

Article

Analysis on Ecological Network Pattern Changes in the Pearl River Delta Forest Urban Agglomeration from 2000 to 2020

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Abstract: The advancement of urbanization has led to a decline in the ecological function and environmental quality of cities, seriously reducing the services and sustainable development capacity of urban ecosystems. The construction of the National Forest Urban Agglomeration of China is conducive to alleviating the ecological and environmental problems brought about by rapid urbanization and promoting sustainable urban development. A time series analysis of ecological network changes can quickly and effectively explore the development and changes of ecological spatial patterns over time. Identifying ecological protection and restoration areas in urban agglomerations is an important way to promote ecosystem restoration and optimize ecological networks. This paper takes the Pearl River Delta forest urban agglomeration as the research area, uses multi-source remote sensing data from 2000 to 2020 (every 5 years), identifies ecological sources based on the morphological spatial pattern analysis (MSPA) method, generates ecological corridors based on the minimum cumulative resistance (MCR) model, constructs a time series ecological network pattern in the Pearl River Delta region, and analyzes the evolution process of the ecological network pattern over time. The results indicate that over time, the core green area in the ecological network pattern of the Pearl River Delta first decreased and then increased, and the complexity of ecological corridors first decreased and then increased. The main reason is that the urbanization process in the early 21st century led to severe ecological fragmentation. Under the promotion of the national forest urban agglomeration construction, the ecological network pattern of the Pearl River Delta was restored in 2015 and 2020. The time series analysis of the ecological network pattern in the Pearl River Delta region of this research confirms the effectiveness of the construction of forest urban agglomerations, providing a scientific reference for the identification of ecological networks and optimization of spatial patterns in forest urban agglomerations.

Keywords: Pearl River Delta; ecological network; time series analysis; morphological spatial pattern analysis; minimum cumulative resistance model; forest urban agglomeration



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1. Introduction

With rapid economic development and the acceleration of urbanization, the scales of cities continue to expand, and the ecological land, such as forests, wetlands, and grasslands, which can provide a variety of ecosystem services, has been occupied and destroyed in large numbers, resulting in the increased vulnerability of ecosystems, the imbalance of ecological functions, and great challenges to ecological security [1–3]. The United Nations has proposed 17 Sustainable Development Goals (SDGs) in the 2030 Agenda for

Sustainable Development [4–7], many of which are closely related to ecological construction. Ecological construction aims to elevate sustainable development to the height of green development, that is, by protecting and restoring the ecosystem, rationally utilizing natural resources, and reducing the impact on the environment, we can better achieve the goal of sustainable development and promote the sustainable development of the ecosystem [8,9]. Ecological construction is an important component in achieving SDG11 (Sustainable Cities and Communities), SDG13 (Climate Action), SDG15 (Life for Land), and other goals.

In 2013, the national forest urban agglomeration construction of China was put on the agenda, which aims to help cities and forests co-exist and play a positive role in environmental protection and urbanization development through measures such as increasing the urban greening rate, protecting the natural ecological environment, and developing eco-tourism. This is conducive to alleviating a series of ecological and environmental problems brought about by rapid urbanization and promoting sustainable urban development. The ecological network is the focus and hotspot of ecological research [1,8,9]. The construction of the ecological network pattern of forest urban agglomerations can effectively connect forests, grasslands, and wetlands among cities, help to expand the existing ecological space, form forest wetlands, strengthen the cohesion of the ecological space of urban agglomerations, and optimize the development pattern of urban agglomerations [10].

More and more scholars have studied the ecological spatial network patterns of cities and urban agglomerations by using multi-source remote sensing data based on multi-source spatial analysis methods, and have achieved some important results [11]. The minimum cumulative resistance (MCR) method was proposed by Knaapen et al. [6] and applied to landscape and urban planning [12,13]. Yu Kongjian [14] applied the MCR method to the construction of ecological security patterns in biological protection, and the MCR method is currently widely used in the fields of land use and species protection. Scholars such as Vogt proposed the morphological spatial pattern analysis (MSPA) method [15], which can more accurately describe and quantify the spatial distribution pattern of ground objects [16]. The MSPA method provides a quantitative description of the spatial distribution, connectivity, and morphological characteristics of land objects, which can help to identify key habitat structures and spatial patterns [17–19]. The MCR method, on the other hand, can comprehensively consider the impact of terrain, land-use types, human activities, etc., and can predict ecological processes such as species dispersal paths, habitat connectivity, and fractures, and build potential ecological corridors [20]. Combining the two methods can analyze the spatial pattern of the ecosystem more comprehensively and provide a scientific basis for ecological protection and management.

