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Synergistic Enhancement of Carbon Sinks and Connectivity: Restoration and Renewal of Ecological Networks in Nanjing, China

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Abstract: Urbanization has led to a reduction in green space, weakening the region's carbon sink capacity and stability and bringing a series of ecological problems, making the restoration and improvement of the ecological environment crucial. This study used Nanjing, China, as a case to construct an ecological network by applying Morphological Spatial Pattern Analysis (MSPA) and the Linkage Mapper (LM) tool based on circuit theory. The connectivity of ecological patches was evaluated by calculating the delta potential connectivity index (dPC). The CASA model (Carnegie–Ames–Stanford approach) was applied to quantify carbon sequestration in Nanjing. We propose an innovative carbon sink index (CSI) that integrates three indicators: capacity, efficiency, and variability. This index assesses the carbon sink function of ecological patches from both static and dynamic perspectives. Using the Future Land Use Simulation (FLUS) model, we simulated carbon sequestration changes in 2035, providing insights for risk assessment and future optimization strategies. The results reveal a significant positive correlation between node connectivity and both carbon sink capacity and efficiency, indicating that enhancing connectivity at key nodes can effectively improve its carbon sequestration. On this basis, by coupling dPC and CSI indices to classify ecological network nodes, we proposed four strategies for optimization: ecological conservation, structural connectivity, carbon sink improvement, and synergistic enhancement. Finally, by adding 26 ecological stepping stones, 32 ecological corridors, and optimizing landscape components, we achieved dual improvements in both the structural and functional aspects of the ecological network. After optimization, the network connectivity increased by 1.6% and the carbon sink increased by 3.82%, demonstrating a significant improvement. This study emphasizes that by protecting, enhancing, and restoring ecological spaces, the carbon sequestration function and stability of urban ecological networks can be effectively improved. These findings provide valuable insights for the scientific management of ecological spaces in urbanized areas.

Keywords: carbon sink index; landscape connectivity; ecological network optimization; multi scenario simulation; urban planning

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1. Introduction

As urbanization continues to accelerate globally, cities are confronting unprecedented climate and ecological challenges [1]. The ongoing expansion of urban land often encroaches on natural ecosystems, leading to habitat fragmentation [2,3], biodiversity loss [4], and the decline of ecosystem services and stability [5]. These changes reduce the carbon sequestration potential of green spaces and limit the effectiveness of regional ecological

networks as carbon sinks [6,7]. With China's commitment to sustainable development and carbon neutrality goals [8], there is a pressing need to restore and improve the ecological environment. Optimizing urban ecological structures and promoting sustainable urban development are therefore central areas of current research.

Ecological network construction has become a crucial conservation strategy, playing an essential role in ecological environment restoration. The core principle is to maintain connectivity between isolated and fragmented ecological sources and corridors, ensuring the continuous provision of ecological services and carbon sink functions [9,10]. Researchers generally follow a process of "source identification, resistance surface construction, and corridor extraction" in ecological network construction [11–13]. Ecological sources, often patches with complete landscape structures and strong ecological functions, are identified using methods like MSPA [14], which precisely locates areas vital for landscape connectivity [15]. The minimum cumulative resistance model is commonly used to determine ecological corridors [16], identifying optimal pathways for biological movement. However, it falls short in defining the spatial extent and key nodes of these corridors. To address this, circuit theory, drawn from physics, has been applied in ecological networks [17]. By simulating biological movement as electrical current, circuit theory helps identify critical locations and sets corridor width thresholds based on the intensity and frequency of the current, providing a more accurate picture of ecological connectivity [18–20].

Many studies highlight the significance of ecological networks in enhancing the carbon sequestration potential of green spaces [21–23]. These networks provide a critical spatial foundation for the material and energy cycles within urban areas, supporting ecological processes that are integral to low-carbon development and carbon balance [24]. From a network perspective, quantifying the spatiotemporal changes in carbon sequestration due to land-use changes, ecological networks offer valuable insights into how carbon sinks and sources can be balanced to promote sustainable urban growth [25]. Research has demonstrated that modifications in green space network structure can enhance carbon sequestration by enhancing ecosystem resilience, energy flow, and overall functionality [26–28]. Vegetation, which plays a central role in carbon sequestration, is influenced by various environmental factors [29,30]. Healthy ecosystems promote a positive circulation of materials and energy [31–33], and in degraded urban ecosystems, the construction of ecological corridors and stepping stones can enhance plant growth conditions, boosting their carbon absorption potential [34,35]. Therefore, restoring and renewing urban ecological networks is essential for repairing damaged local ecosystems and serves as a strategic approach to large-scale landscape restoration, which is critical for achieving carbon balance [36].

Despite growing interest, research that links carbon sinks with ecological networks remains in the early stages. Most existing studies focus on modeling specific years of ecological space networks, with little attention given to the interactions between ecology and carbon sequestration at the urban scale [37]. Additionally, research on carbon storage at the spatial level tends to focus on land use variability, neglecting the enhancement of individual patch quality [38]. Moreover, there is a lack of scientific frameworks for quantitatively evaluating the structural and functional interactions of ecological networks [39,40]. The existing research often relies on single aggregate indicators to measure carbon sequestration in green spaces, overlooking the complexity and dynamic nature of ecosystems [41]. To clarify the role of urban green spaces in the carbon cycle and guide future urban development, there is an urgent need for a framework that integrates the structural characteristics of green spaces with carbon sequestration potential while promoting network optimization.

Building on previous research and addressing knowledge gaps, this study aims to accomplish the following: (1) establish an ecological network optimization framework that couples green space structure with carbon sink function, considering their dynamic

complexities; (2) use Nanjing as a case study to analyze the connectivity of ecological nodes and the spatiotemporal variation in carbon sinks; and (3) link landscape patch connectivity with carbon sequestration to identify strong and weak ecological nodes and propose targeted optimization strategies. By quantitatively evaluating the effects of these strategies on carbon sequestration and network connectivity, this study aims to enhance the carbon sink potential of urban ecological spaces, improve local environmental quality, and provide valuable insights for sustainable urban development planning.

2. Materials and Methods

2.1. Study Area

Nanjing, a pivotal city within China's Yangtze River Delta urban cluster, is located in the southwestern part of Jiangsu Province. As the capital of Jiangsu Province, it spans an area of 6587.02 km^2, covering 11 municipal districts. The city's geographic coordinates range from 31°14″ to 32°37″ north latitude and 118°22″ to 119°14″ east longitude (Figure 1). By the end of 2023, Nanjing's permanent population reached 9.55 million, with a GDP of 1.74 trillion CNY, ranking second in Jiangsu Province and third within the Yangtze River Delta region. The subtropical warm climate provides ample sunshine throughout the year, with an average annual temperature of 15.4 °C and annual precipitation of 1100 mm. Nanjing's landscape is dominated by plain valleys and low altitude hills, with an average elevation of 28 m and a maximum elevation of 418 m. Nanjing is rich in natural resources, with 31% forest coverage and 11.4% water resources, providing abundant carbon sink potential.

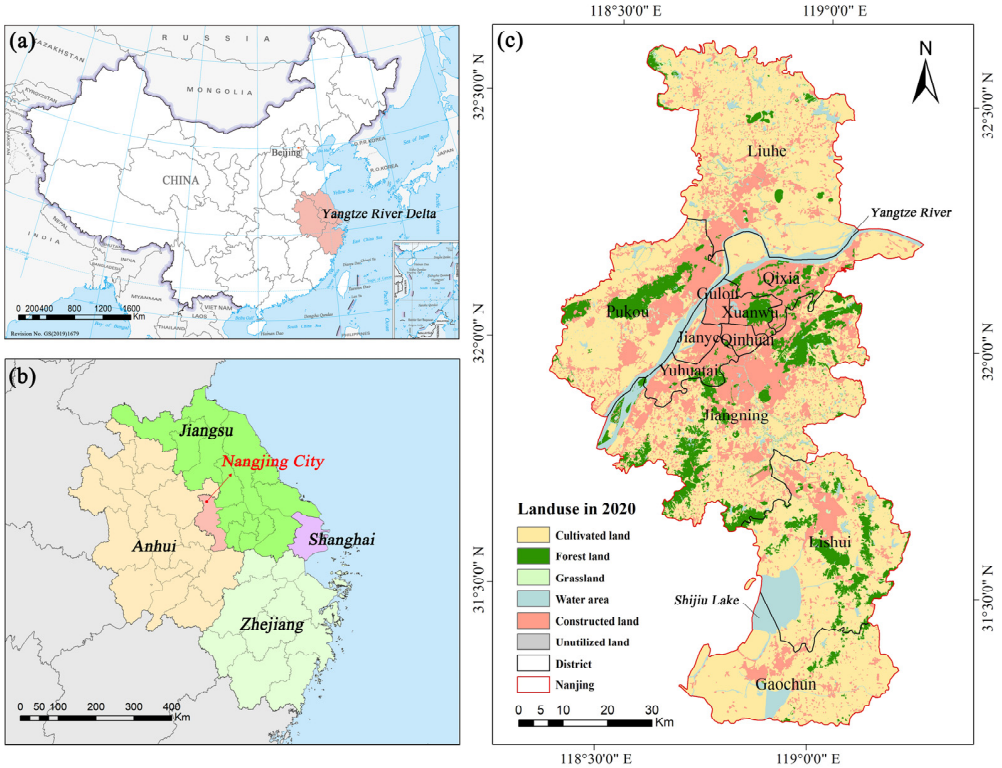

Figure 1. Geographic location analysis of Nanjing, China. (**a**) Geographic location of Yangtze River Delta in China; (**b**) Geographic location of Nanjing in the Yangtze River Delta; (**c**) Land use of Nanjing in 2020.

The Nanjing municipal government attaches great importance to the construction of low-carbon cities, prioritizing ecological restoration and enhancing carbon sink functions. However, rapid urbanization has led to the loss of ecological spaces, a decline in biodiversity,

the degradation of water and soil quality [42], atmospheric pollution, and heat island effects, posing serious challenges to the carbon sink function of ecosystems [43]. Since 2013, Nanjing has implemented various ecological restoration efforts, including the development of greenways, green space planning, and greening projects along the Yangtze River. However, the overall trend of ecosystem degradation has not been fundamentally reversed [44,45]. In light of these challenges, it is necessary to quantitatively evaluate the carbon sink of green spaces from a systematic and multidimensional perspective and propose targeted optimization strategies to address ecological issues in the process of urbanization.

2.2. Data Sources and Processing

This study primarily used multiple datasets from three periods in 2000, 2010, and 2020, as shown in Table 1. According to the classification formulated by the Chinese Academy of Sciences, the land-use data were reclassified into six types: cultivated land, forest land, grassland, water area, construction land, and unutilized land. The climate and environment data include elevation, slope, temperature, precipitation, and solar radiation. Utilizing the Google Earth Engine platform and remote sensing images, the NDVI index was calculated. Socioeconomic data include population, GDP, roads, and transportation stations. All data were uniformly processed using the WGS_1984_UTM_Zone_51N projection coordinate system, with a spatial resolution of 30 m × 30 m.

Table 1. List of research data and sources.

