisure tourism), with weights of 0.12, 0.10, 0.22, 0.20, 0.15, 0.13, and 0.08, respectively. The comprehensive index of ecosystem service value was obtained by multiplying the area of each ecosystem type by the modified equivalent factor, and then normalizing it to the range (0-1). The comparison of biodiversity and ecosystem service value before and after optimization is shown in Fig. 10.

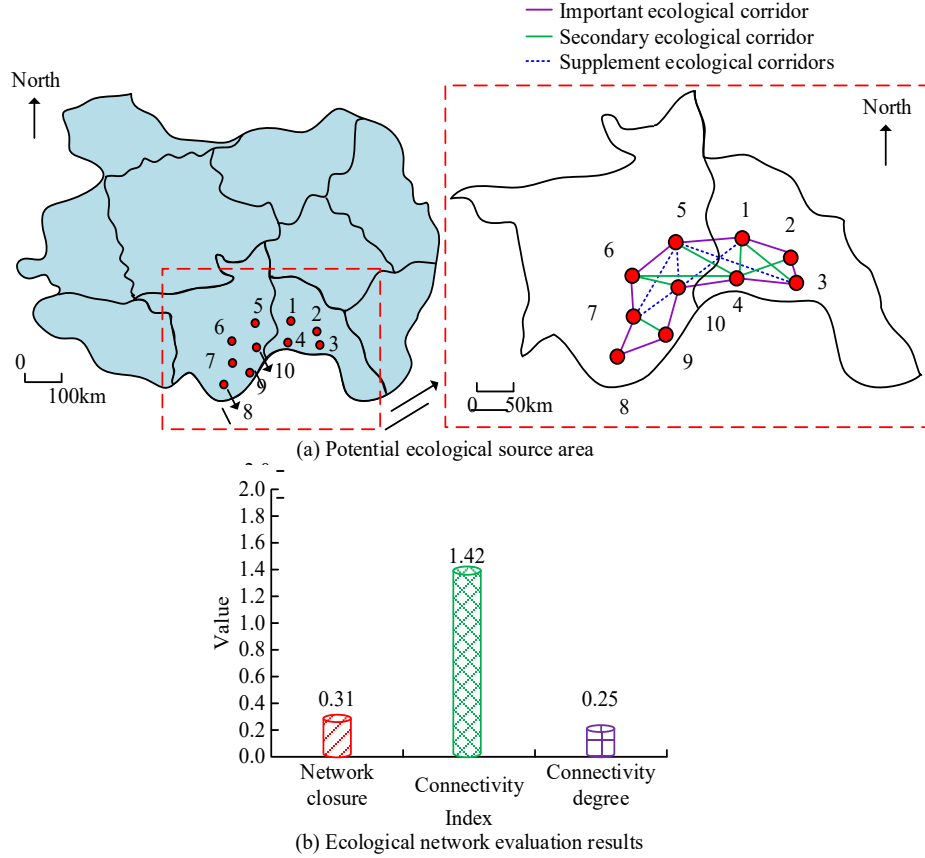


Fig. 8. Ecological network and its evaluation results

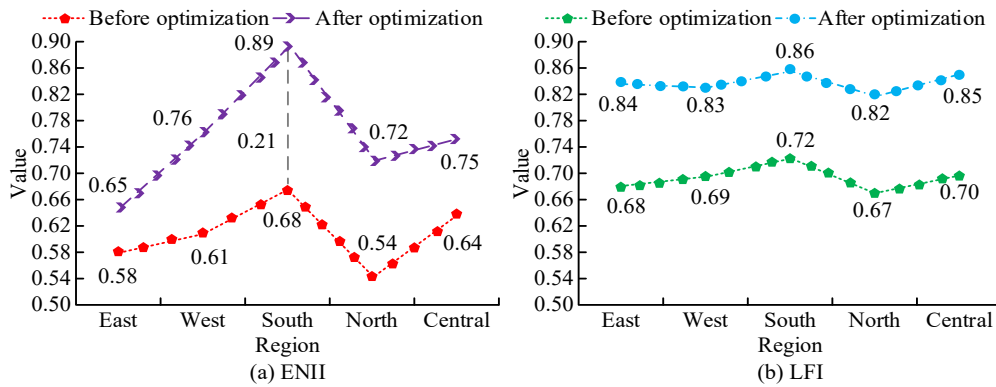


Fig. 9. Comparison of ENII and LFI before and after optimization

In Fig. 10(a), the southern region showed the largest increase in the biodiversity index, by 0.32, while the eastern region showed the smallest, by 0.11. In Fig. 10(b), on the ecosystem service value index, the values of different regions before optimization were basically below 0.65, while their values after optimization were basically above 0.75. LAS-HOS has achieved synergistic growth in biodiversity and ecosystem service value in the research area through differentiated measures. The comparison of landscape connectivity and land use efficiency before and after optimization is shown in Fig. 11.

