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Study on the Structural Properties of an Ecospatial Network in Inner Mongolia and Its Relationship with NPP

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Abstract: In the context of strengthening the construction of ecological civilization and accelerating the "carbon peak" in China, the regional ecological pattern and its connection with carbon sink capacity have become an urgent topic. Given that Inner Mongolia is a large carbon emission province and the conflict between economic development and ecological protection is particularly prominent, we took Inner Mongolia as an example to extract its ecospatial network, then calculated the integrity index, topological indices, and recovery robustness of the network and evaluated integrity and other properties of the ecospatial network structure by combining them with the ecological background. In addition, we analyzed the relationship between the topological indices and net primary productivity (NPP). The results showed that the network was scale-free and heterogeneous, with low integrity, connectivity and stability, which were the focus of future optimization. The nodes with important functions were mainly distributed in the farm-forest ecotone, grasslands, and the agro-pastoral ecotone; under the simulation attack, the node recovery robustness was stronger than the corridor recovery robustness, and NPP was negatively and significantly correlated with the woodland nodes and grassland nodes. In terms of ecological restoration, the unused land in the west is a key area, and it is necessary to add new ecological nodes and corridors. In terms of enhancing carbon sequestration capacity, under the premise of ensuring network connectivity, the appropriate and rational merging of ecological nodes and corridors within woodlands and grasslands is a particularly effective means. This study provides a reference for evaluating and optimizing the ecological pattern of areas with prominent ecological problems and improving the carbon sink of ecosystems in terms of their ecospatial network structure.

Keywords: ecospatial network; complex network; Inner Mongolia; topological indices; ecological structure; NPP

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1. Introduction

In recent years, under the influence of various human activities led by resource exploitation activities, the ecological security of the landscape has been seriously threatened, and the occurrence of ecological problems such as soil erosion, land desertification, surface mining subsidence, and water scarcity shows a significant upward trend [1–4]. In order to protect biodiversity and maintain the stability of ecosystems, how to analyze the ecology of environments that have been damaged after resource exploitation is a topic that must be studied in order to protect or restore the ecology in a targeted manner.

Some scholars proposed the concept of ecospatial networks or ecological networks from the perspective of landscape connectivity and ecosystem structure integrity [5–7]; that is, on the basis of a comprehensive evaluation of natural and human factors in the region, important ecological source patches in the region were extracted and regarded as ecological nodes, and then the belt corridors between ecological resource patches were regarded as ecological corridors, according to which an ecospatial network was constructed to improve habitat fragmentation and the decline in ecological service functions at the landscape scale. Complex ecospatial networks are a hot spot of ecological structure research at present [8–10]. Based on complex systems theory, ecospatial networks have the properties of complex networks, so they can be studied as a kind of complex network [11,12]. A complex system refers to a system whose operation is characterized by complexity [13], which usually includes node complexity, structural complexity, and the interaction between complexities. Complex networks are an important branch of complex system research. After some certain properties of complex systems are abstracted as complex networks, the relationship and interaction between various elements in complex systems can be reflected by the topological structures of their nodes and corridors. Applying complex systems theory to the study of ecosystems can give the properties of complex networks to ecospatial networks and give ecological meaning to complex networks; these properties can include such aspects as sparsity [14], the small-world effect [15], and being scale-free [16], so that the relevant characteristics of an ecospatial network can be described quantitatively and the intrinsic connections in an ecospatial network can be explored [17,18]. At present, ecospatial networks are mostly applied to studies on urban spatial planning, landscape risk assessment, etc.; Hu et al. [19] used the MSPA-MCR model to construct the Wuhan ecological network, quantitatively analyzed the importance of ecological source sites and ecological corridors, and pointed out key areas for ecological restoration. Wang et al. [9] used the construction of ecological networks from a complex network perspective as a comprehensive research framework to conduct a study on the resilience of Wuhan ecological networks, and the results showed that ecological nodes corresponded to a wide range of land cover types, landscape components were dominated by farmland, forests, and water bodies, and the structural and functional resilience of the network was related to the redundancy of the network. Yang et al. [20] constructed small-scale ecological networks for mining areas and evaluated ecological source sites of importance in the ecological security pattern, and their recommendation for network restructuring was to reduce edge effects. Zhao et al. [2] constructed an ecological network for the current problems of landscape fragmentation and poor connectivity of patches in urban ecosystems, taking Tianjin as an example, and made optimization suggestions for improving corridor connectivity and network closure. However, studies on ecological environments damaged due to resource overuse on a large scale are relatively rare.

On the other hand, due to the deterioration of the ecological environment, the human demand for ecosystem services has gradually increased. According to the Kyoto Protocol (1992) [21], the Paris Agreement (2015) [22], the Green Deal [23], the 14th Five-Year Plan for National Economic and Social Development of the People's Republic of China [24] and other relevant documents and regulations, achieving carbon neutrality and mitigating global warming has become a world consensus; therefore, the carbon absorption capacity of ecosystems needs to be further strengthened, and it is necessary to explore the factors related to the carbon sequestration capacity of an ecosystem in an ecospatial network at the macroscopic scale for subsequent top-level planning research work. Net primary productivity (NPP) is the amount of organic matter accumulated by green plants per unit of time and area, namely the part of organic carbon fixed by plants through photosynthesis minus the part consumed by respiration, also known as the net first productivity. It is the main factor in studying the carbon source/sink properties of an ecosystem and an important indicator of the surface carbon cycle. At present, the research on NPP is mostly centered on its relationship with climate and precipitation [25–27]; however, there is still a gap in research that combines NPP with ecospatial networks and explores the influence of the topological properties of ecospatial networks on the carbon sequestration capacity of ecosystems with respect to the relationship between NPP and ecospatial networks.

Inner Mongolia has a vast watershed area rich in natural resources and a very important ecological position. Moreover, the Yellow River flows through the region for 843.5 km, which is an important part of China's ecological barrier [28,29]. In recent years, the contradiction between economic development and ecological protection in Inner Mongolia has become increasingly prominent. Forest resources, grassland resources, water resources and other resources have been greatly exploited, and ecological and environmental problems have persisted for a long time, leading to a growing shortage of environmental carrying capacity and causing serious impacts on the regional ecological environment. Zhang et al. [30] pointed out that the land area subjected to wind erosion and desertification in the arid and semi-arid regions of Inner Mongolia accounted for 64.4% of the total area of the country, which was the most serious desertification area in China; according to Liu et al. [31], the area of degraded grassland accounted for 31.8% of the total area of grassland, and among the five major grasslands, the Horqin grassland, the Ordos grassland and the Ulanqab grassland had basically disappeared. Li-Yan et al. [32] pointed out that due to overgrazing, blind reclamation, and low vegetation cover, Inner Mongolia has the most serious soil erosion in the country; Chi et al. [33] concluded from a survey that due to the expansion of farmland, the forest resources in Inner Mongolia, led by the original forests of the Daxinganling, have been drastically reduced and the modulus of soil wind erosion has increased by 5 million tons. At present, the total carbon emission in Inner Mongolia ranks fourth in China, and the per capita carbon emission intensity is the highest. As the country accelerates the "carbon peak", it is especially difficult for Inner Mongolia, with its high energy consumption and high carbon emission. Therefore, this paper took the Inner Mongolia Autonomous Region as an example, extracted the potential ecospatial network in the region, and calculated the integrity index, degree and degree distribution, clustering coefficients and other complex network topological indices and robustness. Combined with the significance of these indexes in the ecospatial network, the connectivity and importance of each ecological node and ecological corridor in the network were analyzed in relation to the ecological background, and the integrity, connectivity, and stability of the network were evaluated. In addition, the relationship between the topological indices of ecospatial networks and the carbon sequestration capacity of ecosystems was initially explored by Pearson correlation analysis and regression analysis. This study is intended to provide technical support and reference for the analysis and evaluation of the overall ecospatial network structure and ecological security pattern of Inner Mongolia and the improvement of ecosystem carbon sequestration and oxygen release capacity.

2. Materials and Methods

2.1. Study Area

The Inner Mongolia Autonomous Region is located in the north of China, spanning the three major regions of Northeast, North and Northwest China, between $37^\circ24'$~$53^\circ23'$ N and $97^\circ12'$~$126^\circ04'$ E, as shown in Figure 1. The total area of the region is 1.183 million square kilometers, accounting for 12.3% of the total land area of China. The average altitude is 1000 m, and the terrain is inclined from northeast to southwest, covering a variety of landforms, of which the plateau accounts for about 53.4%. There are loess hills and stony hills distributed at the intersection of mountains to high plains and plains and mixed with low mountains, valley bottoms and basins in between, with serious problems such as soil and water loss and desertification. Inner Mongolia is rich in plant and animal resources and mineral resources and is the province with the largest amount of new minerals in China. It contains 26.24% of the national total of coal reserves, ranking first in the country. The total water resources of the region are 54.595 billion cubic meters, accounting for 1.92% of the total water resources of the country, but there is a problem of uneven distribution in the region. Since the water distribution does not match the distribution of population and cultivated land, most areas are in a state of water scarcity.