Data	Subdata	Year (s)	Accuracy/(m)	Sources
Land use	LUCC	2000, 2005, 2010, 2020	30	GlobeLand30 (https://zenodo.org/records/12779975, accessed on 1 May 2024)
Remote sensing	Landsat5	2000, 2010	30	GSCloud (http://www.gscloud.cn/, accessed on 1 May 2024)
	Landsat8	2020	30	
Climate and environmental	DEM	2020	30	GSCloud
	Slope	2020	30	Calculated by DEM
	NDVI	2000, 2010, 2020	30	calculated by Landsat
	Temperature and Precipitation	2000, 2010, 2020	1000	CMA (https://data.cma.cn/, accessed on 1 May 2024)
	Solar radiation	2000, 2010, 2020	1000	TerraClimate (https://www.climatologylab.org/, accessed on 1 May 2024)
Socioeconomic	Population density and GDP	2020	1000	CAS (https://www.resdc.cn/, accessed on 1 May 2024)
	Stations and Road network	2020	30	OSM (https://www.openstreetmap.org/, accessed on 1 May 2024)
Planning	Land-use demand	2035	-	Nanjing Territorial Spatial Master Plan (2021–2035)
	Ecological protection red line	2035	-	Territorial Spatial Planning of Jiangsu Province (2021–2035)

2.3. Study Design

This study was conducted in four phases (Figure 2). The first phase involved the construction and connectivity evaluation of the ecological network (See Section 2.3.1 for details). MSPA was used to screen ecological sources, and the Linkage Mapper (LM) tool of circuit theory was used to construct ecological networks. On this basis, we quantitatively

evaluated its structural connectivity. The second phase focused on the measurement and indicator construction of the carbon sink (See Section 2.3.2 for details). The CASA model was used to calculate the carbon sinks, supplemented by empirical values to calculate water carbon sinks. A carbon sink index was proposed to be constructed based on static and dynamic dimensions. The third phase was land-use simulation (See Section 2.3.3 for details). The FLUS model was applied to predict carbon sink changes over the next 15 years under the inertia development and master plan scenarios in 2035 to assess the carbon sink variation for 2020 and to provide a foundation for optimizing the network. The fourth phase focused on the optimization framework for the ecological network (See Section 2.3.4 for details). With the goal of enhancing both the carbon sink function and structural connectivity, the study identified the optimal and worst ecological nodes and proposed optimization strategies. By combining the current situation, planning requirements, and future development scenarios of Nanjing, an implementation path to enhance the city's ecological resilience and carbon sink function was proposed.

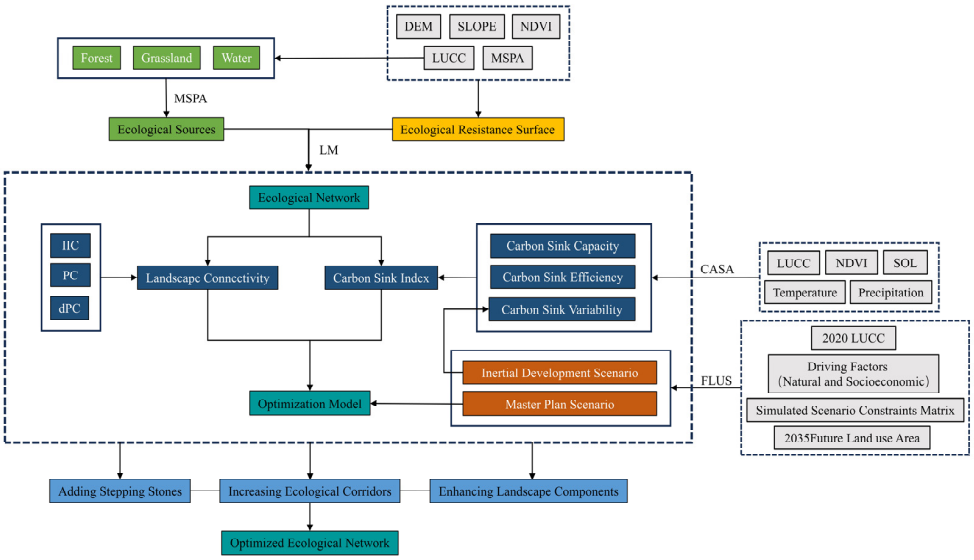

Figure 2. Framework diagram of ecological network optimization research in Nanjing city.

2.3.1. Construction and Connectivity Evaluation of Ecological Network

MSPA is a method based on morphological algorithms used to identify key patches in ecosystems. It classifies pixels into seven landscape types: core, islet, perforation, edge, bridge, loop, and branch, aiming to improve the scientific identification of ecological patches and corridors from the perspective of spatial connectivity [46]. In this study, we used the Guidos Toolbox 3.3 software to analyze land-use data from 2000, 2010, and 2020. Forests, grasslands, and water areas were treated as foreground, and cultivated lands, construction lands, and unutilized lands were considered background. An 8-neighborhood analysis method was adopted to extract core areas larger than 1 km^2 as ecological sources. The interactions between ecological sources are influenced by landscape surface resistance, which is determined by both natural factors and human disturbances [47,48]. To accurately describe the distribution of resistance, this study integrated five key factors: MSPA classification, land-use type, NDVI index, slope, and elevation. The Delphi method was used to scientifically determine the weight of each factor (Table A1), and the fuzzy affiliation tool was used for data normalization. The cumulative resistance surface was generated using the raster calculator in ArcGIS 10.6. Finally, the ecological sources and cumulative resistance surface were input into the LM model [49,50]. This model identifies the least-cost

paths between ecological sources, effectively integrating fragmented ecological patches and forming a cohesive ecological network [51].

Geographically adjacent ecological sources have stronger resistance to disturbances due to their modularity and proximity [52]. As a core indicator for measuring the degree of connectivity between ecosystem patches, landscape connectivity is crucial for assessing ecosystem stability and functional integrity [53–55]. After the successful construction of an ecological network, this study analyzed the characteristics of landscape connectivity using patches as the basic unit. The integral index of connectivity (IIC) and potential connectivity (PC) of the patches were calculated using the Conefor 2.6 platform, and the relative change rate of the potential connectivity (dPC) after each patch disappeared was measured to assess the criticality of each patch in the ecological network structure. The calculation formulas are as follows.

$$IIC = \frac{1}{A_L^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{a_i a_j}{1 + nl_{ij}} \quad (1)$$

$$PC = \frac{1}{A_L^2} \sum_{i=1}^{n} \sum_{j=1}^{n} a_i a_j P_{ij}^{*} \quad (2)$$

$$dPC = \frac{(PC - PC_{remove})}{PC} \times 100\% \quad (3)$$

where n is the total number of patches; a_i and a_j are the areas of landscape patches i and j; nl_{ij} refers to the number of shortest path connections between patches i and j; P_{ij}^{*} is the maximum value of the path probability product between patches i and j; A_L is the area of the study area; PC_{remove} is the index of potential connectivity after removing a certain type of landscape element. *IIC* and *PC* values range from 0 to 1, with lower values indicating lower landscape connectivity. The higher the *dPC* value, the more important the patch is for landscape connectivity.

2.3.2. Measurement and Index Construction of Carbon Sink

The CASA model is a solar energy utilization model based on land cover, vegetation classification, and climatic data, which describes the temporal variation of carbon fluxes within terrestrial ecosystems [56,57]. This model calculates the net primary production (NPP) of vegetation based on photosynthetically active radiation and actual light energy utilization efficiency. NPP represents the plants' own carbon sequestration capacity and provides a basis for estimating the carbon sink of ecosystems [58]. The CASA model considers the effects of spatiotemporal heterogeneity and environmental stress on photosynthesis, and compared to the InVEST model, it is more accurate in estimating carbon storage in urban green spaces [59]. This study mainly refers to the CASA model improved by Zhu [60], and its calculation formulas are as follows.

$$NPP(x,t) = APAR(x,t) \times \varepsilon(x,t) \quad (4)$$

$$APAR(x,t) = SOL(x,t) \times FPAR(x,t) \times 0.5 \quad (5)$$

where *APAR* represents the photosynthetically active radiation (MJ·m^{-2}), ε is the actual light energy utilization (gC·MJ^{-1}). *SOL* is the total solar radiation photosynthetically active radiation (MJ·m^{-2}), *FPAR* is the proportion of photosynthetically active radiation absorbed by vegetation, and 0.5 is the proportion of solar active radiation available to vegetation. (x,t) denotes the x image element at time t. *SOL* and *FPAR* were calculated based on remote sensing and meteorological data. Referring to the existing local studies and the research results of Zhu Wenquan's CASA model [60], the light energy utilization rate of cultivated land was taken as 0.542 g·MJ^{-1}, forest land was taken as 0.985 g·MJ^{-1}, grassland was taken

as 0.608 g·MJ^{-1}, water area was taken as 0, and construction and unused land was adopted as a uniform value of 0.389 g·MJ^{-1}.

Watershed carbon sequestration is a small proportion of total carbon fluxes and involves ecological processes that differ only at larger spatial scales. Therefore, in this study, watershed carbon sequestration was measured by the empirical coefficients method used by previous authors for sediment rates in river and lake systems [61–64] (Table 2).

Table 2. Carbon sink rate of wetlands in the Yangtze River Delta region.

Wetland Types	Carbon Sink Rate ($tCO_2 \cdot km^{-2} \cdot a^{-1}$)
Lake	199.31
Riverine	277.31
Everglade	498.36

Carbon sink is a vital component of the ecological functions of green spaces, and its effectiveness is complex and multifaceted. In planning research, it is crucial to adopt a multi-dimensional quantitative analysis approach to build a comprehensive and diverse evaluation system. This allows for an accurate assessment of the challenges that green spaces face in carbon sequestration during urban development, providing a foundation for targeted optimization. This study innovatively proposed the carbon sink index (CSI), which integrates both static and dynamic dimensions. Static indicators reflect the strength of carbon sequestration capacity, while dynamic indicators capture the extent of change influenced by internal and external factors. The construction of CSI comprehensively covered the three core characteristics of carbon sink capacity, efficiency, and variability in green spaces.

The carbon sink capacity index (CSCI) is a key metric for evaluating the carbon sequestration potential of urban green spaces. Its variations are primarily influenced by the spatial layout and components of green spaces [65,66], allowing for the precise quantification of how each patch contributes to the overall carbon sink. The carbon sink efficiency index (CSEI) measures the effectiveness of urban green spaces in converting input resources into carbon sequestration. Referring to the concept of forest carbon sink efficiency [67], this metric quantifies the amount of carbon sequestered per unit area, revealing insights into the landscape composition, community structure complexity, and ecological quality of the green space [66]. In addition, the carbon sink variability index (CSVI) tracks changes in carbon sequestration from 2020 to 2035 under an inertia development scenario. By capturing fluctuations in carbon sink performance, the CSVI serves as an early warning system, supporting future carbon sink management strategies and decision-making.

2.3.3. Scenario Simulations of Land Use

Since the 1990s, spatial simulation models have been increasingly applied in the study of landscape patterns and ecological processes [68]. Among these, the FLUS model is widely adopted due to its high accuracy, bidirectional logic, and strong scenario-based guidance. This model integrates neural networks and cellular automaton with adaptive inertia mechanism [69,70]. Firstly, the model calculates the suitability probabilities for land use based on user-input driving factors using an artificial neural network (ANN) algorithm. Secondly, the FLUS model optimizes the traditional cellular automata model, improving the accuracy of land-use predictions under the influence of multiple factors [71]. In this study, we selected 10 natural and social driving factors, including elevation, slope, population density, GDP, distance to urban centers, distance to major, secondary, and tertiary roads, and distance to airports and train stations. These data sources are detailed in Table 1.

This simulation established two contrasting scenarios: the inertia development scenario and the master plan scenario. In the inertia development scenario, urban expansion continuously encroaches on surrounding green spaces, disrupting ecological corridors between nodes and weakening the overall functionality of the ecological network [72]. This scenario aims to highlight the feedback mechanisms of green spaces under severe challenges and provides a scientific basis for ecological risk warning [73]. In contrast, the master plan scenario focused on exploring the ecological potential space, based on Nanjing's land-use plan for 2035, proposing a sustainable development strategy [74]. The land-use demand for the inertia development scenario relied on the CA-Markov model [75], calculated with data from two periods in 2005 and 2020. The future land use and ecological protection red line were set according to the master plan.

A cost matrix (Table A2) is used to constrain land-use transitions. For land types that cannot be converted to other types, the corresponding value of the matrix is set to 0. If conversion is allowed, the value is set to 1. The model's accuracy is validated using the Kappa coefficient and FOM index. The Kappa value ranges from 0 to 1, with values greater than 0.75 indicating high simulation accuracy. When the Kappa value meets the required threshold, a higher FOM value suggests better simulation performance [76,77]. Finally, the simulated land use in 2035 is processed by the MSPA and LM models to construct the ecological network. The CSCI and CSVI values are then estimated for each scenario, providing a comprehensive evaluation of the ecological network's carbon sink potential.