In Fig. 11(a), in terms of landscape connectivity, the pre-optimized values for the eastern, western, southern, northern, and central regions were 0.54, 0.55, 0.58, 0.53, and 0.56, while their optimized values were 0.69, 0.71, 0.76, 0.70, and 0.73, with differences of 0.15, 0.16, 0.18, 0.17, and 0.17 before and after optimization. In Fig. 11(b), the southern region showed greater changes in land use efficiency before and after optimization, followed by the northern region, with increases of 0.19

and 0.16. This change also confirmed the effectiveness of LAS-HOS: the enhanced radiation in the southern core area and the extension of cross-regional corridors have improved connectivity and utilization efficiency, while the restoration of ecological islands in the north has also achieved significant results. Landscape connectivity and land-use efficiency across various regions have improved.

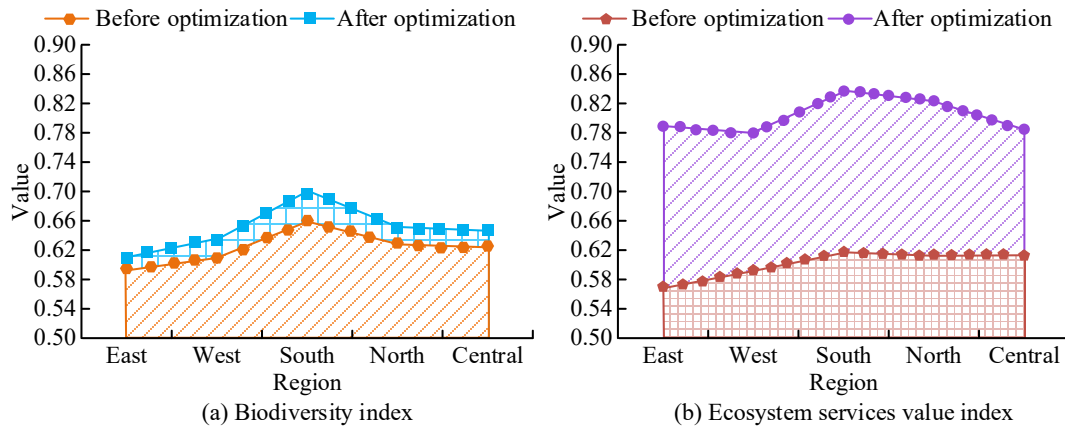


Fig. 10. Comparison of biodiversity and ecosystem service value before and after optimization

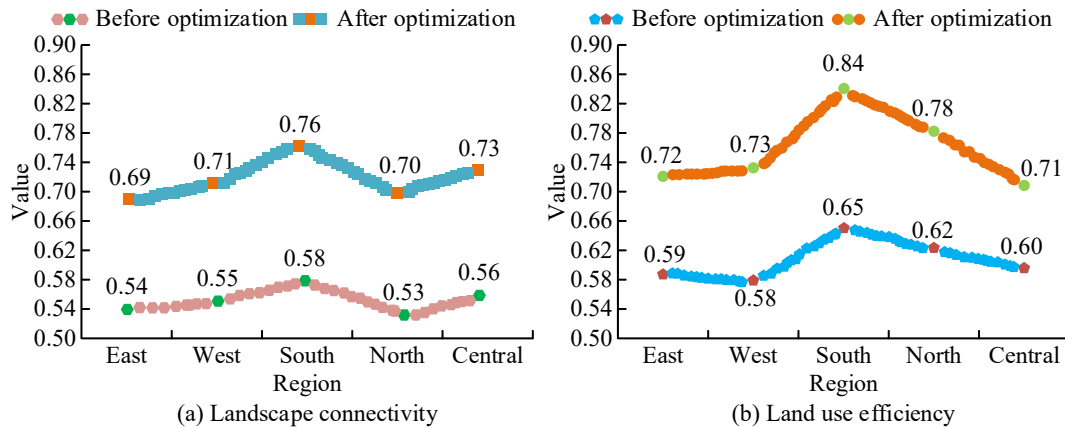


Fig. 11. Comparison of landscape connectivity and land use efficiency before and after optimization

In addition to improving quantitative indicators, the research area's landscape space has achieved significant practical landscape optimization. In terms of spatial pattern, the addition of 8 ecological steppingstones in the northwest has broken the original pattern of scattered and poorly connected ecological source areas, forming a continuous ecological space of "steppingstones ecological source areas". The karst bare land has formed a contiguous ecological buffer zone through vegetation restoration, and the fragmented landscape pattern in the northern region has been significantly improved. In terms of landscape style, the extension of the radiating corridor in the core area has achieved the infiltration of high-quality ecological landscapes from the south to the northwest, connecting water resource nodes such as lakes and streams in the mountains with the ecological barrier of the plateau mountains, forming an integrated karst characteristic scenic garden forest landscape of "mountain water forest corridor". In terms of ecological landscape function, the construction of buffer zones along key corridors has integrated ecological protection and landscape recreation. Ecological trails and viewing nodes are set up within the buffer zones, which not only enhance ecological connectivity but also enrich the recreational experience of landscape architecture. The boundary landscape between construction land and ecological space is softened, forming a transitional space that combines ecological function and landscape value.