Wei Hong et al. combined the minimum cumulative resistance model and morphological spatial pattern analysis method to construct an ecological security network for the Loess Plateau in China [21]. It provided a valuable reference for constructing the ecological security network and optimizing the ecological space in ecologically fragile areas of western China. Liu Jia et al. used Linkage Mapper to generate potential corridors, and then identified and extracted potential stepstone patches through the gravity model and betweenness centrality to construct the optimal ecological network of the source region of the Yellow River based on the minimum cumulative resistance model and morphological spatial pattern analysis method [22]. Wu Bin et al. identified ecological sources using the MSPA method based on land-use data from 2007, 2012, and 2017 in mountainous karst areas, extracted potential ecological corridors using the MCR model, and identified the ecological network for three periods [23]. However, many researchers have focused more on improving methods for constructing ecological resistance surfaces in a certain region, and few have explored the spatiotemporal evolution characteristics of ecological spatial networks. Qiu Shi et al. combined with the modified minimum cumulative resistance model, constructed a time series forest ecological spatial network with 1 km spatial resolution in China from 2000 to 2018 (2000, 2005, 2010, 2015, and 2018) based on the complex network theory and graph theory [24]. Wu Jiansheng et al. constructed an ecological network of the dispersion scale of five species from 1990 to 2020 based on the morphological spatial pattern

analysis method [25], identified the ecological groups in the network, and used the core node-based community evolution path tracking algorithm to analyze the ecological groups.

The Pearl River Delta region plays an important role in China's economic development, ecological protection, ecological services, and regional coordinated development. In terms of the ecological security network pattern, there are still problems regarding unbalanced and insufficient development among regions. Therefore, researchers have been working on the ecological security network pattern in the Pearl River Delta region [26]. He Xiong et al. evaluated the multi-center spatial structure of the Pearl River Delta urban agglomeration based on multi-source big data fusion [27]. Feng Shu et al. identified the ecological sources, ecological corridors, and ecological nodes to form the ecological network of the Greater Bay Area based on MSPA and MCR [28]. Exploring and analyzing the changes in the ecological spatial pattern over time at the scale of the entire forest city agglomeration is the key to improving the ecological quality of the Pearl River Delta national forest city agglomeration.

However, so far, no research has conducted a time series analysis of the ecological network of the Pearl River Delta national forest urban agglomeration. Analyzing the changes in ecological networks over time can effectively explore the evolution process of the spatial development patterns of urban agglomerations, thereby discussing the influencing factors of the spatial pattern changes in the Pearl River Delta and confirming the effectiveness of the construction of national forest urban agglomerations. Based on these, basic data on spatial geography, remote sensing monitoring, land cover, and other aspects of the Pearl River Delta urban agglomeration at 30 m spatial resolution from 2000 to 2020, with a 5-year interval (2000, 2005, 2010, 2015, 2020), were selected for research in this paper. The morphological spatial pattern analysis (MSPA) method and the minimum cumulative resistance (MCR) model were adopted to extract ecological sources and identify the 2000–2020 (every 5 years) time series ecological corridors and ecological networks in the Pearl River Delta national forest urban agglomeration. Thus, this paper can provide a scientific basis and technical support for the optimization decision-making of the ecological spatial pattern of the Pearl River Delta national forest urban agglomeration.

2. Materials and Methods

2.1. Research Area and Data Sources

2.1.1. Research Area

The Pearl River Delta is located in the south-central part of Guangdong Province, China, on the lower reaches of the Pearl River, and borders the South China Sea. It has superior natural conditions and rich marine resources of animals and plants. The Pearl River Delta is a pioneer region in China's reform and opening up, with a high level of economic development. It accounts for less than one-third of Guangdong Province's area, and comprises 53.35% of Guangdong Province's population and 79.67% of its total economic output.