2.3.4. Optimization Framework of the Ecological Network

To restore and enhance the ecological network, we examined the carbon sink capacity and connectivity of ecological sources. The CSI was used to measure the carbon sink function of these sources, while the dPC index assessed their structural connectivity. Based on these indices, we first examined the relationship between carbon sinks and connectivity, and then proposed a strategy to enhance both in synergy. During the coupling process of these two indices, we identified the top 20% of patches in terms of CSI and dPC as strong ecological nodes and the bottom 20% as weak ecological nodes. Optimization strategies were then developed based on the performance of patches in both indices, including ecological conservation, structural strengthening, carbon sink improvement, and synergistic enhancement (Figure 3). Finally, we compared the connectivity and carbon sink before and after the optimization of the ecological network to validate the effectiveness of the proposed strategies.

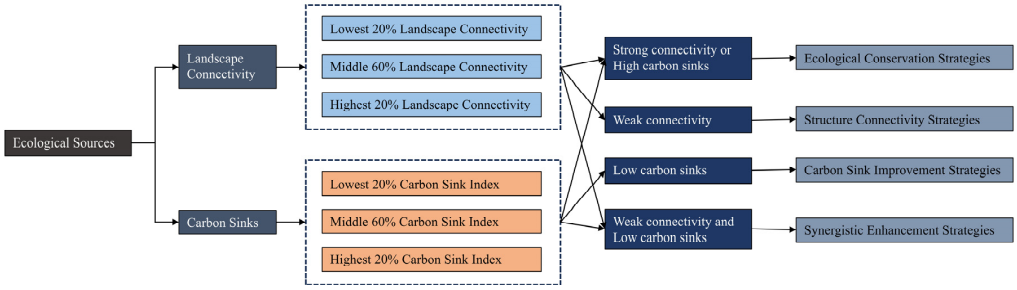

Figure 3. Optimization strategies for ecological networks in Nanjing.

3. Results

3.1. Construction and Analysis of Ecological Network in Nanjing City

3.1.1. Nanjing Ecological Spatial Network

The MSPA results show that the number of ecological sources identified in 2000, 2010, and 2020 were 88, 100, and 78, respectively, with corresponding areas of 966.08 km^2,

1053.50 km^2, and 877.51 km^2. Notably, the increase in the number of sources in 2010 was primarily due to the large-scale conversion of cultivated land to water areas in the southern part of the study area. With the help of ArcGIS platform, we weighed and overlaid five types of factors to generate comprehensive resistance distribution maps for Nanjing in 2000, 2010, and 2020. Based on the LM model, we generated ecological corridors, with 195 corridors in 2000, 208 in 2010, and 180 in 2020. Combined with the screened ecological sources, we constructed the ecological network for the study area (Figure 4). It was found that large-scale ecological sources in Nanjing are primarily distributed south of the Yangtze River, while the sources north of the river are smaller and scattered. The distribution of corridors aligns with the sources land pattern, being sparse in the north and denser in the south. The region to the west of the Yangtze River exhibits a more fragmented network structure, mainly due to the absence of large green spaces to serve as a structural framework. Over the past two decades, the overall number of sources and corridors in Nanjing initially increased but then declined, and the acceleration of urbanization has significantly affected the distribution pattern of ecological spaces.

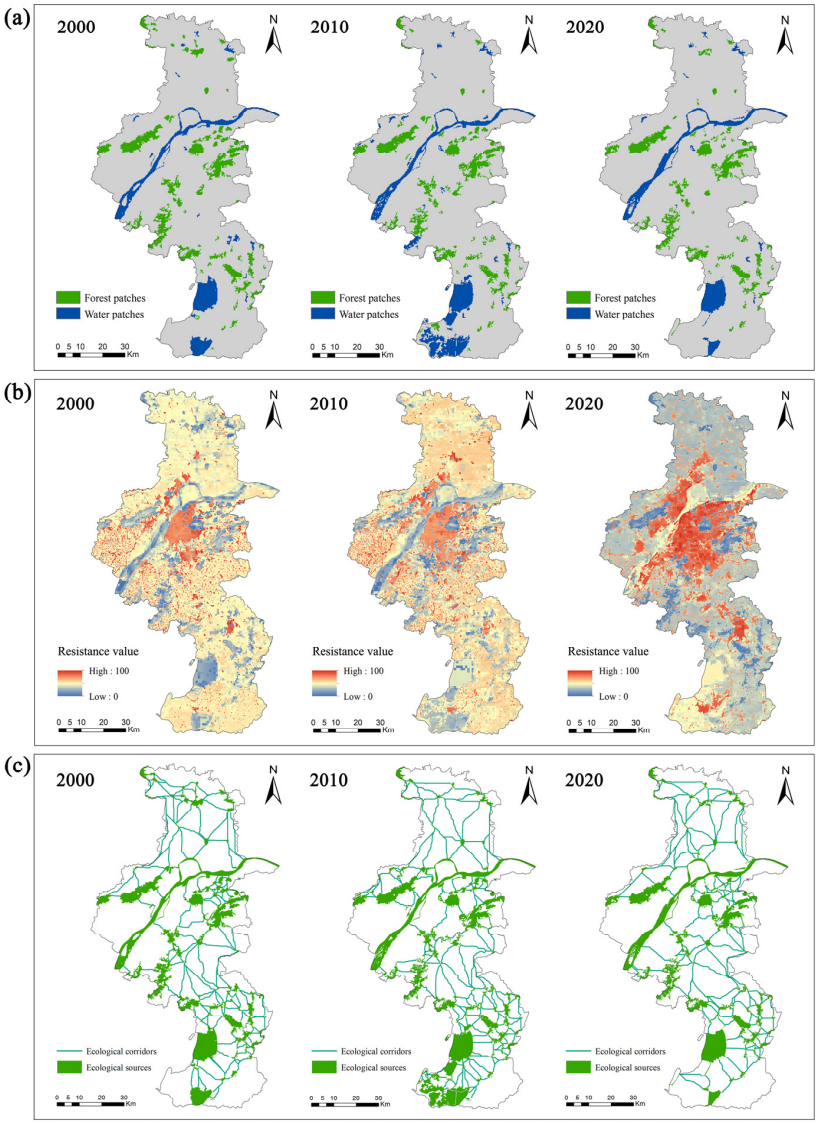

Figure 4. Construction of the ecological network in Nanjing. (**a**) Ecological sources of Nanjing in 2000, 2010, and 2020; (**b**) Resistance surfaces of Nanjing in 2000, 2010, and 2020; (**c**) Ecological network of Nanjing in 2000, 2010, and 2020.

3.1.2. Nanjing Ecological Network Connectivity Analysis

Based on the analysis using the Conefor26 platform, we obtained the IIC index and PC indices of the ecological network in 2000, 2010, and 2020, with values of 2.18, 2.59, 2.09 (IIC) and 3.66, 4.68, 3.14 (PC), all of which showed a trend of initially increasing and then significantly decreasing. In 2020, the spatial distribution of patch importance indices (dPC) is shown in Figure 5, where patches are numbered in ascending order of area. The results showed that patches with high dPC values were primarily concentrated around Shijiu Lake (patch 77) and the Yangtze River (patch 78), as well as large forest patches along the riverbanks (patches 76 and 75). These areas form the core groups of the ecological network. Patches with moderate dPC values (patches 51, 69, 73, 74, etc.) were mainly located on the southern edge of the urban area. In contrast, smaller patches distributed widely in the north and south exhibited lower dPC values and lacked structural connectivity, indicating the fragmentation of the ecological network.

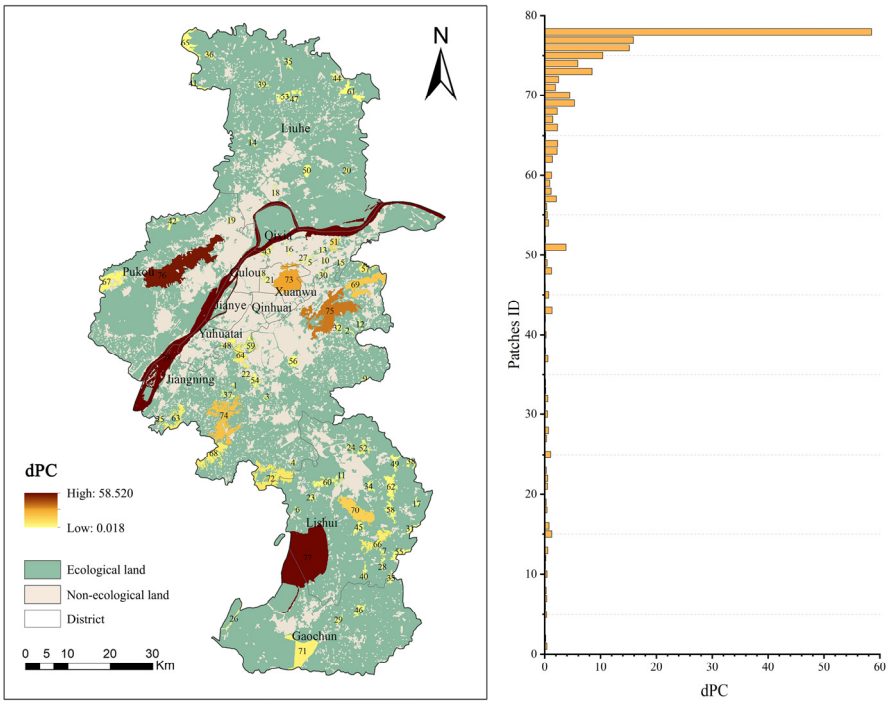

Figure 5. Spatial distribution of dPC index for ecological sources of Nanjing in 2020.

3.2. Comprehensive Evaluation of Carbon Sink by Multi-Scenario Simulation in Nanjing

3.2.1. Results of Land-Use Simulations

We used the FLUS model to simulate land use of Nanjing for 2035 and compared the spatial patterns under two different scenarios: inertial development (Scenario I) and master plan (Scenario II) (Figure 6a). Through calculation, the Kappa coefficient of the FLUS model reached 0.763 and the FOM coefficient was 0.302, verifying the accuracy of the model and its parameters for predicting future land-use changes in Nanjing. In Scenario I, the construction land expanded dramatically, increasing by 10.83%. This growth comes at the cost of a drastic reduction in cultivated land and forest land, with cultivated land decreasing by 513.96 km^2 and forest land decreasing by 71.60 km^2. This indicated that under the inertia development model, urban expansion directly led to a considerable reduction in ecological space. In contrast, in Scenario II, the construction land increased by 7.03%, and although the cultivated land decreased by 406.04 km^2, the forest land increased by 41.62 km^2. Both scenarios showed a decrease in water system areas, with Scenario I experiencing a more severe decline.