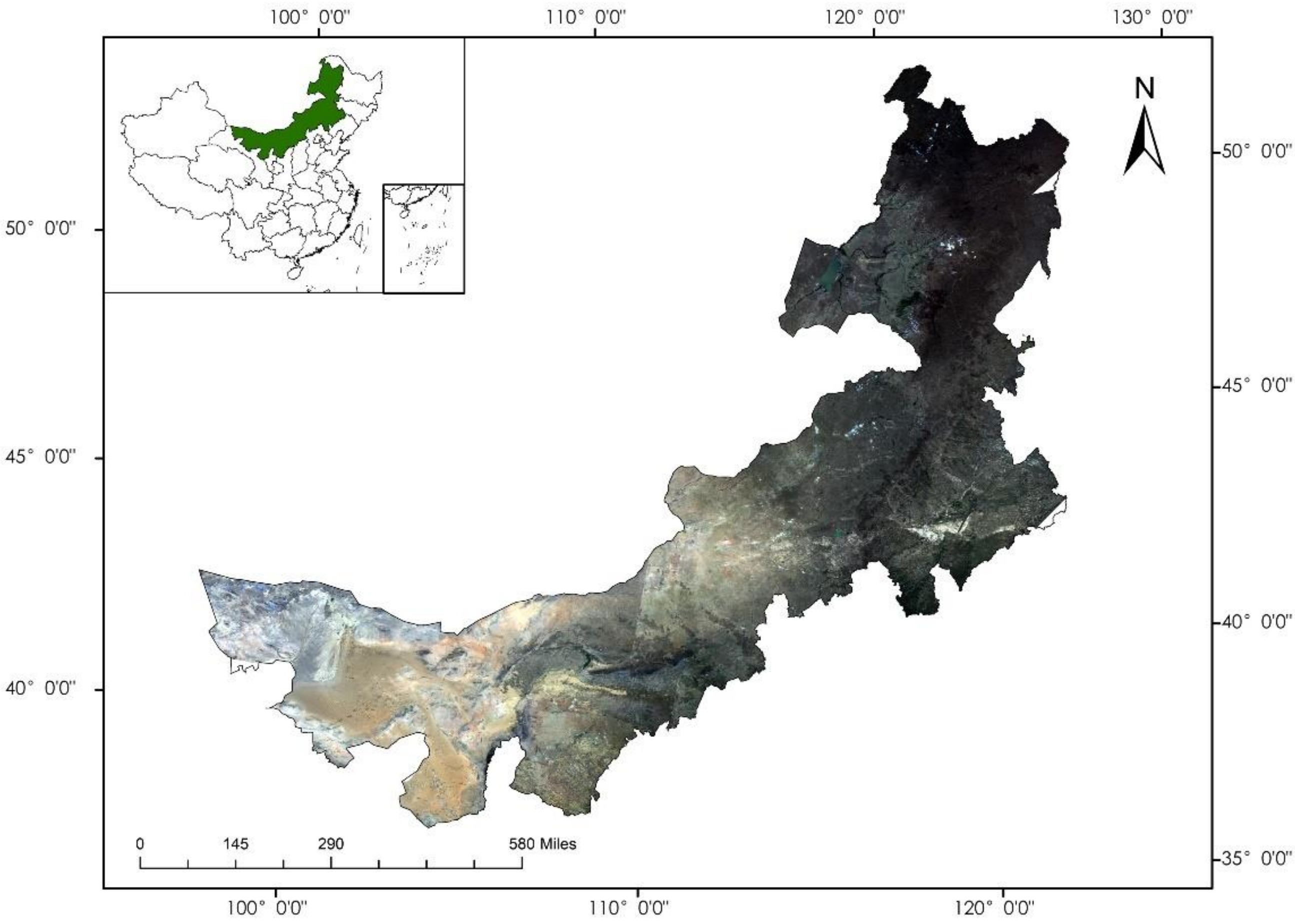


Figure 1. Location of the study area.

2.2. Data Sources

The administrative division data of Inner Mongolia used to determine the extent of the study area in this paper were obtained from the Resource and Environment Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 5 December 2021); the DEM data used to extract the elevation and slope came from the ASTER GDEM dataset on the Geospatial Data Cloud platform with a resolution of 30 m (http://www.gscloud.cn/, accessed on 5 December 2021); the remote sensing data used to calculate NDVI and NDWI came from the Landsat8 dataset on Google Earth Engine platform, with a resolution of 30 m (https://developers.google.cn/earth-engine, accessed on 5 December 2021); the land use data came from the global land cover data provided by GlobeLand30, with a resolution of 30 m and data dated to 2020 (http://www.globallandcover.com/, accessed on 5 December 2021); the annual precipitation data came from the Chinese ground-based meteorological observation dataset provided by China Meteorological Data Network, with data dated to 2021 (https://data.cma.cn, accessed on 5 December 2021); and the NPP data came from the MODIS Land Standard Product MOD17A3H dataset with a resolution of 500 m for the year 2021 (https://ladsweb.modaps.eosdis.nasa.gov/, accessed on 5 December 2021). All the data mentioned above were used in the same scope as the study area, and the forms used included both the image data and the attribute data it carried.

Data processing mainly used ArcGIS, ENVI, MATLAB, SPSS, and other software.

2.3. Extraction of Complex Ecospatial Network

Based on the complex network theory, the substances and energy in the ecosystem continuously flow and exchange between ecological source patches through ecological corridors. Therefore, the extracted ecological source patches can be used as ecological nodes, and the ecological corridors can be used to connect ecological nodes. In this way, a potentially complex ecospatial network in the study area can be constructed. In general, the extraction of complex ecospatial networks can be divided into three steps: ecological source extraction, cumulative resistance surface construction, and ecological node and corridor extraction.

2.3.1. Ecological Source Patch Extraction

An ecological source patch in landscape ecology is land that mainly plays natural ecological functions and ecosystem service functions or land with a fragile ecological environment and high sensitivity [34]. This paper selected the land patch data of forest lands, shrub forests, grasslands, river canals, lakes, and reservoirs, which were of great value to ecological service functions such as soil and water conservation. By calculating the area of each patch, the average NDVI, the average NDWI and the shape index evaluated its importance for the ecosystem to play its natural ecological function and then screened out the ecological source patches.

2.3.2. Cumulative Resistance Surface Construction

The flow of energy in the ecosystem may be impeded to varying degrees by different topography, vegetation cover, hydrological distribution, land use and other factors at different locations. The cumulative resistance surface of the study area was constructed by selecting relevant data according to the study purpose, which could comprehensively reflect the impeding effect of all locations in the study area on the ecological energy flow and the trend of ecological energy flow. In this paper, the cumulative resistance surface was constructed by combining the elevation, slope, vegetation, hydrology, and land use data of the study area. Gentle terrain, high vegetation cover, and proximity to water sources are conducive to the ecological energy flow; cultivated land, construction land and other types of land will impede the ecological energy flow.

2.3.3. Ecological Corridor Extraction

In the process of ecological energy flowing in the ecospatial network, the flow path with the least comprehensive ecological resistance and the least energy consumption is called the ecological corridor of the ecospatial network [35,36]. Ecological corridors have roles such as improving habitat connectivity, and the flow of ecological energy from ecological corridors can produce optimal ecological benefits. In this paper, the cost-minimum path module of ArcGIS was used to construct a minimum cumulative resistance model by using cumulative resistance surface and ecological source patches and then extracted potential ecological corridors [37,38]. The calculation formula of the minimum cumulative resistance model is written as follows:

$$V_{MCR} = f_{min} \sum_{j=1}^{n} \sum_{i=1}^{m} (D_{ij} R_i) \tag{1}$$

where V_{MCR} is the minimum cumulative resistance value, f_{min} is the minimum cumulative resistance value of a land unit, m is the number of land units, n is the number of ecological source patches, D_{ij} is the spatial distance between the ecological source patch i and the land unit j; and R_i is the resistance of land unit i to energy flow.

2.4. Evaluation Indexes of Complex Ecospatial Network

(1) Ecospatial network integrity

The integrity of the ecospatial network mainly reflects the quantitative relationship between the ecological source patch and the ecological corridor. To a certain extent, it can measure the complexity and ecological efficiency of the network. It mainly includes several evaluation indexes including the closure α, the line-point rate β and the network connectivity γ. The index α is used to reflect the degree of loops in the network. The higher the index α, the better the circularity and circulation of the network. The index β is used to reflect the average number of lines connected to each node in the network. The index γ is used to reflect the connectivity of nodes in the network. The above indexes are calculated as follows [39]:

$$\alpha = \frac{L - V + 1}{2V - 5} \tag{2}$$

$$\beta = \frac{L}{V} \tag{3}$$

$$\gamma = \frac{L}{3(V - 2)} \tag{4}$$

For a network, L is the number of ecological corridors; V is the number of ecological nodes. When $\beta < 1$, the network belongs to a tree structure; when $\beta = 1$, the network belongs to a single loop structure; when $\beta > 1$, the complexity of the network connection belongs to a higher level. When $\gamma = 0$, no corridors are connected between nodes; when $\gamma = 1$, nodes in the network are highly connected;

(2) Ecological node degree and degree distribution

The number of corridors connected to a node in the ecospatial network is called the degree of the node, and the average of the degrees of all nodes in the ecospatial network is called the average degree [40]. The degree of a node reflects the importance of the node in the ecospatial network in a sense. The greater the degree of a node, the more nodes it is connected to, and the higher the connectivity of that node; the greater the average degree of nodes, the higher the overall connectivity of the network. For a given network adjacency matrix $A = (a_{ij})_{N \times N}$, the calculation formulas of an average degree are as follows [41]:

$$\langle k \rangle = \frac{1}{N} \sum_{i=1}^{N} k_i \tag{5}$$

where k_i is the degree of the i node; k is the average degree of the network; and N is the total number of nodes in the network. The proportion of nodes with degree k in the entire network is called the degree distribution of nodes in the ecospatial network;