The Pearl River Delta urban agglomeration includes nine cities in Guangdong Province, including Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing. From a spatial perspective, the entire research area is formed into an isosceles triangle with rounded corners (Figure 1). The built-up areas are relatively concentrated, and the forest area is vast. The forest coverage rate of the Pearl River Delta reaches 51.8%. To the south of the research area are Hong Kong, China and Macau, China, as well as coastlines and islands. The Pearl River Delta urban agglomeration has diverse ecological spaces, such as rivers, beaches, forests, and wetlands, with dense populations and economic factors.

The basic data shown in Figure 1 include the 2020 Gaofen-1 satellite remote sensing image of the Pearl River Delta region, which has a resolution of 16 m. The GXL v1 software was used to preprocess images of the Pearl River Delta region, including mosaic and orthorectification. The projection coordinate system is WGS-1984-UTM-Zone-49N.

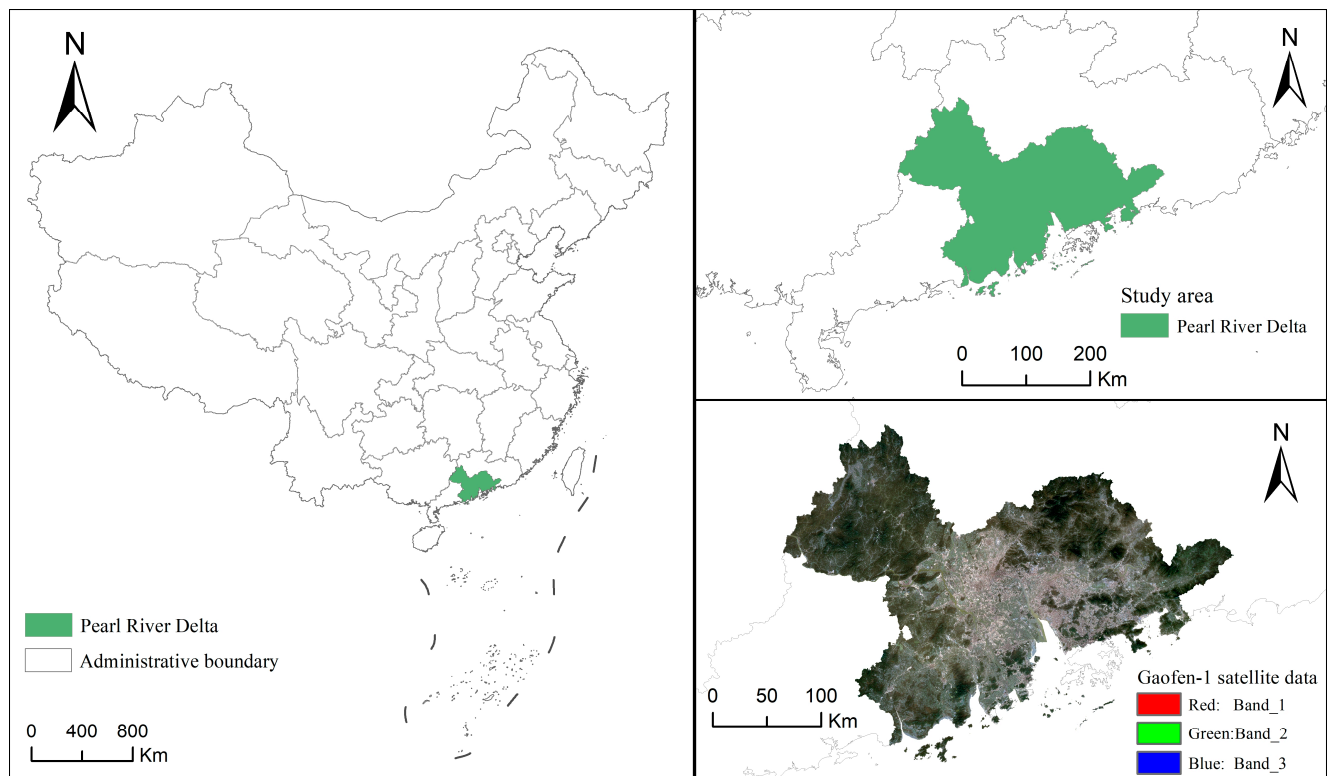


Figure 1. Pearl River Delta research area.