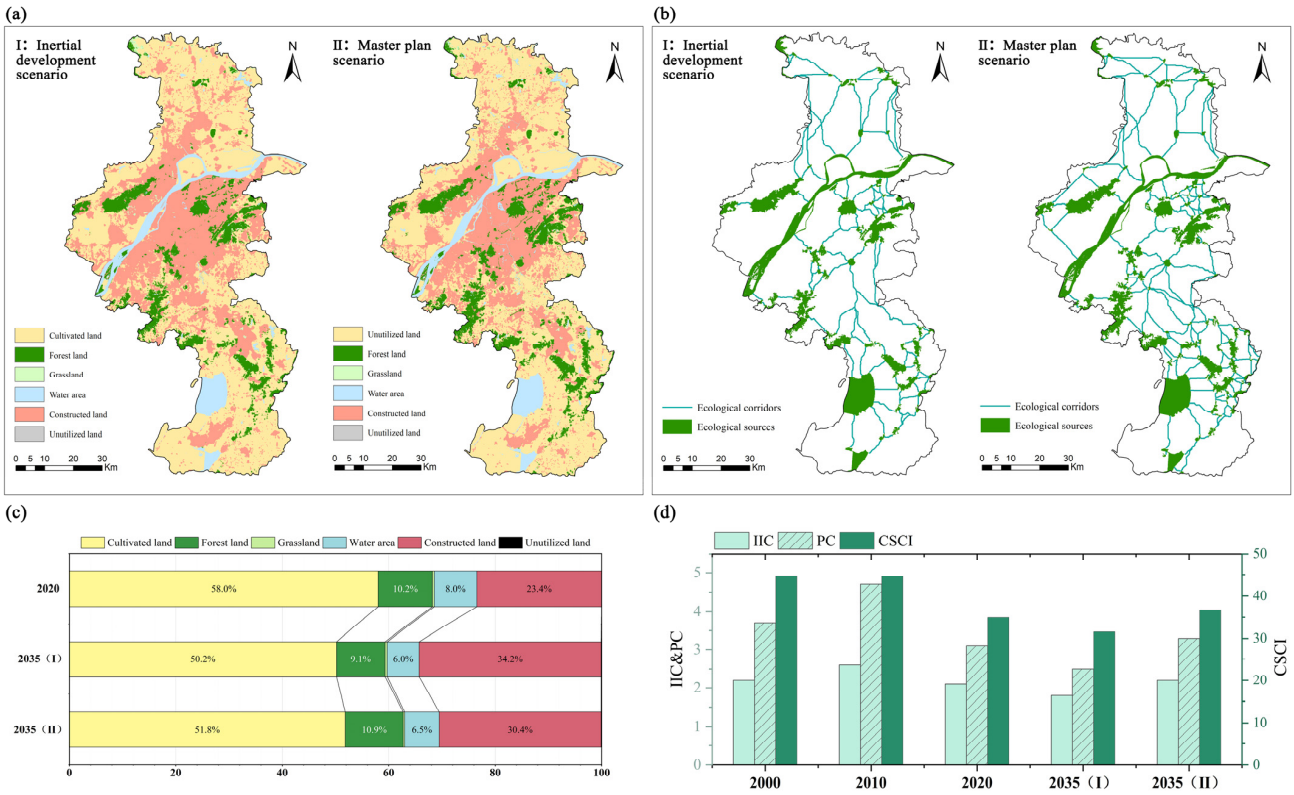

Figure 6. Land use and ecological network under simulated scenarios of Nanjing in 2035. (**a**) Land use under simulated scenarios of Nanjing in 2035; (**b**) Ecological network under simulated scenarios of Nanjing in 2035; (**c**) Comparison of land-use area before and after simulation in Nanjing; (**d**) Comparison of carbon sinks and connectivity before and after simulation in Nanjing.

Figure 6b illustrates the ecological network under the two scenarios for 2035. Scenario II demonstrates a denser ecological network and a more stable localized group structure compared to Scenario I. Specifically, in Scenario I, there were 53 ecological source patches and 104 corridors, both of which had decreased compared to 2020. The primary changes in the network occurred in the central and northern regions, where the loss of core patches led to a sharp reduction in the number of corridors. In Scenario II, the total number of ecological source patches increased to 83, and the number of corridors reached 179. This represents an increase in source patches from 78 in 2020, and the corridor count was similar to 2020 levels. Scenario II showed significant improvements at the northern and southern ends. The northern corridors have become more homogeneous due to the appearance of small patches and effectively connect the original ecological network gap areas. The improved network performance at the southern was reflected in the corridor structure becoming more compact, especially in the localized clusters centered around Shijiu Lake, where connections between patches have become more uniform. Additionally, small patches have emerged in previously vacant areas west of the Yangtze River, indicating that the master plan scenario has enhanced the ecological network's coverage across the city.

Calculating the carbon sinks of the ecological sources under the two scenarios, it was found that the carbon sink capacity of Scenario II increased from 349,000 tons in 2020 to 368,000 tons, reflecting a 5.4% increase. In contrast, the carbon sink capacity of Scenario I decreased to 316,000 tons, representing a reduction of 9.5%. From Scenario I to Scenario II, the carbon sink capacity increased by 52,000 tons, equivalent to 14.9% of the 2020 value. This result clearly demonstrates the significant advantage of the master plan scenarios in enhancing carbon sink capacity, emphasizing the importance of following the plan for urban development and ecological construction.

3.2.2. Evaluation of Carbon Sink Index

Figure 7 illustrates the spatial distribution pattern of carbon sink capacity, efficiency, and variability of ecological sources in 2020. The study showed that the carbon storage was positively correlated with patch area. Small patches (<10 ha) have lower carbon storage, while large patches (>20 ha) exhibit higher carbon sequestration capacity. Large forest patches, with their superior ecological quality and structural components, have more significant ecological benefits. Notably, forest patches such as 76, 75, 74, 73, and 72 display higher carbon sequestration efficiency. In contrast, waterbody patches (such as 77 and 78) and many smaller patches show lower carbon sequestration efficiency, especially in areas like Qixia, Jiangning, Lishui, and Liuhe districts. From a spatial evolution perspective, the total carbon storage in ecological sources has been on a downward trend from 2000 to 2020, with an overall decrease of 21.7%. The most significant decline occurred between 2010 and 2020, as large patches were severely affected, leading to a sharp drop in overall carbon sequestration.

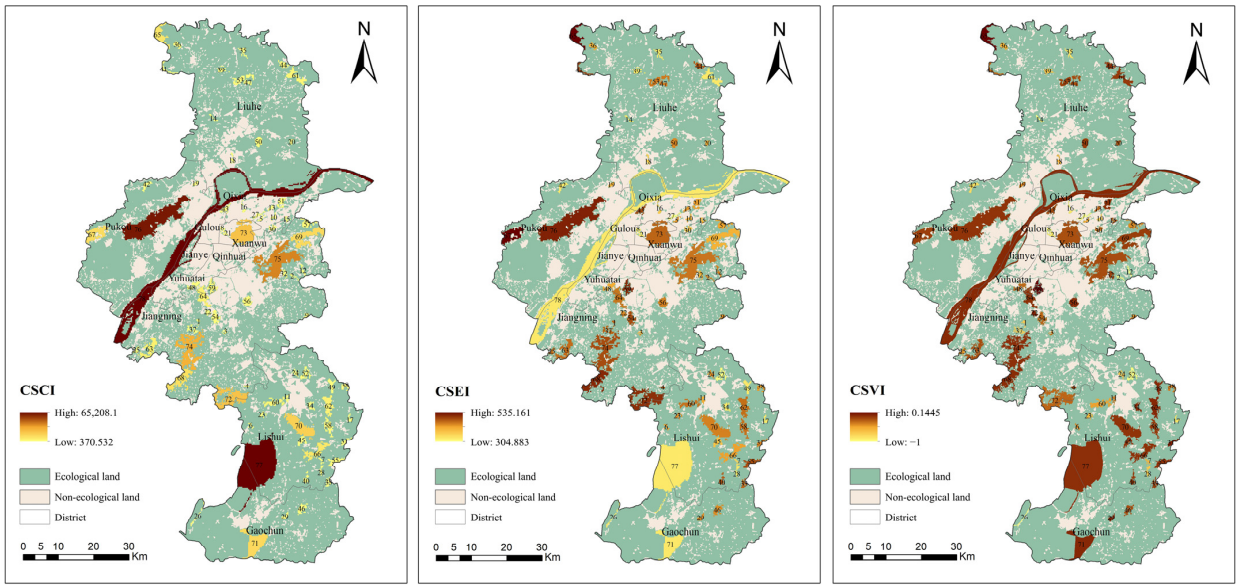

Figure 7. Spatial distribution map of carbon sink capacity, efficiency, and variability for ecological sources of Nanjing in 2020.

To further evaluate the carbon dynamics of ecological sources, this study projected the change rates in carbon storage for each patch from 2020 to 2035, which was used as the carbon sink dynamics index. Under the inertial development scenario, 93.6% of the patches showed a decrease in carbon storage by 2035, with a more pronounced decline in smaller patches, especially in northern Liuhe district, southern Lishui district, and near the central urban areas. Large patches, with their mature green spaces and higher ecological quality, demonstrated stronger resilience, while smaller patches were more vulnerable and faced higher risks.

Figure 8 presents the integrated carbon sink index of patches based on the capacity, efficiency, and the variability from 2020 to 2035. The results reveal that patches 78, 76, 67, 65, and 74 have the highest carbon sink rankings and are the key ecological source sites in Nanjing. Conversely, patches in Lishui, Liuhe, and Gaochun districts, especially smaller patches like 52, 48, 27, 10, and 19, have lower integrated carbon sink values and urgently need restoration and enhancement. Interestingly, despite lower total carbon storage in smaller patches like 65 in the north and 55 in Lishui, their overall carbon sink performance is favorable. The analysis of their sub-indicators shows high carbon sequestration efficiency

and change rates, suggesting good ecological quality and a positive future trend. These patches could serve as models for ecological improvement in other small and medium-sized patches.

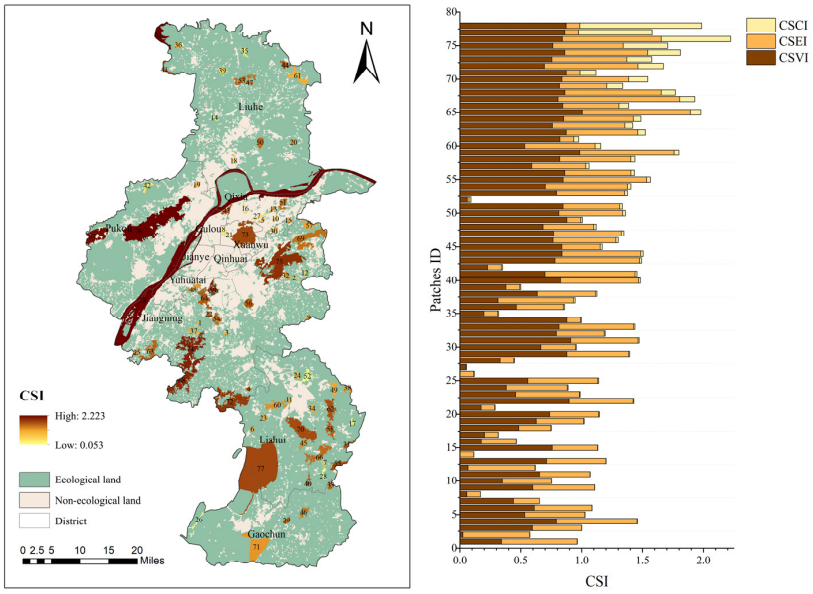

Figure 8. Spatial distribution map of carbon sink index for ecological sources of Nanjing in 2020.

3.3. Optimization and Validation of Ecological Networks

3.3.1. Correlation Analysis Between Carbon Sinks and Connectivity

We obtained the dPC and comprehensive carbon sink index for each ecological source in 2020. To further investigate the potential impact of dPC on the ecosystem's carbon sink capacity, we used Spearman correlation analysis to assess the relationship between carbon sink index and dPC. The results revealed a significant positive correlation between dPC and both carbon sink capacity and efficiency (Figure 9). This suggests that increasing the connectivity of ecological nodes can enhance their carbon sink capacity. Based on this, we propose an optimization strategy that integrates the carbon sink index and connectivity, aiming to strengthen both the structure and function of the ecological network in a complementary way.

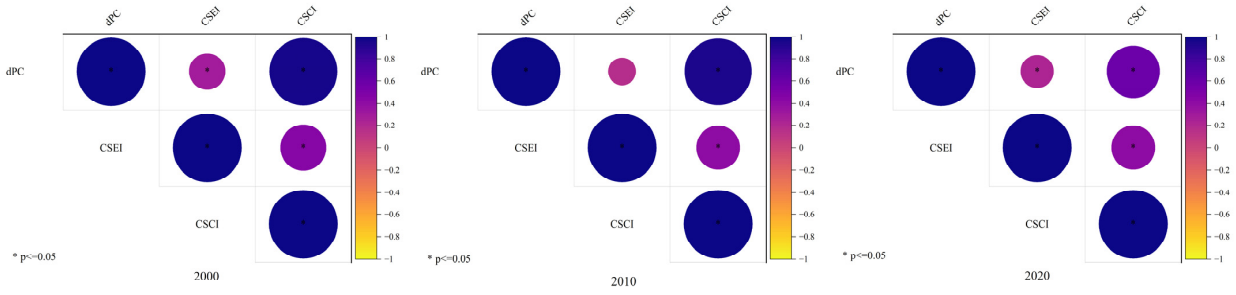

Figure 9. Correlation analysis between carbon sinks and connectivity for ecological sources of Nanjing.