3.3. Supplementary Analysis and Mechanism Explanation

In combination with the ecological characteristics of karst areas in South China Karst, this study selects endemic plants such as *Pterocarpus rosea* and *Davidia involucrata*, terrestrial vertebrates such as macaques and small civet cats, and aquatic organisms such as giant salamanders and scaly white turtles as regional biodiversity indicator species. Such species have high requirements for habitat connectivity, and the construction and optimization of ecological corridors provide them with continuous habitats for migration, feeding, and reproduction, effectively mitigating habitat fragmentation caused by karst landforms and reducing species' geographical isolation. At the same time, the corridor also supports four core ecological processes: species gene exchange, community succession, material cycling, and ecological disturbance response. It not only promotes gene flow among different ecological sources but also drives ecological succession on karst bare land and enables cross-system cycling of carbon, nitrogen, water, and other substances. The corridor also provides disaster-evacuation and migration routes for species and helps maintain the stability of regional biodiversity.

This study uses the ecological network connectivity index as the response indicator and conducts sensitivity analysis of ecological resistance weights using the single-factor perturbation method. The weights of each resistance factor are perturbed up and down by 10%, 20%, and 30%, respectively, and the change rate of the connectivity index is calculated to verify the rationality of the resistance weight setting. The results show that construction land, forest land, and water are highly sensitive factors, and the change rate of the connectivity index after weight perturbation exceeds 20%, indicating that human interference and the resistance setting of the core ecological space have a significant impact on the research results. Farmland, grassland, and garden land are moderately sensitive factors, with change rates between 10% and 20%, while karst bare land is a low-sensitivity factor, with a change rate below 10%. The sensitivity distribution of each factor is consistent with the structural characteristics of the ecosystem in the study area, indicating that the resistance weight set in this study is highly rational and free of obvious weight deviations.

The ENII characterizes the structural integrity of ecological networks from three dimensions: ecological source integrity, corridor connectivity, and node effectiveness. It has an inherent mechanistic relationship of "structure determines function" with the value of ecosystem services: the improvement of ecological source integrity is the foundation of ecosystem service value, and its area and connectivity directly determine the ecosystem's basic supply capacity. The protection and restoration of core source areas can enhance the core ecosystem service function. Improving corridor connectivity is key to the spatial transmission of ecosystem service value. Improving connectivity and continuity can promote the penetration of high-quality ecological service functions from the southern core area to the northwestern edge area and narrow regional differences in service functions. Improving node effectiveness ensures synergy among ecosystem service functions. Optimizing its quantity and distribution can achieve synergy and efficiency among hydrological regulation, leisure tourism, and other service functions, and enhance the comprehensive value of ecosystem services. Overall, the improvement in ENII reflects the optimization of the ecological network structure, which in turn promotes the enhancement and spatial balance of ecosystem service functions. The two exhibit a significant positive correlation, and ENII can serve as an important structural indicator for improving ecosystem service value.

4. Conclusion

In response to the hierarchical optimization problem of LAS, this study focused on the A-level landscape architecture in southern China, adopted the MCC method, and proposed optimization strategies. There were 10 ESAs in the research area with importance levels greater than or equal to 1, and they were mainly distributed in the south. In terms of ecological network evaluation, the NCI was 0.31, the connectivity index was 1.42, and the connectivity rate was 0.25, indicating a loose structure in the study area and insufficient connectivity among actual corridors. After optimization, although there were regional differences in the increase of biodiversity (0.11 in the eastern region and 0.32 in the southern region), overall synergistic growth was achieved. Landscape connectivity has improved significantly, with connectivity indices in the eastern, western, southern, northern, and central regions increasing by 0.15, 0.16, 0.18, 0.17, and 0.17, respectively. Due to the radiation enhancement strategy in the core area, the southern region had the most prominent improvement. In terms of land-use efficiency, the growth rate in the southern region reached 0.19, and the northern region also improved by 0.16, reflecting the synergistic effect of core-area leadership and edge-area restoration. HOS, based on ecological network evaluation, can effectively address the ecological imbalance in LAS, providing a feasible path to improving ecosystem integrity and functionality. However, the applicability of research strategies in different geomorphological and climatic regions has not been validated. Future work can expand the research scope to include different types of landscape areas for comparative analysis, thereby enhancing the universality and scientific validity of optimization strategies.

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Declaration of AI Tools

The author confirms that no AI tools were used in the preparation of this manuscript.

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