2.1.2. Data Sources

The annual Normalized Difference Vegetation Index (NDVI) data used in this research were obtained from the Resources and Environmental Science and Data Center, Chinese Academy of Sciences (<https://www.resdc.cn/> (accessed on 26 September 2022)) with a 30 m spatial resolution. The data were integrated using the Google Earth Engine (GEE) remote sensing cloud computing platform, using Landsat 5/8 remote sensing images from the United States to calculate the annual NDVI maximum dataset since 1986. During the calculation process, the NDVI was calculated for all the Landsat 5/8 remote sensing images throughout the year, and then the maximum NDVI value for each pixel location was obtained for the year, generating the annual NDVI maximum data.

Global 30 m land-cover dynamic monitoring products with fine classification system from 2000 to 2020 (GLC_FCS30) [29] in this research were obtained from the website <https://zenodo.org/records/3986872> (accessed on 26 June 2022). GLC_FCS30-1985_2020 products were produced by using the continuous time series Landsat imagery on the Google Earth Engine platform [29–32], containing 29 land-cover types.

Digital elevation model (DEM) data with a 30 m resolution were obtained from the Geospatial Data Cloud (<https://www.gscloud.cn/> (accessed on 22 January 2022)). The slope data used in this paper were extracted from the DEM data.

The time series nighttime light remote sensing data were obtained from the website <https://eogdata.mines.edu/> (accessed on 23 June 2022). A DMSP/OLS and VIIRS nighttime light time series product with radiation consistency was selected in this research, which was generated using the robust ridge sampling regression (RSR) method [33,34]. Due to the different orbit times of the sensors, the nighttime light remote sensing data used in 2000, 2005, and 2010 were DMSP/OLS products, while the VIIRS products were used in 2015 and 2020.

The above time series data were uniformly resampled with a spatial resolution of 30 m, which served as the data basis for constructing the resistance surface in Section 2.2 of this paper.

2.2. Research Methods

This research focused on the temporal and spatial changes of the ecological network spatial pattern in the Pearl River Delta national forest urban agglomeration. The technical processing flowchart is shown in Figure 2.