3.3.2. Optimization of Ecological Network

The study deeply explored the coupling relationship between carbon sink index (CSI) and structural connectivity (dPC) based on the ecological source data of Nanjing in 2020 and accordingly identified four categories of ecological sources that need targeted optimization. Under the guidance of the upland planning and 2035 simulation scenarios, we carried out a bidirectional optimization of Nanjing's ecological network in terms of function and structure and mapped the optimization pattern (Figure 10).

1. Strategies for Ecological Conservation

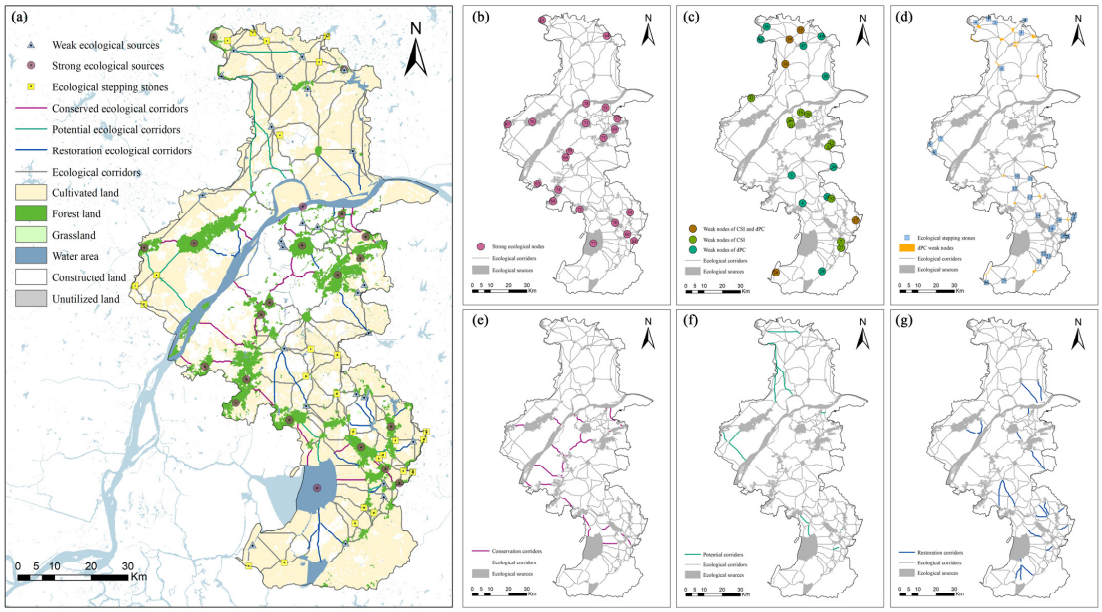

Figure 10. Optimization strategies of ecological network in Nanjing. (**a**) Overall plan for optimizing the ecological network in Nanjing; (**b**) Distribution map of ecological strong nodes in Nanjing; (**c**) Distribution map of ecological weak nodes in Nanjing; (**d**) Distribution map of added ecological stepping stones in Nanjing; (**e**) Distribution map of ecological conservation corridors in Nanjing; (**f**) Distribution map of ecological potential corridors in Nanjing; (**g**) Distribution map of ecological restoration corridors in Nanjing.

For the 21 ecologically strong nodes with CSI or dPC in the top 20%, we adopted an ecological conservation strategy. These nodes are mostly larger scale patches with higher ecological maturity. The Yangtze River (Node 78), a key aquatic ecosystem in the Yangtze River Delta region, plays a crucial role in water conservation, climate regulation, and biodiversity preservation. Similarly, Shijiu Lake (Node 77), a wetland habitat for many bird species, is essential for maintaining ecological balance in the southern region. For these important wetland patches, we propose waterway management and restoration measures to improve their ecological quality. Meanwhile, forest patches such as Nodes 76, 75, and 74, as the primary carbon storage green spaces in Nanjing, should reduce the interference of human activities and formulate strict protection policies to ensure their natural state and ecological continuity. Grasslands distributed between forest patches, which are important habitats for wildlife and significant carbon sinks, should be managed to support natural regeneration, with controlled grazing to ensure their long-term sustainability. Moreover, we place special emphasis on protecting 26 structural corridors that connect ecological strong nodes. Measures such as controlling urban expansion and optimizing landscape composition within the corridors are crucial to maintaining their connectivity and ecological functions.

2. Strategies for Structural Connectivity

For the 15 nodes with dPC in the latter 20%, we implemented a strategy to enhance structural connectivity. These nodes are primarily located in the northern Liuhe district and the southern Lishui and Gaochun districts. To increase connectivity, we screened small wetlands, water bodies, and forest areas with a landscape shape index greater than 2 and an area larger than 0.3 km2 as stepping stones, totaling 21 locations. In response to the fragmented network structure in the western Yangtze River region and parts of Lishui, we added five additional stepping stones (locations 7, 8, 9, 12, and 13), bringing the total

number of stepping stones to 26. Additionally, we enhanced connectivity by introducing more ecological corridors. The 11 new corridors in the simulated 2035 master plan scenario can be regarded as potential corridors for future planning, which are mainly located in the northern part of Nanjing, the central region to the west of the Yangtze River, and the southern Lishui district. Furthermore, we restored 21 corridors that existed in 2010 but were broken and made extinct in 2020, mainly distributed in the north of the Yangtze River, around the old city, around the sub-city of Lishui, and south of Shijiu Lake, which are habitual pathways for biological migration and information interaction [73]. In total, 32 ecological corridors, including both potential and restoration types, will be added.

3. Strategies for carbon sink improvement

For the 15 weak nodes in the bottom 20% of the CSI, we adopted a carbon sink improvement strategy. Based on the characteristics of patches in terms of carbon sink capacity, efficiency and variability, targeted optimization measures were proposed (Figure 11). For patches with low carbon sink capacity, such as patches 8, 21, and 16 in the central urban area, which are limited by area expansion, it is suggested to enhance the carbon sink capacity by optimizing the landscape components. In the central and southern parts of the city, patches 2, 12, 7, and 17, which are forest areas, could benefit from linking surrounding green spaces to expand their size and create continuous ecosystems. For wetland patches 14, 39, and 28, large-scale ecological restoration is recommended, supported by the development of eco-tourism industries and suburban parks, to effectively increase the size of habitat patches, so as to enhance carbon storage.

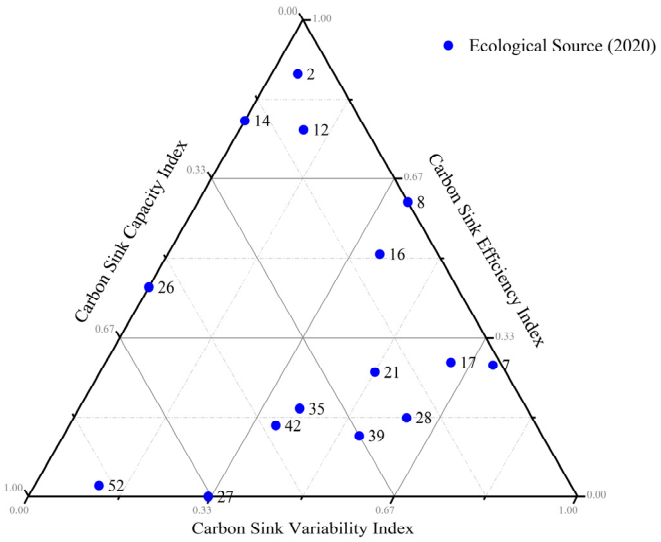

Figure 11. Ternary diagram of carbon capacity-efficiency-variability for 15 weak carbon sink nodes in Nanjing.

For patches with poor carbon sink efficiency, such as patches 27, 52, 17, and 7, the focus should be on improving the structural composition. Specific measures include optimizing community composition, adjusting age structure, and enhancing spatial arrangement. This could involve increasing the proportion of trees and shrubs, promoting evergreen and deciduous trees, and favoring high-carbon vegetation to improve community carbon storage. Additionally, increasing the proportion of younger trees can enhance carbon sink potential, while improving vertical plant structure and building layered plant communities will further strengthen carbon sink capacity. For wetland patches 21, 28, 39, 35, and 42, increasing the proportion of forest, grassland, and aquatic plants is essential to improve carbon sink efficiency.

Regarding carbon sink variability, patches 2, 12, 14, 26, 27, and 52 show weak performance. Simulation results indicate that these patches will experience significant reduction in area by 2035 due to surrounding land-use encroachment, particularly patches 14 and 26, where water systems are almost entirely lost, leading to sharp declines in carbon sink capacity. These patches, mostly located on the outskirts and in rural areas, represent regions with high ecological risk. Future development in these regions should be carefully controlled. If development activities are required, internal composition enhancement strategies should be applied to mitigate the carbon sink loss caused by the reduction in patch size.

4. Strategies for Synergistic Enhancement

For the five dual-weak nodes, where both CSI and dPC fall within the bottom 20%, we applied a collaborative optimization strategy. These nodes are mostly small water patches with low carbon sink density, distributed at the northern and southern ends of the study area, which are characterized by higher ecological risk. To address these issues, we recommend focusing on ecological restoration to enhance the carbon sequestration capacity of wetlands. Additionally, improving connectivity with nearby major water systems is essential to create a specialized water network, thereby boosting both ecological function and connectivity.

3.3.3. Optimized Verification

The carbon sequestration of the optimized ecological network was estimated, with the efficiency of the updated source sites and corridors calculated based on the average values for forest, grassland, and water patches in 2020. The optimized ecological sources showed an increase of 11,019.6 tons in carbon sequestration. Of this, 7162.2 tons resulted from the addition of ecological stepping stones, while 2857.3 tons came from improvements in the internal composition of the sources. The carbon sequestration in ecological corridors increased by 2740.2 tons, resulting in a total improvement of 13,759.8 tons of the entire ecological network. This represents a 3.82% increase in total carbon sequestration compared to the pre-optimization values, demonstrating a significant improvement (Table 3).

Table 3. Changes in carbon sink before and after optimization of Nanjing's ecological network.

Types	Unoptimized (t)	Optimized (t)
Ecological sources of carbon sink	349,433.48	360,453.03
Ecological corridors carbon sink	104,97.61	132,37.85

The number of optimized ecological sources increased to 114, covering a total area of 894.20 km^2, which represents a 1.9% growth compared to the pre-optimization area. The number of ecological corridors also grew to 232, with a total length of 1330.99 km, reflecting a 15.54% increase. Guided by the optimization strategy, the PC index and IIC index have improved by 1.6% and 0.5%, indicating a notable enhancement in the overall structural connectivity of the ecological network (Table 4).

Table 4. Changes in structural indices before and after optimization of Nanjing's ecological network.

Types	2020	2035-I	2035-II	Optimized
Number of ecological sources	78	53	83	114
Area of ecological sources (km^2)	877.51	796.47	915.75	894.20
Number of ecological corridors	180	104	179	232
Length of Ecological Corridor (km)	1151.93	923.33	1150.51	1330.99
PC (10^{-3})	3.14	2.53	3.22	3.19
IIC (10^{-3})	2.09	1.78	2.15	2.10

4. Discussion

4.1. Significance of Coupling Carbon Sinks in Ecological Network Research

The integration of ecological networks and carbon sinks is increasingly seen as a pivotal approach for addressing climate change and biodiversity loss simultaneously. Research on this integration emphasizes its significant role in generating synergies, enhancing ecological connectivity, and improving carbon storage capacity. Numerous studies have shown that landscapes with connected green spaces have higher carbon sequestration efficiency compared to isolated patches [78,79]. For instance, in the European Union, the Natura 2000 network not only conserves biodiversity but also facilitates carbon storage across protected areas. Similarly, China's "ecological redline" policy focuses on restoring ecosystems through protected corridors, incorporating carbon sink functions into national conservation strategies [80]. These integrated efforts demonstrate that strengthening ecological connectivity can directly enhance carbon sink efficiency.