(3) Ecological node clustering coefficient

Based on the complex network theory, it is assumed that the ecological node v_i is connected to the adjacent nodes through k_i ecological corridors, which means that the v_i node has k_i nodes adjacent to it. Note that k_i in this subsection is different from k_i in Section 2. There may be at most C corridors between these k_i nodes. The ratio of the actual number of corridors E_i between the k_i neighboring nodes of node v_i and the number of corridors that exist at most $C_{k_i}^2$ is called the clustering coefficient of this node, and its formula is as follows [42]:

$$C_i = \frac{E_i}{C_{k_i}^2} \tag{6}$$

The average of the clustering coefficient of all nodes in the network is called the average clustering coefficient C. The average clustering coefficient is used to reflect the closeness of the connections between nodes in the network. The larger C is, the stronger the small-world property of the network is. When $C = 0$, there is no corridor connection between all nodes; when $C = 1$, all nodes are connected;

(4) Ecospatial network robustness

The ability of an ecospatial network to maintain its ecological properties or ecological service functions under the interference and attack of various external factors is called the robustness of the ecospatial network [10,43]. Analyzing the robustness of an ecospatial network can measure the ability of the ecospatial network to resist external attacks and recover after suffering damage. In this paper, the robustness of the ecospatial network was evaluated by simulating a random attack and a malicious attack on it, where the random attack represented the random removal of several nodes from the network and the malicious attack represented the removal of the node with the largest degree from the network and its corresponding corridor. The robustness of the ecospatial network can be measured from two aspects: node recovery robustness and corridor recovery robustness, which reflect the recovery capabilities of ecological nodes and ecological corridors, respectively, and they are calculated as follows [44]:

$$D = 1 - (N_r - N_d)/N \tag{7}$$

$$E = 1 - (M_r - M_e)/M \tag{8}$$

where D is the node recovery robustness index, N_r is the number of nodes removed, N_d is the number of nodes recovered, and N is the number of nodes. e is the corridor recovery robustness index, M_r is the number of corridors removed, M_e is the number of corridors recovered, and M is the number of corridors;

(5) Correlation analysis

In this paper, the Pearson correlation coefficient was used to calculate the correlation coefficient and significance level between NPP and the ecospatial network topological indices so as to analyze the correlation between NPP and the ecospatial network. The formula for calculating the Pearson correlation coefficient is [45]:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{9}$$

where r_{xy} is the correlation coefficient between x and y; n is the number of nodes; x_i is the NPP of the i node; y is the degree or clustering coefficient of the i node; and $\overline{x}$ and $\overline{y}$ are the mean of x and y, respectively.

3. Results and Discussion

3.1. Construction of Complex Ecospatial Network

First, we extracted the ecological source. A total of 143,524 ecological source patches were obtained after screening, including 33,517 forest land ecological source patches, 17,084 shrub forest ecological source patches, 58,772 grassland ecological source patches, 25,103 river and canal ecological source patches, 7645 lake ecological source patches, and 1403 reservoir ecological source patches. The distribution of ecological source patches in the study area is shown in Figure 2.

The screening results of ecological source patches show that the ecological source patches in the study area are mainly distributed in the northeast and less distributed in the southwest, which indicates that the ecological background in the northeast of the study area is better, while the southwest needs to be optimized. In terms of the distribution area, the ecological source patches are mainly woodland and grassland, which are mainly distributed in the northern and central parts.

Second, we constructed the cumulative resistance surface. According to the research purpose and the basic situation of the study area, this paper selected elevation, slope, NDVI, NDWI and land use type as the factors to construct the ecological resistance evaluation system. The results are shown in Figure 3. Analysis of the evaluation results of each ecological resistance factors shows that the western and central parts of the study area have higher elevations, while the northern and eastern parts are lower; the slope range is between 0 and 76.7°, with a higher slope in the north and larger overall undulation. Analysis of the evaluation results of each ecological resistance factor shows that the NDVI value is lower and NDWI value is higher in the west and south, such as the area near Alashan League, and the NDVI value is higher and NDWI value is lower in the north and east, such as the area near Hulunbeier City. The northern part is dominated by cultivated land and woodland, the central part is dominated by grassland and water, and the western part is dominated by unused land.

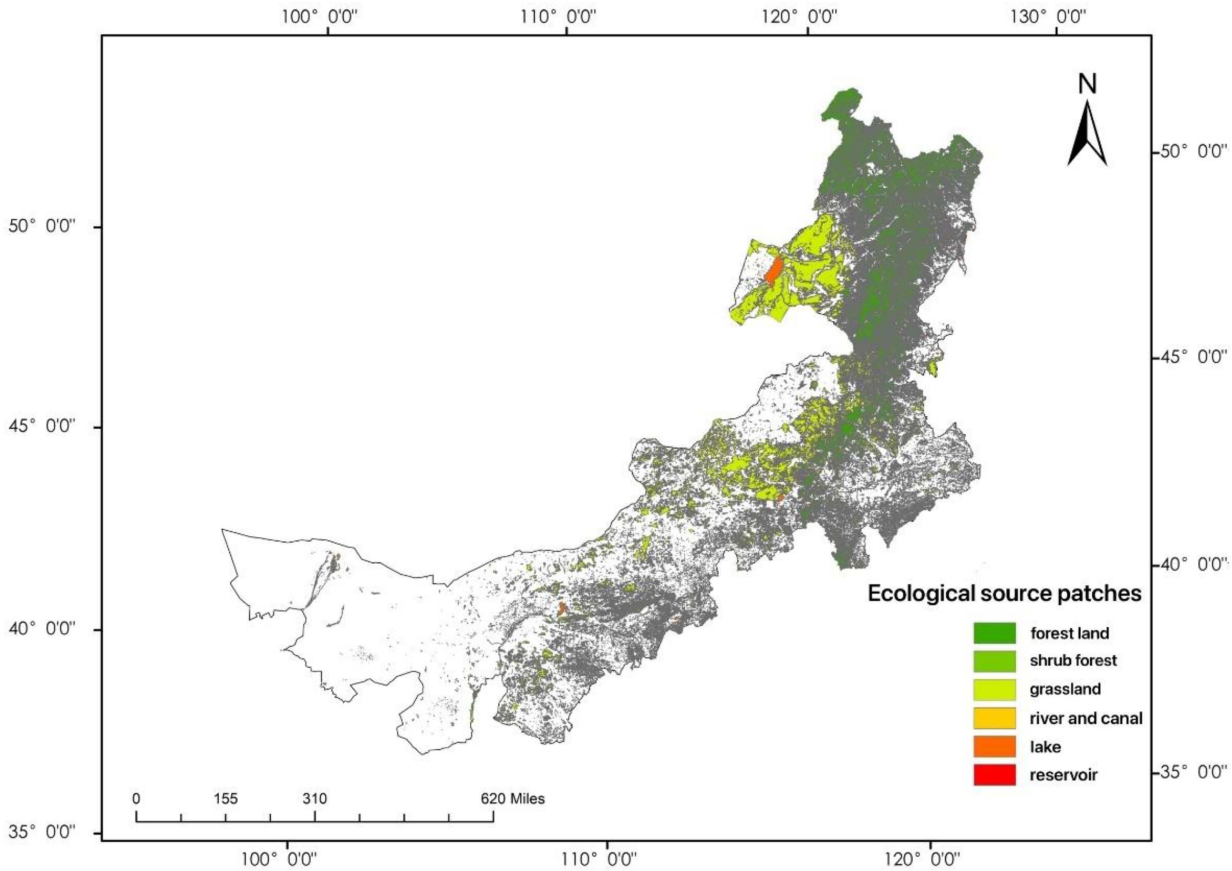


Figure 2. Distribution of ecological source patches in the study area.

This paper used ArcGIS to assign the ecological resistance value of each ecological resistance factor according to the grading standard in Table 1. We then used the grid calculator to superimpose the evaluation results of each factor to obtain the comprehensive evaluation result and used the Cost-Distance module to obtain the cumulative resistance surface. The results are shown in Figure 4.

According to the resistance surface data, the ecological resistance value in the study area is between 3 and 27. The low resistance values in the areas near Tongliao City and Hulunbuir City in the north indicated relatively low ecological resistance, while the high resistance values in most areas in the west indicated higher ecological resistance.

Finally, based on the obtained ecological source patches and cumulative resistance surfaces, the ecological nodes and ecological corridors in the study area were extracted by using the Cost-Path model, and a complex ecospatial network was constructed, as shown in Figure 5. A total of 861 ecological nodes and 1519 ecological corridors were extracted.