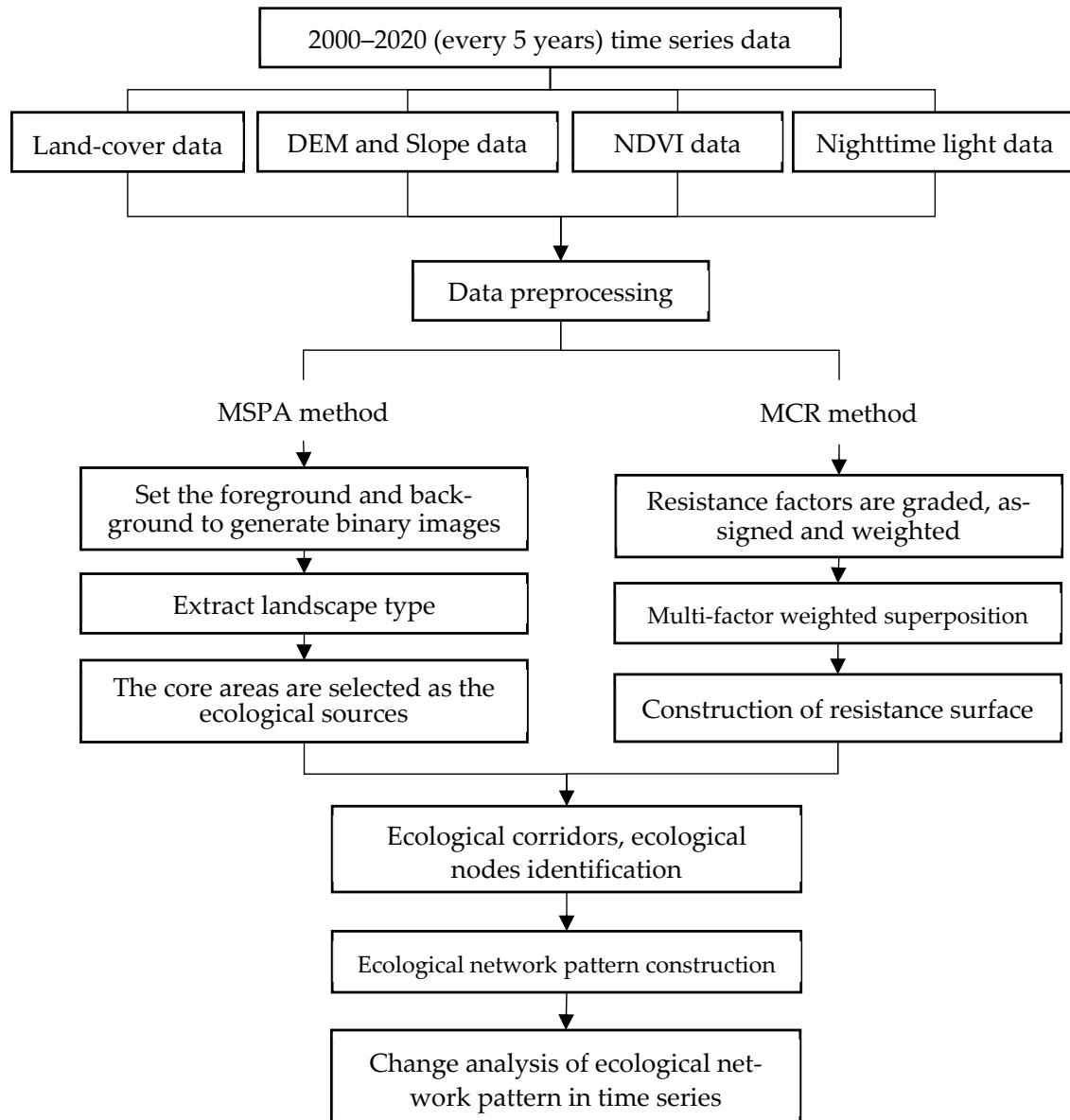


Figure 2. Data processing flowchart of the ecological network pattern.

The ArcGIS 10.8.2 and Guidos 1.7 software were used to extract ecological sources by using the morphological spatial pattern analysis (MSPA) method, and the minimum cumulative resistance (MCR) model was used to generate ecological resistance surfaces. Then the time series ecological corridors and ecological networks were constructed.

2.2.1. Morphological Spatial Pattern Analysis Method

Morphological spatial pattern analysis (MSPA) is a processing method that applies a series of graphic principles of morphological transformation to segment, recognize, and classify images. It divides binary images into seven types that do not overlap with each other: core, islet, bridge, loop, edge, perforation, and branch (Table 1). The MSPA method was first used in the research of forest landscape patterns, and then it was also used in the

analysis of spatial and temporal pattern changes of the green infrastructure network, the construction of the green infrastructure network, the connectivity analysis of the ecological network, the determination of ecological network source patches, and the construction of the ecological network [17,18,35–37].

Table 1. Landscape type definition and ecological implication of MSPA.

Landscape Types	Definition	Ecological Implication
Core	A set of pixels whose distance from the foreground pixel to the background pixel is greater than a parameter of a specified size.	Large natural patches, wildlife habitats, forest reserves, etc.
Islet	No foreground patches are connected, and the area is less than the minimum threshold of the core area.	Isolated, fragmented small natural patches that are not connected to each other and usually include small urban green spaces within built areas.
Perforation	The hole inside the central area, with the background forming the outer edge of the foreground.	The construction land in the core area of the ecological space does not have ecological benefits.
Edge	Outer edge of the foreground.	The transition between the core area and the construction land, and has the edge effect.
Loop	At least two points are connected to the same core area.	The ecological corridor connected to the same core area is small in scale and low in connection with the surrounding natural patches.
Bridge	There are at least two points connected to different core regions.	The pocketed ecological land connecting the core areas is a corridor in the regional green infrastructure, which promotes the flow of energy and the formation of networks within the region.
Branch	Only one side is connected to the edge zone, bridge zone, or loop zone.	Ecological patches that are only connected to a section of the core area have poor landscape connectivity.