In this study, we integrate carbon sinks with ecological networks by coupling CSI with dPC. This approach allows for the precise identification of critical and vulnerable nodes in Nanjing's ecological network, enabling the formulation of targeted optimization strategies. Previous research on ecological networks has typically focused on singular aspects such as security or connectivity [81,82], often overlooking the multidimensional variations in patch function. This has led to an incomplete understanding of the ecological attributes of these areas [51]. By incorporating carbon sinks, this study offers a more comprehensive methodology, enabling a more accurate and holistic strategy for enhancing various types of patches, ensuring a more efficient use of resources and a more effective implementation.

The construction of the CSI in this research incorporates both static and dynamic dimensions, forming a multi-dimensional evaluation system that captures total carbon sequestration, efficiency, and dynamic changes. This system provides a comprehensive reflection of carbon storage capacity and future risks. To model these dynamic changes, the study used the FLUS model to simulate two land-use scenarios for 2035: the inertia development scenario, which serves as a risk alert, and the master planning scenario, which guides optimization. By considering these scenarios, the optimization strategies proposed in this study are both forward-looking and sustainable, ensuring the long-term improvement of ecological connectivity and carbon sink in Nanjing's urban environment.

4.2. Effectiveness of Ecological Network Optimization Strategies

Compared to the initial network, the optimized network shows significant improvements in connectivity and carbon sequestration. The optimization successfully addresses issues such as the lack of direct connections between ecological patches and fragmented corridors. The focus of the optimization strategy is to enhance the efficiency of nodes and corridors while maintaining the integrity of the original network. This approach maximizes ecosystem service value with minimal land expansion by improving the functionality and stability of existing ecological elements at a low construction cost.

The optimization strategy proposed in this study aims to build a healthier and more stable ecosystem from four aspects: ecological conservation, structural connectivity, carbon sink improvement, and synergistic enhancement. Ecological conservation nodes are typically the most crucial and sensitive areas in the ecosystem, and maintaining their ecological function is vital for the stability of the entire system [83]. The structural connectivity strategy focuses on adding stepping stones and ecological corridors. Small patches are often overlooked in conservation due to their higher risk of extinction [84], but they can serve as essential stepping stones, promoting species migration, providing habitats and shelters [85], and improving overall connectivity within the network. Research has shown that patch connectivity is significantly correlated with carbon sink capacity and efficiency,

meaning that enhancing connectivity not only strengthens the ecosystem's resilience but also promotes carbon sequestration.

The carbon sink improvement strategy aims at repairing damaged patches. Research has found that carbon sink capacity is positively correlated with patch size, and increasing the area and complexity of blue-green patches can significantly improve carbon sequestration benefits. Highly aggregated, adjacent, and connected blue-green patches are associated with greater carbon storage potential [86]. Therefore, optimizing landscape composition, linking adjacent patches, and expanding patch sizes can substantially improve the ecosystem's carbon sink capacity, offering a robust response to climate change. Lastly, the synergistic enhancement strategy targets the double-weak nodes in the ecosystem through integrated management measures, reducing ecological risks and ensuring the stability of the entire system.

4.3. Challenges in the Implementation of Optimization Strategies

The optimization strategy for ecological networks involves the creation and restoration of certain corridors, which are derived from circuit theory within the LM model. However, in real urban environments, the addition of new corridors may face several challenges. A primary challenge is the scarcity of land resources, particularly in rapidly urbanizing areas where land-use conflicts between ecological network development, urban expansion, and agricultural growth are becoming more prominent [87]. Another key challenge is the technical limitations in optimizing ecological networks. For example, the determination of corridor thresholds is highly sensitive when evaluating network connectivity. Incorrect threshold settings can lead to poor ecological outcomes or excessively high construction costs [88]. Additionally, outdated management practices, such as the lack of dynamic feedback on the network's changes and the validation of its stability and connectivity alongside urban development, hinder the effectiveness of ecological protection measures in adapting to future urban growth.

At the micro-community level, ecological network optimization requires further refinement to support the comprehensive development of green spaces. This involves deeper studies into vegetation community structure, species selection, and physiological responses to enhance the efficiency of carbon cycling within ecosystems [89]. Future research should focus on the specific application of ecological restoration techniques and the establishment of standards for corridor construction to improve the practicality and effectiveness of the strategies. Furthermore, it is critical to consider essential factors such as the number, size, and spatial distribution of ecological sources, along with the distribution of high-resistance zones, which are vital when constructing an ecological network.

4.4. International Significance of Ecological Network Optimization

As a key city in the rapidly urbanizing Yangtze River Delta region, Nanjing faces significant challenges in restoring and renewing its urban green spaces. These spaces are constrained by various external factors, such as urban construction, which makes large-scale ecological development difficult. This study proposes an optimization strategy tailored to Nanjing's unique characteristics, focusing on enhancing smaller ecological spaces and corridors to improve the connectivity and stability of the city's ecological network. In turn, it aims to increase the carbon sequestration of urban green spaces. This strategy not only addresses the gap in carbon sink research for Nanjing but also offers practical guidance for building low-carbon and sustainable cities. It represents a strategic shift from expansion to development within existing urban infrastructure, in line with the principles of sustainable development.

Globally, the development of ecological networks has become crucial for biodiversity conservation and regional ecological security. The International Union for Conservation of Nature (IUCN) and the Convention on Migratory Species (CMS) both emphasize the importance of maintaining and restoring ecological connectivity. Europe's Pan-European Ecological Network (PEEN) connects isolated habitats through ecological corridors, forming a regional and even transnational ecological network system [90]. Nanjing's ecological network optimization strategy aligns with these international practices, demonstrating the global importance and urgency of such initiatives. By adopting this approach, Nanjing can not only enhance its own ecological environment but also serve as a model for other rapidly urbanizing regions, offering valuable insights for their ecological planning efforts. This strategy embodies an integrated approach, where urban planning not only focuses on economic growth but also on environmental sustainability. As the dual role of ecological networks in carbon storage and biodiversity conservation becomes increasingly recognized, the global shift toward nature-based solutions underscores the importance of integrating ecological connectivity into urban planning for long-term disaster resilience and climate adaptation.

4.5. Limitations and Prospects in Technical Methods

Previous studies on Nanjing have evaluated carbon sequestration and anthropogenic carbon emissions, providing a more precise assessment of the regional carbon balance [91,92]. However, this study does not account for carbon emissions and focuses solely on the carbon sink function of the ecological network, which introduces certain limitations. In many studies, the InVEST model has been used to simulate carbon storage [93,94]. This approach simplifies the carbon cycle process and is better suited for large-scale studies. In contrast, this study uses the CASA model, which is specifically designed to simulate carbon cycling. It allows for more detailed parameter adjustments tailored to different study areas, making it better suited for understanding the unique characteristics of specific ecosystems. While the CASA model offers more precise insights, it is data-intensive, operationally complex, and primarily focuses on vegetation carbon sinks, excluding carbon sequestration from water bodies. Due to research constraints, the estimation of water body carbon sinks relies on coefficients from similar regions, which could introduce some degree of error. Future studies should address this limitation by conducting more in-depth surveys and sampling to achieve more accurate assessments.

Additionally, this study uses the FLUS model to predict green space carbon sinks for 2035. However, the model faces challenges in simulating land-use changes in rapidly developing regions with complex urban spatial patterns, leading to unclear spatial differences [95]. Future research could consider using the PLUS model or improving the FLUS model to enhance its accuracy [96,97]. Moreover, since the NDVI data for 2035 cannot be directly observed, this study relies on 2020 data for estimations, which limits the accuracy of predictions. Therefore, future work should focus on developing more accurate methods for carbon sink assessment that can better account for long-term land-use changes and the evolving requirements of ecological network optimization.

5. Conclusions

This study establishes an integrated ecological network optimization framework coupled with carbon sinks. Using Nanjing as a case study, we constructed the ecological network using MSPA and LM tools and evaluated connectivity. The CASA model, combined with water body carbon absorption coefficients, was used to quantify carbon sinks. A three-dimensional evaluation system for green space carbon sinks was established. The FLUS model was applied to predict land-use changes for 2035, offering early warnings

and planning guidance for carbon sink dynamics in ecological sources. By combining connectivity and carbon sink indices, key nodes in the ecological network are identified, and targeted optimization strategies are proposed. The key findings are as follows: (1) Nanjing's ecological space exhibits a clear north–south division. From 2000 to 2020, network connectivity declined, and the total carbon sink in ecological sources decreased by 21.7%; (2) Large patches performed well in both carbon sink volume and efficiency, whereas smaller patches were at a disadvantage. In the 2035 inertia development scenario, 93.6% of the carbon sink in ecological sources declined, with a total reduction of 9.46%. In contrast, under the master plan scenario, the carbon sink volume increased by 4.9%, emphasizing the importance of strategic planning; (3) Node connectivity is significantly positively correlated with both carbon sink capacity and efficiency. Based on this, four optimization strategies are proposed: ecological conservation, structural connectivity, carbon sink improvement, and synergistic enhancement. By adding 26 ecological stepping stones, 32 ecological corridors, and optimizing landscape components, the total carbon sink increases by 3.82% and connectivity improves by 1.6%. This research provides practical pathways for ecological network restoration and carbon sink enhancement in Nanjing and other cities, offering valuable insights in the context of global urban ecological and climate change challenges.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Values and weights of ecological resistance surface factors.

Resistance Surface Factors	Categories	Resistance Values	Weights
MSPA	Cores	5	0.24
	Bridges	10	
	Loops	20	
	Branches	30	
	Islets	50	
	Edges	60	
	Perforations	70	
	Background	100	

Table A1. *Cont.*

Resistance Surface Factors	Categories	Resistance Values	Weights
LUCC	Cultivated land	1	0.29
	Forest land	20	
	Grassland	30	
	Water area	50	
	Unutilized land	70100	
	Constructed land		
Slope (°)	-	-	0.15
DEM (m)	-	-	0.12
NDVI	-	-	0.20

Table A2. Land transfer restriction matrix for scenario simulations.

	Inertia Development Scenario (I)						Master Plan Scenario (II)					
	Cu	**F**	**G**	**W**	**Co**	**U**	**Cu**	**F**	**G**	**W**	**Co**	**U**
Cultivated land (Cu)	1	1	1	0	1	0	1	1	1	0	1	0
Forest land (F)	1	1	1	0	1	0	1	1	1	0	1	0
Grassland (G)	1	1	1	0	1	0	1	1	1	0	1	0
Water area (W)	1	0	1	1	1	0	1	0	1	1	0	0
Constructed land (Co)	0	0	0	0	1	0	0	0	0	0	1	0
Unutilized land (U)	1	1	1	1	1	1	1	1	1	1	1	1