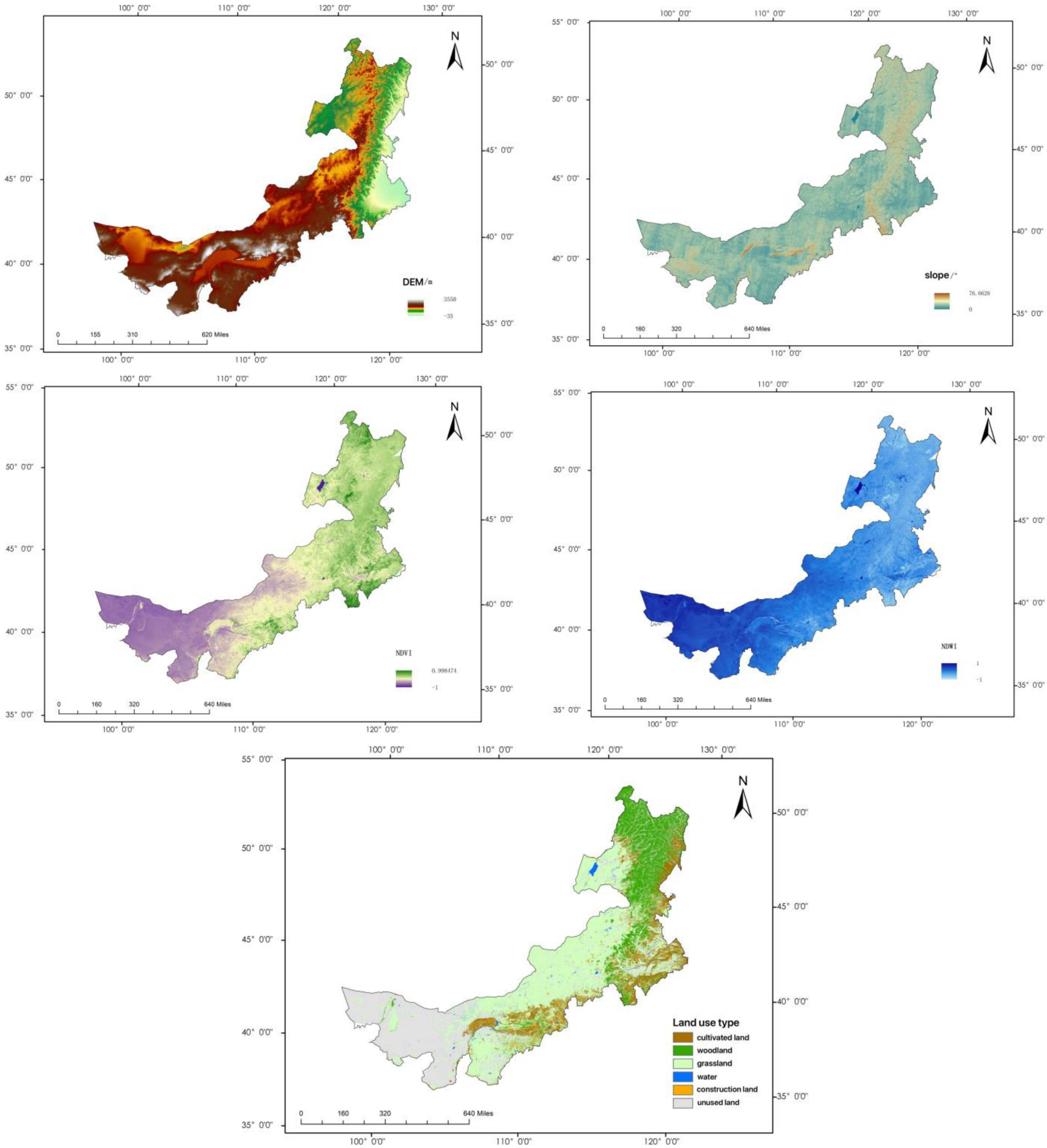


Figure 3. Ecological resistance factor in the study area.

Table 1. Classification and value of ecological resistance factors.

Number	Primary Impact Factor	Secondary Impact Factor	Classification	Resistance Value
1	Topography	DEM (m)	<500	1
			500~1000	3
			1000~2000	5
			2000~3000	7
			>3000	9
		Slope (°)	<2	1
			2~6	3
			6~15	5
			15~25	7
			>25	9
2	Vegetation cover	NDVI	<0	9
			0~0.2	7
			0.2~0.4	5
			0.4~0.6	3
			>0.6	1
3	Hydrological distribution	NDWI	<0	9
			0~0.3	7
			0.3~0.6	5
			0.6~0.8	3
			0.8~1.0	1
4	Land cover	Land use type	Woodland	1
			Grassland or waters	3
			Cultivated land	5
			Construction land	7
			Unused land	9

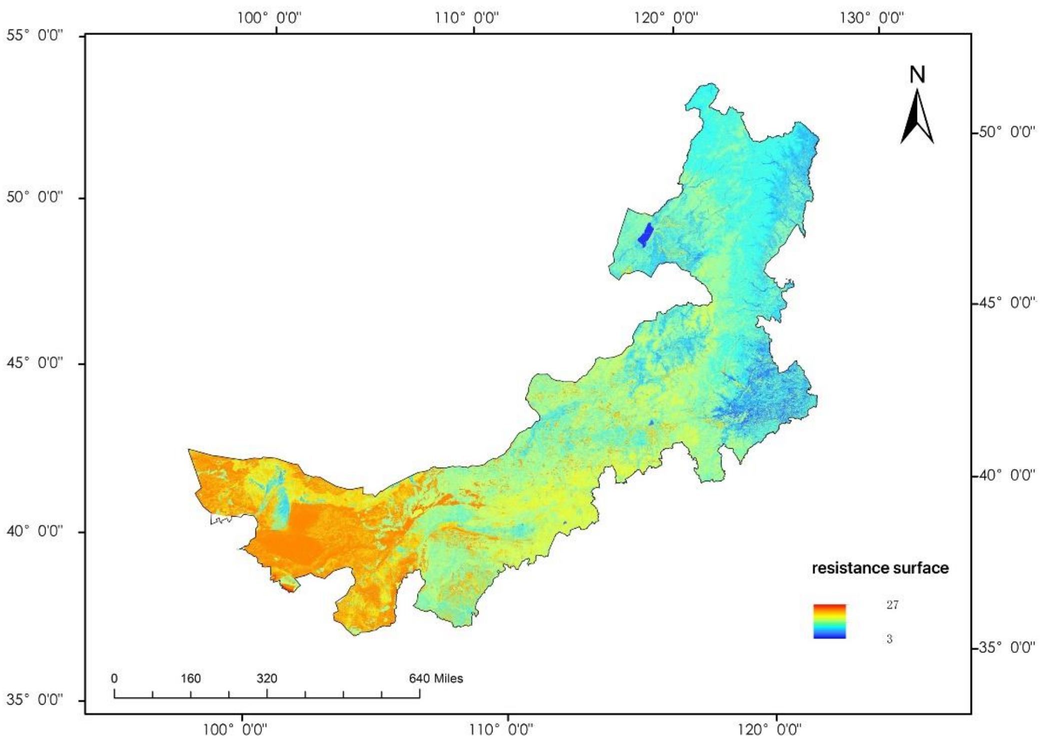


Figure 4. Cumulative resistance surface in the study area.

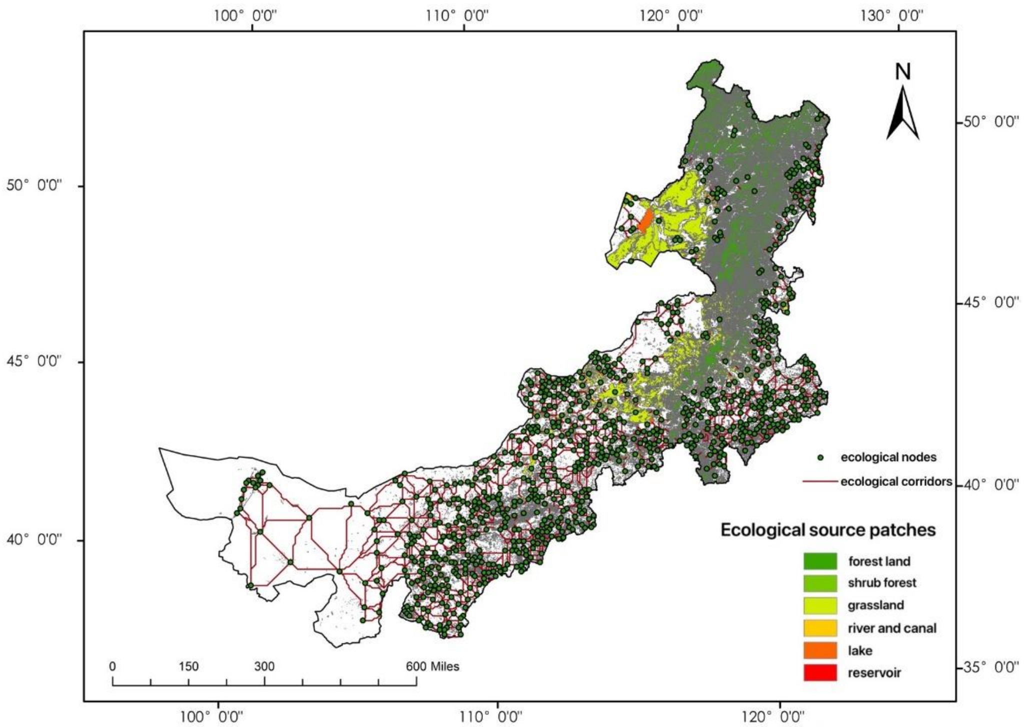


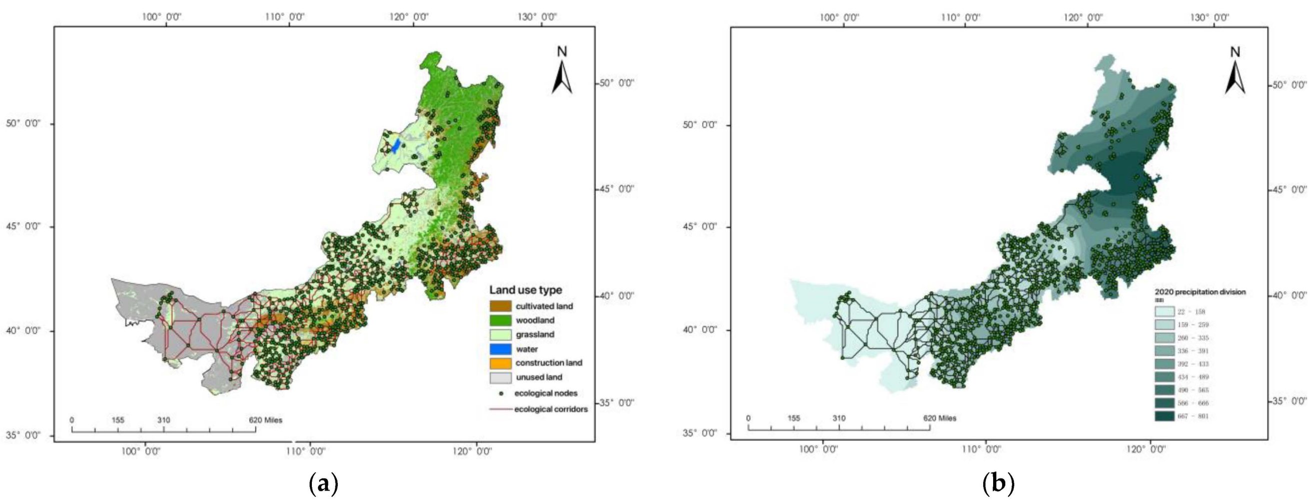
Figure 5. Ecological nodes and ecological corridors in the study area.

The ecological nodes and corridors in the study area are mainly distributed in the central and eastern parts, indicating that the ecological corridors in these regions are more complex in trajectory and have good ecological circulation. The distribution of ecological nodes in the northern and western regions is relatively sparse. The distance between ecological nodes in the west is greater, and the corridors are longer; in other areas, the ecological nodes are relatively closer, and the corridors are shorter.

3.2. Complex Ecospatial Networks Evaluation

3.2.1. Ecospatial Network Structure Analysis

In this paper, we analyzed the ecological network structure in combination with the land use types and annual precipitation in Inner Mongolia, and the results are shown in Figure 6.



(**a**) (**b**)

Figure 6. (**a**) Ecospatial network and land cover types in the study area; (**b**) ecospatial network and precipitation division.

Firstly, the ecospatial network structure was analyzed in combination with land use types. As shown in Figure 6a, the study area is mainly composed of woodland, grassland, cultivated land and unused lands, such as sandy land, Gobi, and saline-alkali land, while water and residential land are relatively small. Overall, the network structures such as woodlands in the north and sandy lands in the west are relatively simple. The ecological nodes in the north are mostly distributed near the forest-grassland ecotone and the farm-forest ecotone; in the west, due to habitat fragmentation, land desertification and a series of impacts caused by them, there are fewer ecological nodes, which are partly gathered in small grassland patches and partly scattered and far apart with the fragmented grassland patches. The stability of the ecospatial network structure in these areas is relatively low. The distribution of ecological nodes in these areas is relatively dense and uniform, with interlocking ecological corridors and better network integrity and connectivity.

As shown in Figure 6b, affected by monsoon circulation and topography, the overall annual precipitation in Inner Mongolia gradually decreases from east to west, and the complexity of the ecospatial network structure first increases and then decreases from east to west. The areas with annual precipitation between 22 and 158 in the west and between 667 and 801 in the northeast are the areas with the least and most annual precipitation, respectively, and the ecospatial networks in these two areas are relatively sparse, with few and scattered nodes. The areas with annual precipitation between 392 and 666 are rainy areas, and the ecospatial network is aggregated in a small scale; in the areas with annual precipitation between 159 and 391, the ecospatial network is aggregated in a large scale, with numerous and dense ecological nodes and corridors and strong network stability. Overall, the correlation between the ecospatial network structure and annual precipitation is not strong, so the subsequent study will not combine with annual precipitation anymore.

3.2.2. Ecospatial Network Integrity

The results of the ecospatial network integrity evaluation in the study area are shown in Table 2. These results indicate that the ecospatial network has a low degree of closure and fewer loops; in other words, there are fewer paths for species migration and diffusion, and the overall circulation and circulation of the network are general. The β index is 1.76, which is greater than 1, indicating that the ecospatial network has a more complex connection level compared with the tree-like structure and demonstrates strong resistance and recovery; the γ index is 0.59, which indicates that the node connectivity is at a medium level and not every node is connected to each other. Overall, the ecospatial network integrity of the study area is average, and it is necessary to optimize and improve it.

Table 2. Ecospatial network integrity index.

Number of Ecological Nodes	Number of Ecological Corridors	Network Closure (α)	Line Point Rate (β)	Network Connectivity (γ)
861	1519	0.3838	1.7642	0.5894

3.2.3. Ecological Node Degree and Degree Distribution

The degree distribution of ecological nodes is shown in Figure 7.

Figure 7 shows that there is no node with a degree of 0 in this ecospatial network, indicating that no node exists independently, and all nodes are connected to the network. The average degree is 3.52, indicating that the overall connectivity level is relatively low; about 95% of the ecological nodes have degree values in the 0~10 range; that is, the number of corridors connected by most nodes is between 0 and 10, which indicates that the connectivity of most nodes in the network is at a medium level, and the number of corridors connected by most ecological source patches is small. A small number of nodes have degree values in the 10~15 range; that is, a small number of nodes are connected to 10~15 corridors, and these nodes can play a more important ecological role in the network. Observing the overall distribution characteristic of the node degree, the curve trend is more in line with the power-law distribution compared to the Poisson distribution. The power-law distribution is also known as the scale-free distribution, and the ecospatial network conforming to the power-law distribution tends to show obvious scale-free properties after removing the nodes with degrees of 0 and 1. The power-law distribution characteristic of the ecospatial network degree distribution in the study area indicates that its scale-free property is stronger than the uniformity property, and the network inhomogeneity is high.

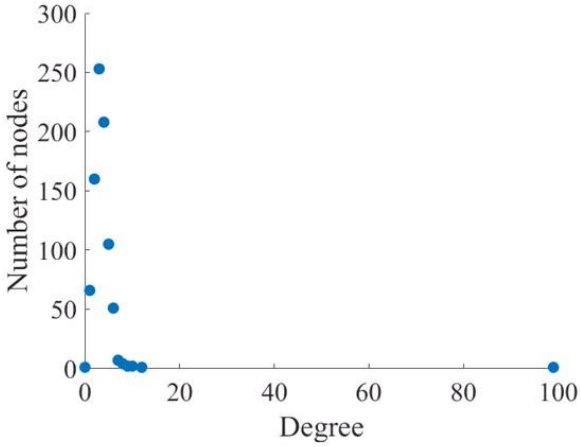
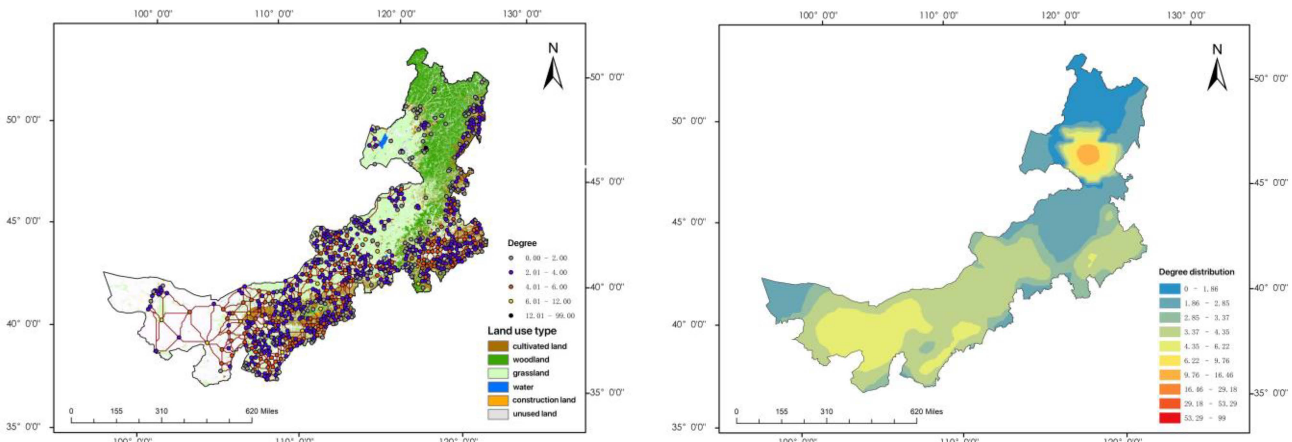


Figure 7. Degree distribution.

Figure 8b was obtained by predicting the degree distribution of nodes in the whole region of Inner Mongolia by kriging. Combined with the land use types in Inner Mongolia, it can be seen from Figure 8a that there are 227 nodes with degrees in the low-value range of 0~2, mostly located in the woodland and forest-grassland ecotones. As shown in Figure 8b, most of the predicted values of node degree in the woodland are between 0 and 1.86, while a small part of the area is affected by a node with a high degree, and the predicted value gradually decreases from 9.76 to 16.46. This shows that in this ecospatial network, most of the ecological nodes located in the woodland and the forest-grassland ecotone have relatively low connectivity and do not play an important role in the ecospatial network. There are 461, 156 and 16 nodes in the range of 2~4, 4~6 and 6~12, respectively, accounting for 77% of the total number of nodes, which are mostly located in the farm-forest ecotone, grassland, and agro-pastoral ecotone. These nodes have relatively high connectivity and play a key role in maintaining the stability of the ecospatial network. It also indicates that the land cover types where these nodes are located have important ecological service functions in the Inner Mongolia ecosystem.