References

1. Touma, D.; Stevenson, S.; Lehner, F.; Coats, S. Human-driven greenhouse gas and aerosol emissions cause distinct regional impacts on extreme fire weather. *Nat. Commun.* **2021**, *12*, 212. [CrossRef] [PubMed]
2. Chu, M.; Lu, J.; Sun, D. Influence of Urban Agglomeration Expansion on Fragmentation of Green Space: A Case Study of Beijing-Tianjin-Hebei Urban Agglomeration. *Land* **2022**, *11*, 275. [CrossRef]
3. Hou, Y.; Wang, L.; Li, Z.; Ouyang, X.; Xiao, T.; Wang, H.; Li, W.; Nie, X. Landscape fragmentation and regularity lead to decreased carbon stocks in basins: Evidence from century-scale research. *J. Environ. Manag.* **2024**, *367*, 121937. [CrossRef] [PubMed]
4. Newbold, T.; Hudson, L.; Hill, S.; Contu, S.; Lysenko, I.; Senior, R.; Borger, L.; Bennett, D.; Choimes, A.; Collen, B.; et al. Global effects of land use on local terrestrial biodiversity. *Nature* **2015**, *520*, 45–50. [CrossRef] [PubMed]
5. Huang, J.; Song, P.; Liu, X.; Li, A.; Wang, X.; Liu, B.; Feng, Y. Carbon Sequestration and Landscape Influences in Urban Greenspace Coverage Variability: A High-Resolution Remote Sensing Study in Luohe, China. *Forests* **2024**, *15*, 1849. [CrossRef]
6. Zhang, W.; Xu, H. Effects of land urbanization and land finance on carbon emissions: A panel data analysis for Chinese provinces. *Land Use Policy* **2017**, *63*, 493–500. [CrossRef]
7. Zhang, M.; Huang, X.; Chuai, X.; Yang, H.; Lai, L.; Tan, J. Impact of land use type conversion on carbon storage in terrestrial ecosystems of China: A spatial-temporal perspective. *Sci. Rep.* **2015**, *5*, 10233. [CrossRef] [PubMed]
8. Li, W.; Zhang, S.; Lu, C. Exploration of China's net CO_2 emissions evolutionary pathways by 2060 in the context of carbon neutrality. *Sci. Total Environ.* **2022**, *831*, 154909. [CrossRef]
9. Huang, L.; Wang, J.; Fang, Y.; Zhai, T.; Cheng, H. An integrated approach towards spatial identification of restored and conserved priority areas of ecological network for implementation planning in metropolitan region. *Sustain. Cities Soc.* **2021**, *69*, 102865. [CrossRef]
10. Wang, S.; Wu, M.; Hu, M.; Fan, C.; Wang, T.; Xia, B. Promoting landscape connectivity of highly urbanized area: An ecological network approach. *Ecol. Indic.* **2021**, *125*, 107487. [CrossRef]
11. Isaac, N.J.B.; Brotherton, P.N.M.; Bullock, J.M.; Gregory, R.D.; Boehning-Gaese, K.; Connor, B.; Crick, H.Q.P.; Freckleton, R.P.; Gill, J.A.; Hails, R.S.; et al. Defining and delivering resilient ecological networks: Nature conservation in England. *J. Appl. Ecol.* **2018**, *55*, 2537–2543. [CrossRef]
12. Cunha, N.S.; Magalhães, M.R. Methodology for mapping the national ecological network to mainland Portugal: A planning tool towards a green infrastructure. *Ecol. Indic.* **2019**, *104*, 802–818. [CrossRef]
13. Yu, K. Security patterns and surface model in landscape ecological planning. *Landsc. Urban Plan.* **1996**, *36*, 1–17. [CrossRef]

14. Wu, B.; Bao, y.; Wang, Z.; Chen, X.; Wei, W. Multi-temporal evaluation and optimization of ecological network in multi-mountainous city. *Ecol. Indic.* **2023**, *146*, 109794. [CrossRef]
15. Zhang, R.; Zhang, L.; Zhong, Q.; Zhang, Q.; Ji, Y.; Song, P.; Wang, Q. An optimized evaluation method of an urban ecological network: The case of the Minhang District of Shanghai. *Urban For. Urban Green.* **2021**, *62*, 127158. [CrossRef]
16. Wu, X.; Zhang, J.; Geng, X.; Wang, T.; Wang, K.; Liu, S. Increasing green infrastructure-based ecological resilience in urban systems: A perspective from locating ecological and disturbance sources in a resource-based city. *Sustain. Cities Soc.* **2020**, *61*, 102354. [CrossRef]
17. McRae, B.H.; Beier, P. Circuit theory predicts gene flow in plant and animal populations. *Proc. Natl. Acad. Sci. USA* **2007**, *104*, 19885–19890. [CrossRef] [PubMed]
18. Kwon, O.-S.; Kim, J.-H.; Ra, J.-H. Landscape Ecological Analysis of Green Network in Urban Area Using Circuit Theory and Least-Cost Path. *Land* **2021**, *10*, 847. [CrossRef]
19. Peng, J.; Yang, Y.; Liu, Y.; Hu, Y.; Du, Y.; Meersmans, J.; Qiu, S. Linking ecosystem services and circuit theory to identify ecological security patterns. *Sci. Total Environ.* **2018**, *644*, 781–790. [CrossRef]
20. Liu, J.; Yin, H.; Kong, F.; Li, M. Structure optimization of circuit theory-based green infrastructure in Nanjing, China. *Acta Ecol. Sin.* **2018**, *38*, 4363–4372.
21. Zhu, X.; Mu, X.; Hu, G. Ecological network analysis of urban energy metabolic system—A case study of Beijing. *Ecol. Model.* **2019**, *404*, 36–45. [CrossRef]
22. Xia, C.; Chen, B. Urban land-carbon nexus based on ecological network analysis. *Appl. Energy* **2020**, *276*, 115465. [CrossRef]
23. Ahern, J. Urban landscape sustainability and resilience: The promise and challenges of integrating ecology with urban planning and design. *Landsc. Ecol.* **2012**, *28*, 1203–1212. [CrossRef]
24. Zheng, H.; Li, A.; Meng, F.; Liu, G.; Hu, Y.; Zhang, Y.; Casazza, M. Ecological network analysis of carbon emissions from four Chinese metropoles in multiscale economies. *J. Clean. Prod.* **2021**, *279*, 123226. [CrossRef]
25. Xia, L.; Zhang, Y.; Sun, X.; Li, J. Analyzing the spatial pattern of carbon metabolism and its response to change of urban form. *Ecol. Model.* **2017**, *355*, 105–115. [CrossRef]
26. Clauzel, C.; Jeliazkov, A.; Mimet, A. Coupling a landscape-based approach and graph theory to maximize multispecific connectivity in bird communities. *Landsc. Urban Plan.* **2018**, *179*, 1–16. [CrossRef]
27. Lu, F.; Hu, H.; Sun, W.; Zhu, J.; Liu, G.; Zhou, W.; Zhang, Q.; Shi, P.; Liu, X.; Wu, X.; et al. Effects of national ecological restoration projects on carbon sequestration in China from 2001 to 2010. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 4039–4044. [CrossRef]
28. Guo, H.; Yu, Q.; Pei, Y.; Wang, G.; Yue, D. Optimization of landscape spatial structure aiming at achieving carbon neutrality in desert and mining areas. *J. Clean. Prod.* **2021**, *322*, 129156. [CrossRef]
29. Qiu, Z.; Feng, Z.; Song, Y.; Li, M.; Zhang, P. Carbon sequestration potential of forest vegetation in China from 2003 to 2050: Predicting forest vegetation growth based on climate and the environment. *J. Clean. Prod.* **2020**, *252*, 119715. [CrossRef]
30. Amoatey, P.; Sulaiman, H. Quantifying carbon storage potential of urban plantations and landscapes in Muscat, Oman. *Environ. Dev. Sustain.* **2019**, *22*, 7969–7984. [CrossRef]
31. Wan, B.; Liu, T.; Gong, X.; Zhang, Y.; Li, C.; Chen, X.; Hu, F.; Griffiths, B.S.; Liu, M. Energy flux across multitrophic levels drives ecosystem multifunctionality: Evidence from nematode food webs. *Soil Biol. Biochem.* **2022**, *169*, 108656. [CrossRef]
32. Agbelade, A.D.; Onyekwelu, J.C. Tree species diversity, volume yield, biomass and carbon sequestration in urban forests in two Nigerian cities. *Urban Ecosyst.* **2020**, *23*, 957–970. [CrossRef]
33. Tannier, C.; Bourgeois, M.; Houot, H.; Foltête, J. Impact of urban developments on the functional connectivity of forested habitats: A joint contribution of advanced urban models and landscape graphs. *Land Use Policy* **2016**, *52*, 76–91. [CrossRef]
34. Luo, Y.; Wu, J.; Wang, X.; Peng, J. Using stepping-stone theory to evaluate the maintenance of landscape connectivity under China's ecological control line policy. *J. Clean. Prod.* **2021**, *296*, 126356. [CrossRef]
35. Wu, J.; Zhang, S.; Luo, Y.; Wang, H.; Zhao, Y. Assessment of risks to habitat connectivity through the stepping-stone theory: A case study from Shenzhen, China. *Urban For. Urban Green.* **2022**, *71*, 127532. [CrossRef]
36. Fang, M.; Si, G.; Yu, Q.; Huang, H.; Huang, Y.; Liu, W.; Guo, H. Study on the relationship between topological characteristics of vegetation ecospatial network and carbon sequestration capacity in the Yellow River Basin, China. *Remote Sens.* **2021**, *13*, 4926. [CrossRef]
37. Wan, Y.; Wang, Y.; Gao, M.; Jin, L. An empirical assessment of whether urban green ecological networks have the capacity to store higher levels of carbon. *Sci. Rep.* **2024**, *14*, 3132. [CrossRef] [PubMed]
38. Cui, X.; Wei, X.; Liu, W.; Zhang, F.; Li, Z. Spatial and temporal analysis of carbon sources and sinks through land use/cover changes in the Beijing-Tianjin-Hebei urban agglomeration region. *Phys. Chem. Earth Parts A/B/C* **2019**, *110*, 61–70. [CrossRef]
39. Stokstad, E. Global efforts to protect biodiversity fall short. *Science* **2020**, *369*, 1418. [CrossRef] [PubMed]
40. Zhao, D.; Cai, J.; Xu, Y.; Liu, Y.; Yao, M. Carbon sinks in urban public green spaces under carbon neutrality: A bibliometric analysis and systematic literature review. *Urban For. Urban Green.* **2023**, *86*, 128037. [CrossRef]