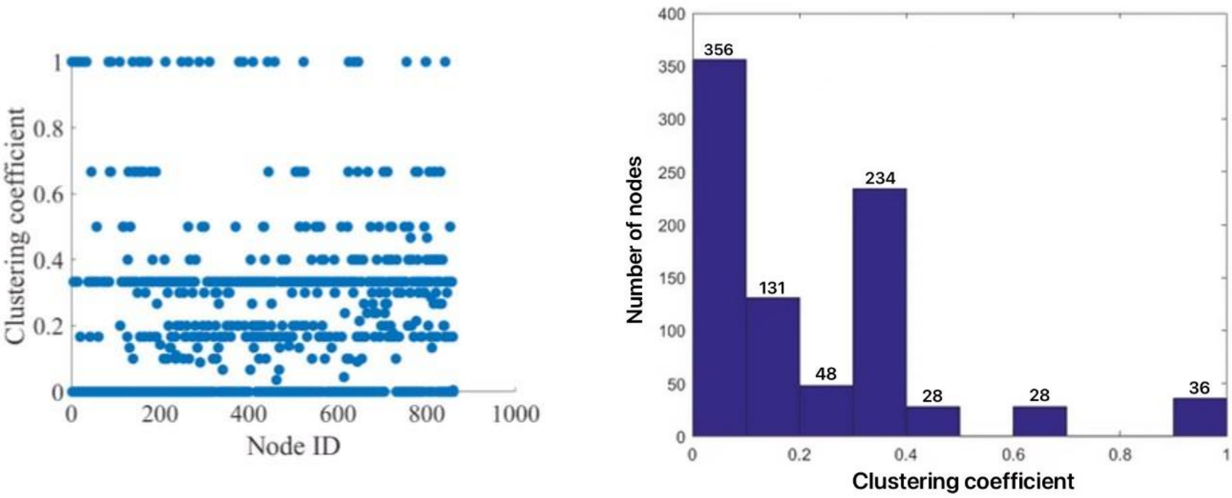


(**a**) (**b**)

Figure 8. (**a**) Node degree spatial distribution; (**b**) spatial distribution prediction.

3.2.4. Ecological Node Clustering Coefficient

The distribution of clustering coefficients in the study area is shown in Figure 9.

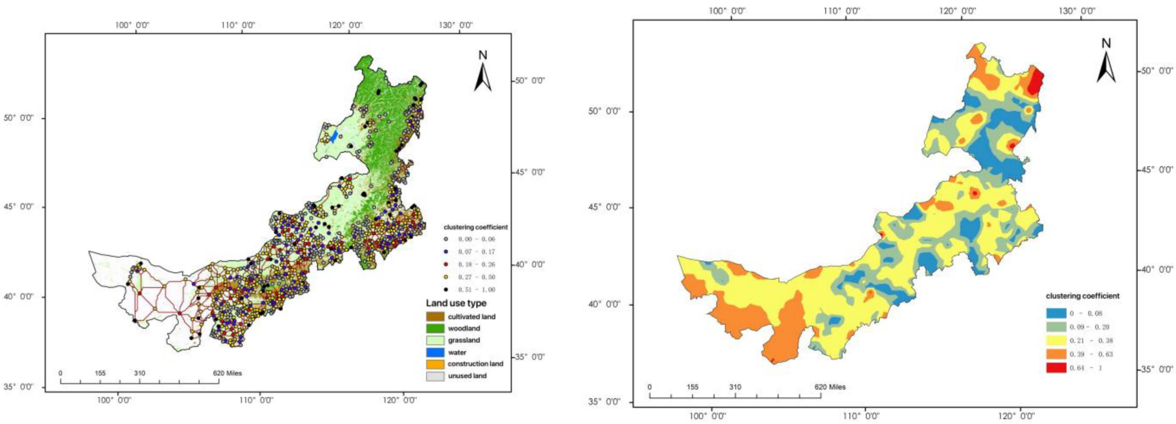


(**a**) (**b**)

Figure 9. (**a**) Distribution of clustering coefficient; (**b**) clustering coefficient distribution histogram.

The average clustering coefficient of the ecospatial network in the study area is 0.2174, indicating that the small-world property of the ecospatial network is low. This may be due to the fact that more than 75% of the nodes in the network are connected to a small number of corridors, which are only between 0 and 5. Figure 9b shows that about 41% of the nodes have a clustering coefficient in the range 0~0.1, which is the range with the largest number of nodes, and most of them have a clustering coefficient of 0. The ecological source patches represented by these nodes have very low or do not have clustering features. About 4% of nodes have clustering coefficients in the range 0.9~1, and these nodes have obvious clustering features; 93% of nodes have low clustering coefficients below 0.5, indicating that this ecospatial network does not show obvious clustering properties on the whole. Overall, the value of the clustering coefficient of each node is not concentrated in a specific value range but is relatively scattered in each interval, which also indicates that the network has the property of inhomogeneity; that is, the ecological source patches are unevenly distributed in location, and the network density varies significantly in different regions, which leads to high instability of the ecospatial network structure.

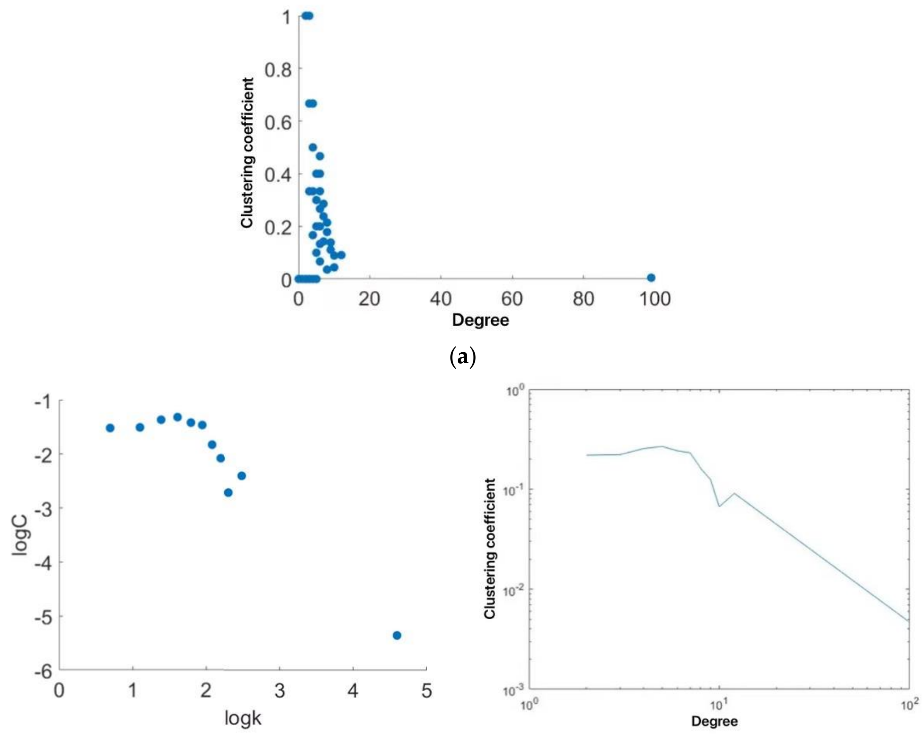
Figure 10b was also obtained by using the kriging method to predict the distribution of clustering coefficients. On the whole, the clustering coefficients on each land cover type were mainly concentrated in the range of 0~0.08, 0.09~0.20, and 0.21~0.63, and there is no obvious regularity between the land cover types and the clustering coefficient. For nodes on different land cover types, the interval covered by the clustering coefficient is basically the same, indicating that the land cover type does not have a significant effect on the clustering coefficients of the nodes.



(**a**) (**b**)

Figure 10. (**a**) Spatial distribution of node clustering coefficient; (**b**) spatial distribution prediction.

The clustering coefficient-degree correlation indicates the relationship between the clustering coefficient and the degree of the node in the ecospatial network. In order to get a more distinct rule between the two, this paper performed logarithmic processing on the clustering coefficient and the degree, as shown in Figure 11. It shows that with the increase in degree, most of the clustering coefficient tends to increase slowly first and then decrease rapidly, which indicates that most of the nodes that tend to cluster in the network have a smaller degree; that is to say, the average number of corridors connected by the nodes distributed in clusters is often relatively small, while those distributed in fragments are larger, and the nodes bear more responsibility in the network. Once such nodes are destroyed, the impact on the ecospatial network will be more serious. On the whole, the clustering coefficient of the nodes in the network does not have an obvious reciprocal relation with the degree of the nodes, and there is no obvious linear relationship after the logarithm processing, indicating that the network is a non-hierarchical network.



(**a**)

(**b**) (**c**)

Figure 11. (**a**) Clustering coefficient–degree correlation distribution; (**b**,**c**) logarithmic distribution.

3.2.5. Ecospatial Network Robustness

The ecospatial network in the study area was simulated as an adjacency matrix using MATLAB, and the malicious attacks and random attacks on ecological nodes and corridors were simulated by matrix calculation. The calculation results are shown in Figure 12.

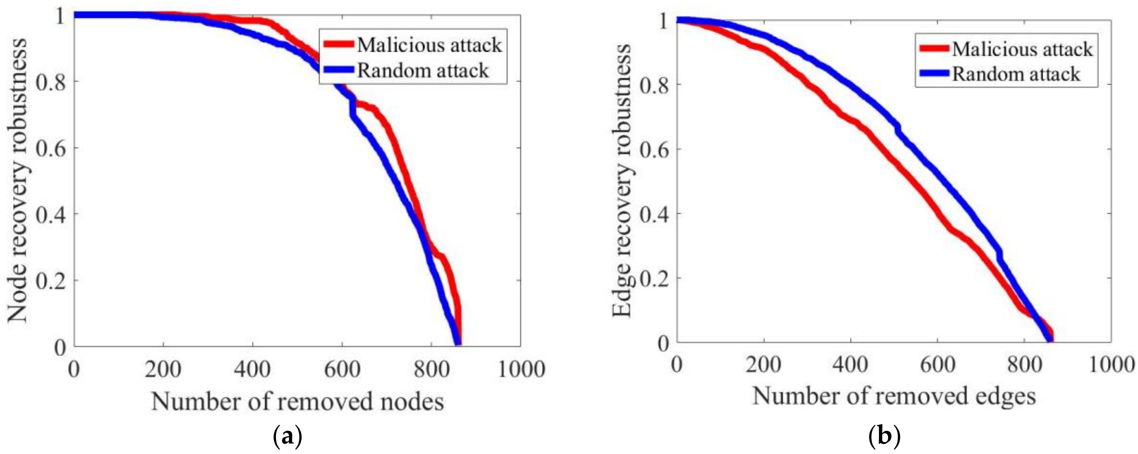


Figure 12. (**a**) Node recovery robustness; (**b**) corridor recovery robustness.

It can be seen from the figure that the initial node recovery robustness of the network is 1. Under random attack, when the number of removed nodes is less than about 150, the network structure can be completely recovered; with an increase in the number of attacked nodes, the node recovery robustness decreases, and the degree of its decrease increases. That is to say, when the number of removed nodes increases, the negative impact of removing a node on the node recovery robustness will become stronger and stronger, and the degree of damage to the network structure will also increase; when the number of removed nodes exceeds 600, the rate of decrease in the node recovery robustness is accelerated. When the number of nodes exceeds 830, the value of node recovery robustness is below 0.1, and the ecological function of the network is almost completely lost. Under malicious attacks, when the number of removed nodes is less than about 300, the network structure can be completely recovered; then, with the increase in the number of removed nodes, the node recovery robustness shows a decreasing trend, and the rate of decrease increases, which is similar to the curve under random attacks. However, several important node number critical points of the malicious attack are larger than the random attack, indicating that the damage caused by random attacks is stronger than malicious attacks in terms of node recovery robustness.

The initial corridor recovery robustness of the network is 1. The corridor recovery robustness curves under random attack and malicious attack are both convex curves. When fewer corridors are removed, the network structure can be recovered; as the number of damaged corridors increases, the corridor recovery robustness decreases significantly, and the rate of decrease increases. When the number of removed corridors is less than 830, the negative impact of malicious attacks on corridor recovery robustness and the damage to the network structure are higher than those of random attacks. The critical point of the corridor number where the corridor recovery robustness drops below 0.1 for malicious attacks is around 830, and for random attacks, it is around 800. At this time, the network structure is close to collapse. When it is more than 830, the damage of random attacks is slightly stronger than malicious attacks.

3.3. The Relationship between Ecospatial Network Topology Index and NPP

3.3.1. Spatial Distribution Characteristics of NPP

The distribution characteristics of NPP throughout Inner Mongolia are shown in Figure 13.

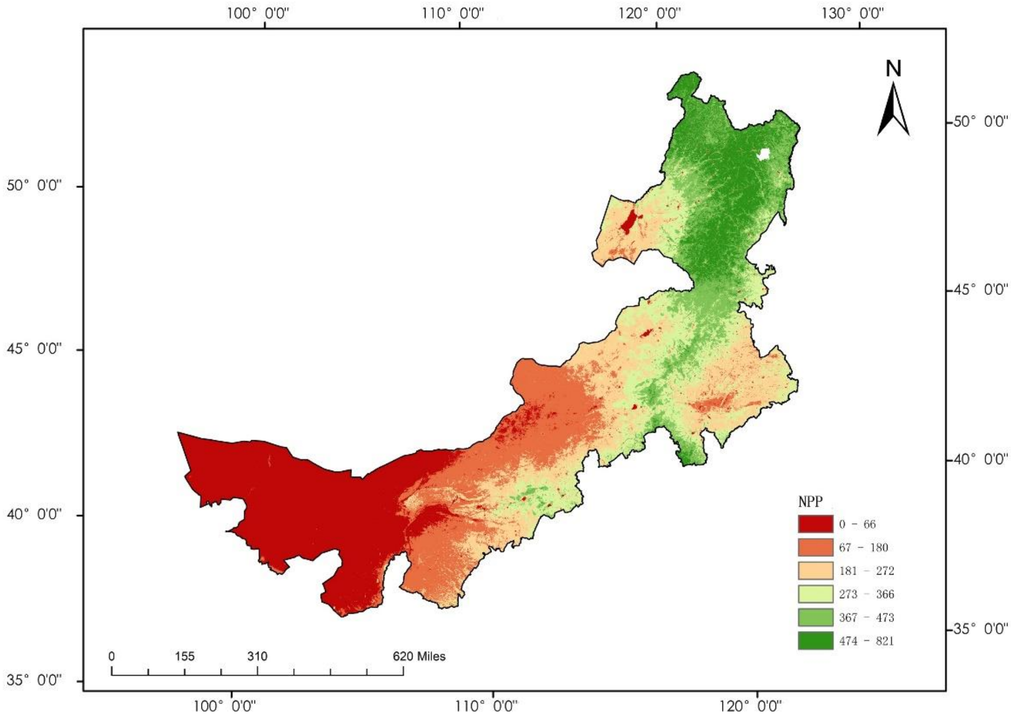


Figure 13. NPP spatial distribution.

As shown in Figure 13, the average value of NPP in Inner Mongolia is 228.419 $g \cdot m^{-2} \cdot a^{-1}$, the maximum value is 821 $g \cdot m^{-2} \cdot a^{-1}$, and the standard deviation is 175.549 $g \cdot m^{-2} \cdot a^{-1}$. Spatially, the high NPP values are mainly distributed in the northern region, mostly in the 474 to 821 range; the NPP value in the western region is relatively low, mostly in the 0 to 66 range; the NPP value in the central region is at a medium level. The vegetation composition is the main reason for the spatial heterogeneity of NPP in the study area. In terms of the ecospatial network structure, the NPP values in the northern and western regions, where the ecospatial network is relatively sparse, are in the maximum and minimum value ranges, respectively; the NPP in the central region, where the ecospatial network is denser, is in the middle range. There are also differences in NPP among different land cover types. The highest average NPP is woodland, which is 467.852 $g \cdot m^{-2} \cdot a^{-1}$; followed by cultivated land at 300.225 $g \cdot m^{-2} \cdot a^{-1}$, residential land at 218.185 $g \cdot m^{-2} \cdot a^{-1}$, grassland at 214.279 $g \cdot m^{-2} \cdot a^{-1}$, water at 143.154 $g \cdot m^{-2} \cdot a^{-1}$, and unused land at 91.861 $g \cdot m^{-2} \cdot a^{-1}$.

3.3.2. Correlation Analysis between Topological Indices and NPP of Different Land Cover Types

Since the topological indices values of ecological nodes in different land cover types in the study area are different, and their correlation and regression relationship with NPP is also significantly different, this paper divides the ecological source patches into three basic land areas: woodland, grassland, and water. The ecological nodes extracted from these three ecological source patches are also divided into three types. The topological indices of these three types of ecological nodes are correlated and regressed with NPP, respectively. Firstly, the Pearson correlation coefficients and significance levels of the degree and clustering coefficients of nodes with different land cover types and NPP were calculated separately using SPSS, where the significance test results less than 0.05 are usually considered to mean that the results are significant, i.e., the results are not due to sampling error and are statistically significant. The results are shown in Table 3.

Table 3. Correlation analysis between NPP and topological indices of different land cover types.

Land Cover Type	Degree		Clustering Coefficient	
	Correlation Coefficient	*p*-Value *	Correlation Coefficient	*p*-Value *
Woodland	−0.444	<0.01	0.084	0.254
Grassland	−0.217	<0.01	−0.070	0.139
Water	−0.076	0.607	−0.116	0.433

* *p*-value is the abbreviation of the significance level, which is the result of the significance test. *p*-value < 0.01 means significance at the 0.01 level.

The results show that only the ecological nodes in woodland and grassland had a significant correlation between NPP and degree ($p < 0.01$), among which there is a strong negative correlation between the degree of nodes in forest land and NPP with a correlation of −0.444; the negative correlation between the degree of nodes in the grassland and NPP is lower with a correlation of −0.217. There is no significant correlation between the degree of ecological nodes in the waters and NPP, as well as the clustering coefficient of ecological nodes in the three land cover types and NPP ($p > 0.05$), and the absolute values of the correlation coefficient are also low, indicating that the correlation is low and the results might be caused by accidental factors and are not statistically significant.

Since there is a significant correlation between the degree of ecological nodes in woodland and grassland and NPP, further regression analysis was applied to these two sets of data.