41. Wang, M.; Shi, Q. Evaluation index system and empirical study on green carbon sequestration efficiency in urban high density area—A case study of Shanghai Huangpu district. *Chin. Landsc. Archit.* **2016**, *32*, 18–24.
42. Dong, J.; Dai, W.; Shao, G.; Xu, J. Ecological Network Construction Based on Minimum Cumulative Resistance for the City of Nanjing, China. *ISPRS Int. J. Geo-Inf.* **2015**, *4*, 2045–2060. [CrossRef]
43. Zhang, H. *Research on the Ecological Security Pattern of Nanjing Based on Ecological Service Function*; Nanjing Normal University: Nanjing, China, 2018.
44. Guo, T.; Wang, Z. Prediction and multi-scenario simulation analysis of the temporal and spatial evolution of ecosystem carbon storage in Nanjing based on LUCC. *Hubei Agric. Sci.* **2022**, *61*, 33.
45. Sun, X.; Xue, J.; Dong, L. Spatiotemporal change and prediction of carbon storage in Nanjing ecosystem based on PLUS model and InVEST model. *J. Ecol. Rural Environ.* **2023**, *39*, 41–51.
46. Li, Y.; Zhang, Y.; Jiang, Z.; Guo, C.; Zhao, M.; Yang, Z.; Guo, M.; Wu, B.; Chen, Q. Integrating morphological spatial pattern analysis and the minimal cumulative resistance model to optimize urban ecological networks: A case study in Shenzhen City, China. *Ecol. Process.* **2021**, *10*, 63. [CrossRef]
47. Liang, C. *The Multi-Scale Spatial Pattern Optimization of Urban Fringe Based on Ecological Adaptivity: A Case Study of Xiamen*; Tianjin University: Tianjin, China, 2024.
48. Xu, F.; Yin, H.; Kong, F.; Xu, J. Developing ecological networks based on mspa and the least-cost path method: A case study in bazhong western new district. *Acta Ecol. Sin.* **2015**, *35*, 6425–6434.
49. Cao, Y.; Yang, R.; Carver, S. Linking wilderness mapping and connectivity modelling:A methodological framework for wildland network planning. *Biol. Conserv.* **2020**, *251*, 108679. [CrossRef]
50. Wei, B.; Su, J.; Hu, X.; Xu, H.; Zhu, M.; Liu, L. Comprehensive identification of eco-corridors and eco-nodes based on principle of hydrological analysis and Linkage Mapper. *Acta Ecol. Sin.* **2022**, *42*, 2995–3009.
51. Zhang, L.; Yue, W.; Chen, Y. Construction of urban ecological security pattern based on of patch composite characteristics:A case study of Hangzhou. *Acta Ecol. Sin.* **2021**, *41*, 4632–4640.
52. Qiu, S.; Yu, Q.; Niu, T.; Fang, M.; Guo, H.; Liu, H.; Li, S.; Zhang, J. Restoration and renewal of ecological spatial network in mining cities for the purpose of enhancing carbon Sinks: The case of Xuzhou, China. *Ecol. Indic.* **2022**, *143*, 109313. [CrossRef]
53. Vogt, P.; Ferrari, J.R.; Lookingbill, T.R.; Gardner, R.H.; Riitters, K.H.; Ostapowicz, K. Mapping functional connectivity. *Ecol. Indic.* **2009**, *9*, 64–71. [CrossRef]
54. Sahraoui, Y.; Foltête, J.-C.; Clauzel, C. A multi-species approach for assessing the impact of land-cover changes on landscape connectivity. *Landsc. Ecol.* **2017**, *32*, 1819–1835. [CrossRef]
55. Saura, S.; Pascual-Hortal, L. A new habitat availability index to integrate connectivity in landscape conservation planning: Comparison with existing indices and application to a case study. *Landsc. Urban Plan.* **2007**, *83*, 91–103. [CrossRef]
56. Wu, C.; Chen, K.; E, C.; You, X.; He, D.; Hu, L.; Liu, B.; Wang, R.; Shi, Y.; Li, C.; et al. Improved CASA model based on satellite remote sensing data: Simulating net primary productivity of Qinghai Lake basin alpine grassland. *Geosci. Model Dev.* **2022**, *15*, 6919–6933. [CrossRef]
57. Wang, Y.; Xu, X.; Huang, L.; Yang, G.; Fan, L.; Wei, P.; Chen, G. An Improved CASA Model for Estimating Winter Wheat Yield from Remote Sensing Images. *Remote Sens.* **2019**, *11*, 1088. [CrossRef]
58. Ruimy, A.; Saugier, B.; Dedieu, G. Methodology for the estimation of terrestrial net primary production from remotely sensed data. *J. Geophys. Res. Atmos.* **1994**, *99*, 5263–5283. [CrossRef]
59. Wang, R.Y.; Mo, X.; Ji, H.; Zhu, Z.; Wang, Y.S.; Bao, Z.; Li, T. Comparison of the CASA and InVEST models' effects for estimating spatiotemporal differences in carbon storage of green spaces in megacities. *Sci. Rep.* **2024**, *14*, 5456. [CrossRef] [PubMed]
60. Zhu, W.; Pan, Y.; He, H.; Yu, D.; Hu, H. Simulation of maximum light use efficiency for some typical vegetation types in China. *Chin. Sci. Bull.* **2006**, *51*, 457–463. [CrossRef]
61. Liao, L.; Wu, M.; Dai, Z.; Liang, J.; Zuo, P. Research analysis of carbon budgets in coastal wetlands based on bibliometrics. *Mar. Environ. Sci.* **2022**, *41*, 32–39.
62. Ma, Y. *Study on Estimation of Carbon Source and Carbon Sink and Optimization of Spatial Pattern in Chengdu Under the Background of Low-Carbon Construction of Park City*; Beijing Forestry University: Beijing, China, 2022.
63. Peng, X.; Yan, Y.; Sun, Z.; Wang, M.; Liang, F.; Fan, H.; Liu, Q.; Zhang, G.; Luo, M.; Tang, Q. Sediment organic carbon content and its storage in Yancheng coastal salt marshes of Jiangsu Province. *Mar. Sci. Bull.* **2023**, *42*, 407–417.
64. Zhai, X.; Cui, L.; Li, W.; Zhao, X.; Zhang, M.; Kang, X. Research on Carbon Sequestration Value of Typical Wetland Ecosystem in China. *J. Hydroecol.* **2024**, *45*, 1–8. [CrossRef]
65. Li, X.; Jiang, Y.; Liu, Y.; Sun, Y.; Li, C. The impact of landscape spatial morphology on green carbon sink in the urban riverfront area. *Cities* **2024**, *148*, 104919. [CrossRef]
66. Zhang, X.; Huang, H.; Tu, K.; Li, R.; Zhang, X.; Wang, P.; Li, Y.; Yang, Q.; Acerman, A.C.; Guo, N.; et al. Effects of plant community structural characteristics on carbon sequestration in urban green spaces. *Sci. Rep.* **2024**, *14*, 7382. [CrossRef]

67. He, X. *Study on Index System Design and Efficiency Evaluation of Forest Carbon Sink Driven by Data*; Fujian Agriculture And Forestry University: Fuzhou, China, 2024.
68. Lett, C.; Silber, C.; Dubé, P.; Walter, J.N.; Raffy, M. Forest Dynamics: A Spatial Gap Model Simulated on a Cellular Automata Network. *Can. J. Remote Sens.* **1999**, *25*, 403–411. [CrossRef]
69. Liu, X.; Liang, X.; Li, X.; Xu, X.; Ou, J.; Chen, Y.; Li, S.; Wang, S.; Pei, F. A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landsc. Urban Plan.* **2017**, *168*, 94–116. [CrossRef]
70. Liang, X.; Liu, X.; Li, X.; Chen, Y.; Tian, H.; Yao, Y. Delineating multi-scenario urban growth boundaries with a CA-based FLUS model and morphological method. *Landsc. Urban Plan.* **2018**, *177*, 47–63. [CrossRef]
71. Li, H.; Chen, H.; Wu, M.; Zhou, K.; Zhang, X.; Liu, Z. A Dynamic Evaluation Method of Urban Ecological Networks Combining Graphab and the FLUS Model. *Land* **2022**, *11*, 2297. [CrossRef]
72. Wu, Z.; Zhang, K.; Wang, H. Construction and Optimization of Green Space Ecological Network under Urban Expansion Scenario Simulation: A Case Study in Some Areas of Nanjing. *Chin. Landsc. Archit.* **2022**, *38*, 56–61.
73. Fan, F.; Liu, Y.; Chen, J.; Dong, J. Scenario-based ecological security patterns to indicate landscape sustainability: A case study on the Qinghai-Tibet Plateau. *Landsc. Ecol.* **2020**, *36*, 2175–2188. [CrossRef]
74. Liao, Z.; Zhang, L. Spatio-temporal analysis and simulation of urban ecological resilience in Guangzhou City based on the FLUS model. *Sci. Rep.* **2023**, *13*, 7400. [CrossRef] [PubMed]
75. Mokarram, M.; Pham, T.M. CA-Markov model application to predict crop yield using remote sensing indices. *Ecol. Indic.* **2022**, *139*, 108952. [CrossRef]
76. Congalton, R.G. A Quantitative Method to Test for Consistency and Correctness in Photointerpretation. *Photogramm. Eng. Remote Sens.* **1983**, *49*, 69–74.
77. Ma, X.; Lin, P.; Chen, M. Simulation of land use spatial layout based on FLUS model: A case study of Huadu District, Guangzhou. *Adv. Soc. Sci.* **2019**, *8*, 1327–1341.
78. Dantas de Paula, M.; Groeneveld, J.; Huth, A. Tropical forest degradation and recovery in fragmented landscapes — Simulating changes in tree community, forest hydrology and carbon balance. *Glob. Ecol. Conserv.* **2015**, *3*, 664–677. [CrossRef]
79. Lu, Z.; Geng, Y.; Li, W.; Yue, R. Integrating spatial carbon factors into ecological network construction in an energy-intensive megaregion toward multi-objective synergy in northern China. *Environ. Impact Assess. Rev.* **2024**, *106*, 107480. [CrossRef]
80. Wang, L.; Zheng, H.; Chen, Y.; Huang, B. Ecological redline policy strengthens sustainable development goals through the strict protection of multiple ecosystem services. *Glob. Ecol. Conserv.* **2024**, *56*, e03306. [CrossRef]
81. Fu, F.; Liu, Z.; Liu, H. Identifying key areas of ecosystem restoration for territorial space based on ecological security pattern: A case study in Hezhou City. *Acta Ecol. Sin.* **2021**, *41*, 3406–3414.
82. Liu, Y.; Yang, S.; Ni, W.; He, J. Comprehensive assessment method on ecological patch importance: A case study in Sichuan Province, China. *Acta Ecol. Sin.* **2020**, *40*, 3602–3611.
83. Kan, H.; Ding, G.; Guo, J.; Liu, J.; Ou, M. Identification of key areas for ecological restoration of territorial space based on ecological security pattern analysis: A case study of the Taihu Lake city cluster. *Chin. J. Appl. Ecol.* **2024**, *35*, 2217–2227.
84. Riva, F.; Fahrig, L. The disproportionately high value of small patches for biodiversity conservation. *Conserv. Lett.* **2022**, *15*, e12881. [CrossRef]
85. Han, L.; Wang, Z.; Wei, M.; Wang, M.; Shi, H.; Ruckstuhl, K.; Yang, W.; Alves, J. Small patches play a critical role in the connectivity of the Western Tianshan landscape, Xinjiang, China. *Ecol. Indic.* **2022**, *144*, 109542. [CrossRef]
86. Yuan, Y.; Guo, W.; Tang, S.; Zhang, J. Effects of patterns of urban green-blue landscape on carbon sequestration using XGBoost-SHAP model. *J. Clean. Prod.* **2024**, *476*, 143640. [CrossRef]
87. Zhang, Y.; Yu, B. Analysis of urban ecological network space and optimization of ecological network pattern. *Acta Ecol. Sin.* **2016**, *36*, 6969–6984.
88. Wang, Y.; Zhao, W.; Liu, C. Optimization and construction of ecological network based on MSPA-Conefor-MCR Path: A case study of Pengze County. *Acta Agric. Univ. Jiangxiensis* **2022**, *44*, 504–518.
89. Ma, L.; Shen, C.; Lou, D.; Fu, S.; Guan, D. Ecosystem carbon storage in forest fragments of differing patch size. *Sci. Rep.* **2017**, *7*, 13173. [CrossRef]
90. Jongman, R.H.G.; Bouwma, I.M.; Griffioen, A.; Jones-Walters, L.; Van Doorn, A.M. The Pan European Ecological Network: PEEN. *Landsc. Ecol.* **2011**, *26*, 311–326. [CrossRef]
91. Liu, C.; Sun, W.; Li, P. Characteristics of spatiotemporal variations in coupling coordination between integrated carbon emission and sequestration index: A case study of the Yangtze River Delta, China. *Ecol. Indic.* **2022**, *135*, 108520. [CrossRef]
92. Chuai, X.; Yuan, Y.; Zhang, X.; Guo, X.; Zhang, X.; Xie, F.; Zhao, R.; Li, J. Multiangle land use-linked carbon balance examination in Nanjing City, China. *Land Use Policy* **2019**, *84*, 305–315. [CrossRef]
93. Wu, W.; Xu, L.; Zheng, H.; Zhang, X. How much carbon storage will the ecological space leave in a rapid urbanization area? Scenario analysis from Beijing-Tianjin-Hebei Urban Agglomeration. *Resour. Conserv. Recycl.* **2023**, *189*, 106774. [CrossRef]

94. Koo, H.; Kleemann, J.; Fürst, C. Impact assessment of land use changes using local knowledge for the provision of ecosystem services in northern Ghana, West Africa. *Ecol. Indic.* **2019**, *103*, 156–172. [CrossRef]
95. Zhao, Q.; Shao, J. Evaluating the impact of simulated land use changes under multiple scenarios on ecosystem services in Ji'an, China. *Ecol. Indic.* **2023**, *156*, 111040. [CrossRef]
96. Xu, X.; Wang, S.; Rong, W. Construction of ecological network in Suzhou based on the PLUS and MSPA models. *Ecol. Indic.* **2023**, *154*, 110740. [CrossRef]
97. Li, P.; Chen, J.; Li, Y.; Wu, W. Using the InVEST-PLUS Model to Predict and Analyze the Pattern of Ecosystem Carbon storage in Liaoning Province, China. *Remote Sens.* **2023**, *15*, 4050. [CrossRef]

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