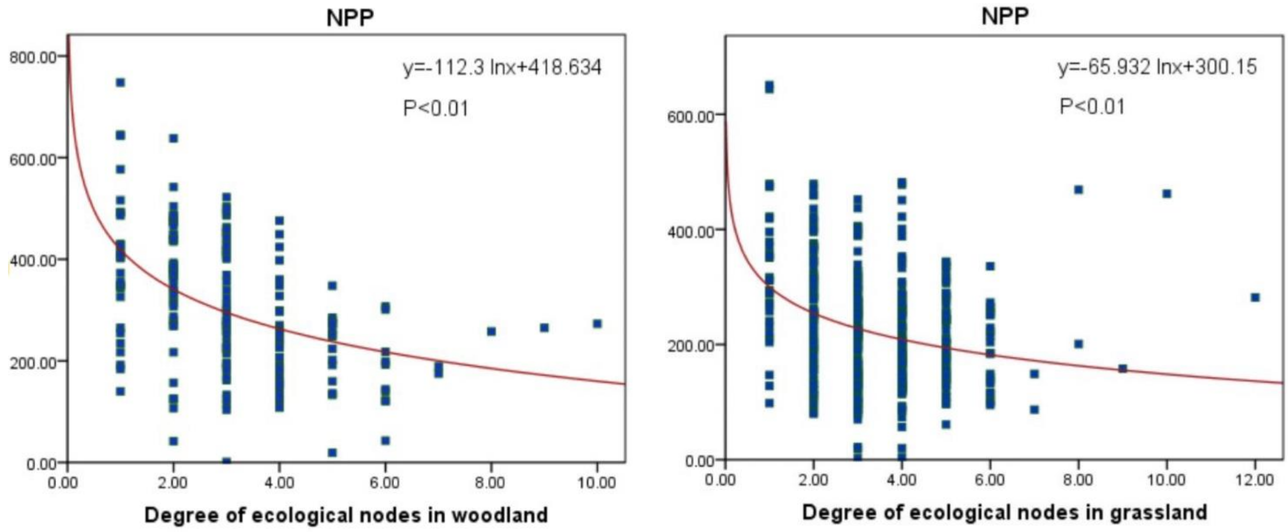
In order to evaluate the fitting ability of the model and select the optimal regression model, this paper used the goodness of fit index (R^2). R^2 indicates the goodness of fit of the model and the stability of model validation; the closer R^2 is to 1, the better the dependent variable can be explained by the independent variable, and the better the model fits [46,47]. SPSS was used to calculate R^2 and the significance level of the linear regression model and each curve regression model for comparison. The results are shown in Table 4.

Table 4. Comparison of the goodness of fit of regression models.

Regression Model	Woodland		Grassland	
	R^2	*p*-Value *	R^2	*p*-Value *
Linear model	0.197	<0.01	0.047	<0.01
Logarithmic function curve	0.210	<0.01	0.089	<0.01
Power function curve	0.105	<0.01	0.047	<0.01
Exponential function curve	0.096	<0.01	0.024	<0.01

* *p*-value is the abbreviation of significance level, which is the result of the significance test. *p*-Value < 0.01 means significance at the 0.01 level.

The results show that all curve models are correlated at the significance level of 0.01. In the regression model between the degree of woodland nodes and NPP, the logarithmic function curve has an R^2 value closest to 1, and the best goodness of fit; in the regression model between the degree of grassland nodes and NPP, the R^2 value of logarithmic function curve is also the closest to 1, and the goodness of fit is the best. Therefore, the logarithmic function curve is selected for fitting. The fitting results are shown in Figure 14.



(**a**) (**b**)

Figure 14. (**a**) Forest NPP–degree correlation distribution and fitting curve; (**b**) grassland NPP–degree correlation distribution and fitting curve.

Figure 14a shows the fitting results between the degree of ecological nodes in woodland and NPP, and the regression equation is $y = -112.3 \ln x + 418.634$. Between the degree of ecological nodes in grassland and NPP, as shown in Figure 14b, the regression equation is $y = -65.932 \ln x + 300.15$. The results show that the degree of nodes in both woodland and grassland has a negative effect on NPP, and the negative effect of nodes in woodland is even stronger. With the increase in degree, NPP gradually decreased, but its decline rate gradually decreased; that is, with the increase in degree, the negative influence of degree on NPP gradually decreased. Therefore, in terms of improving the carbon sequestration and oxygen release capacity of the ecosystem in the study area, under the premise of taking into account the network connectivity, reducing the average degree of the ecospatial network is the key direction of optimization, and the nodes with moderately low degrees in woodlands and grasslands are the key areas for ecospatial network optimization.

4. Discussion

4.1. Ecological Network Construction

In this paper, the importance of land patches was evaluated using parameters such as area and shape index as reference indicators, and a total of 143,524 ecological source sites of six types were screened in the study area accordingly; the cumulative resistance surface was constructed by combining factors such as elevation and slope, and 1519 ecological corridors and 861 ecological nodes were extracted based on the MCR model, according to which a potentially complex ecospatial network was constructed in the study area. This is an ecospatial network construction process that has been generally recognized and widely used in previous studies [11,48–50], and this research method can be used to guide the planning of ecological environment protection and restoration.

Geographically, the nodes and corridors in the ecospatial network were mainly distributed in the central, southern and eastern parts of the country. Compared with the northern and western parts, the ecological nodes and corridors in these areas were relatively clustered, indicating that the landscape patches in these areas were more conducive to the migration of biological species and the flow of ecological energy [51]. In terms of land cover types, nodes and corridors within woodlands and unused land were relatively sparse, and the network structure was relatively simple. In particular, habitat fragmentation within unused land was more serious. Conversely, the agro-pastoral, farm-forest ecotone and grassland areas had relatively complex network structures, indicating that these areas had more critical ecological service roles in the Inner Mongolia ecosystem. Therefore, the unused land in the west is the key area for ecological restoration, and it is necessary to add new ecological nodes and corridors [52] to ensure the mobility of ecosystem materials and energy; while the central, southern and eastern agro-pastoral, farm-forest ecotone and grassland areas are more potential areas for enhancing ecosystem services in the future and are the key areas for related ecological engineering planning.

4.2. Ecological Network Evaluation and Optimization Suggestions

Increasing ecological nodes and corridors is an effective way to optimize ecospatial networks [53], and optimizing ecospatial networks to improve the carbon sequestration capacity of ecosystems is an important way to achieve carbon neutrality [54]. The analysis of network structural characteristics is the basis of network optimization. At the same time, Inner Mongolia is a typical region with serious ecological damage and high carbon emission intensity. Therefore, it is of great practical significance to analyze the structural characteristics of the ecospatial network in Inner Mongolia and its relationship with carbon sequestration capacity.

Combined with the analysis of ecospatial network robustness, the restoration robustness of nodes is slightly stronger than that of corridors, so we suggest that the basic principle of optimization is to primarily increase ecological corridors and increase ecological nodes as a supplement. We calculated the completeness and topological indexes of complex ecospatial networks, and the results mainly illustrated that in terms of spatial distribution, nodes with high topological indexes were mostly distributed in farm-forest ecotones, grasslands, and agro-pastoral ecotones, while nodes with low topological indexes were mostly distributed in woodlands and forest-grassland ecotones. Previous studies have shown that the topological index represents the importance of nodes in maintaining the ecological function of the network to a certain extent [40]. Therefore, in the study area of this paper, the ecological nodes in the farm-forest ecotones, grasslands, and agro-pastoral ecotones have a greater contribution to the network, which further confirms the conclusion in Section 4.1 that these areas are the key areas that can further exert ecological functions through human planning.

At the same time, the distribution of NPP also showed a clear spatial heterogeneity, with higher values in woodlands, farm-forest ecotones, and agro-pastoral ecotones and slightly lower values in grasslands and unused land, which is consistent with the existing research results on the spatial distribution of NPP [55]. It can be found that the spatial distribution of ecological nodes based on topological indicators is similar to the spatial distribution based on NPP; for example, the higher farm-forest and agro-pastoral interlacing areas are also areas with higher NPP values, which indicates that the topological characteristics of ecological nodes within a specific land cover type are related to the carbon sequestration capacity. In other words, it is feasible to enhance the carbon sequestration capacity by optimizing the topological characteristics of ecospatial networks, which is one of the implications of this study. Through the analysis, we found that the degree of nodes in woodlands and grasslands had a significant negative correlation with NPP, and reducing the degree of ecological nodes in woodlands and grasslands is an effective means to improve the carbon sequestration capacity of ecosystems under the premise of ensuring network connectivity, that is, to rationally combine ecological nodes and corridors in these areas to an appropriate extent. This conclusion provides a theoretical basis for the subsequent optimization of ecospatial networks.

4.3. Research Limitations and Future Research Directions

There are still some shortcomings in this study, mainly in the following aspects: (1) only two topological indexes, namely, degree and clustering coefficient, were selected to analyze the correlation with the carbon sequestration capacity of ecosystems, and more topological indexes can be introduced in the future. (2) This paper conducts research in the form of static analysis. In the future, data from different periods can be selected for dynamic research, and the temporal and spatial evolution characteristics of ecospatial networks and NPP can be analyzed separately, so as to explore the influence of ecological pattern evolution on carbon sequestration capacity. (3) The study area of this paper is wide and more focused on the analysis of spatial heterogeneity, which can only give macroscopic suggestions for optimization. In future studies, the scale can be appropriately reduced, and a small area with typical characteristics can be selected to establish an ecospatial network for special research, so as to obtain more targeted suggestions.

5. Conclusions

(1) The structural characteristics of the ecospatial network in the study area were significantly spatially heterogeneous and showed obvious regularity with land cover types. Nodes and corridors in the central, southern, and eastern agro-pastoral, farm-forest ecotones and grasslands were densely distributed with more complex corridor orientations, while the distribution in the western unused land was relatively sparse, and the corridor orientations were relatively simple;

(2) By calculating the completeness index, topology index and robustness of the ecospatial network, it could be seen that the overall circularity and circulation of the ecospatial network were at a medium level, with an obvious scale-free, non-uniform and non-hierarchical nature and strong resilience. The degree distribution of nodes also showed spatial heterogeneity, and nodes with higher degrees were mostly distributed in the farm-forest ecotones, grasslands, and agro-pastoral ecotones; nodes with lower degrees were mostly distributed in the woodlands and forest-grass ecotones;

(3) The degree of nodes within the woodlands and grasslands within the ecospatial network was significantly and negatively correlated with the carbon sequestration capacity, and the fitting results were consistent with the logarithmic function curve. Meanwhile, combined with the above findings, macroscopic suggestions were made for the future planning and construction of the ecospatial network. The unused land in the west is the key area to be restored, and the woodlands, grasslands, and the surrounding agro-pastoral and farm-forest ecotones are the key areas to improve the carbon sequestration capacity of the ecosystem.

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