Landscape connectivity refers to the degree to which the landscape promotes or hinders the movement of organisms or ecological processes between source areas, and it is of great significance in maintaining ecosystem services and protecting biodiversity [38–40]. Commonly used landscape connectivity indices include the integral index of connectivity (IIC) and the probability of connectivity (PC). They can evaluate the connection level between core patches in the region [21,22], and have a good indication function for extracting ecological source patches. They are calculated using the following formula [21,22]:

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

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

where, $i \neq j$, n is the total number of woodland patches, a_i is the area of patch i , a_j is the area of patch j , nl_{ij} is the number of connections between patch i and patch j , and A_L^2 is the total area of woodland landscape. p_{ij}^* represents the maximum product probability of all paths between patch i and patch j .

2.2.2. Minimum Cumulative Resistance Model

In landscape ecology, the MCR model is the process of ecological flow overcoming the resistance of different landscape elements in the process of spatial coverage [14,41–43], and its minimum cost distance is the channel that overcomes the minimum accumulated resistance. The MCR model can determine the shortest path between the starting ecological

source point and the target ecological source point, representing the ecological resistance that ecological elements need to overcome when migrating from one ecological source to another [44]. The possibility of ecological sources expanding outward can be determined by the minimum cumulative resistance, reflecting the connectivity between the spatial units and sources. The specific expression of the MCR model is:

$$MCR = f_{min} \sum_{j=n}^{i=m} (D_{ij} \times R_i), \quad (3)$$

where, D_{ij} represents the spatial distance from the source point j to the landscape unit i ; R_i represents the resistance coefficient of the landscape unit i .

The key to establishing an MCR model is the selection of ecological sources and the construction of a resistance surface system. In this paper, except for the land-cover type data, the other four factors were classified and graded using the natural breaks (Jenks) method. Each factor was internally divided into five categories. The basic principle of the natural breaks method is to identify the classification interval based on the natural grouping that is inherent in the data, and to minimize the difference within the class and maximize the difference between each class [45]. As shown in Table 2, the mean values of the classification discontinuities of DEM are 76.78, 216.04, 401.72, and 660.35. The mean values of the classification discontinuities of Slope are 5.4, 12.23, 19.34, and 27.01. The mean values of the classification discontinuities of NDVI are 0.37, 0.52, 0.66, and 0.78. The mean values of the classification discontinuities of the DMSP/OLS nighttime light remote sensing data are: 534.95, 1662.17, 3222.84, and 4826.29. The mean values of the classification discontinuities of the VIIRS nighttime light remote sensing data are 4.18, 15.20, 30.91, and 79.83. With reference to the relevant research and combined with the expert scoring method, in order to highlight the differences in the effects of ecological resistance factors, the resistance values of ecological factors were assigned 1, 10, 20, 30, and 50 from low to high.

Table 2. Classifications, resistance values, and weights of each ecological resistance factor.

Ecological Resistance Factors	Classifications ¹	Resistance Values	Weights
DEM (m)	<76.78	1	0.2
	76.78–216.04	10	
	126.04–401.72	20	
	401.72–660.35	30	
	>660.35	50	
Slope (°)	<5.40	1	0.2
	5.4–12.23	10	
	12.23–19.34	20	
	19.34–27.01	30	
	>27.01	50	
NDVI	>0.78	1	0.2
	0.66–0.78	10	
	0.52–0.66	20	
	0.37–0.52	30	
	<0.37	50	
Land-cover type	Forests	1	0.2
	Grassland and shrubland	10	
	Water body	20	
	Cropland and bare areas	30	
	Impervious surfaces	50	

Table 2. Cont.

Ecological Resistance Factors	Classifications ¹		Resistance Values	Weights
Nighttime light data ²	DMSP/OLS	VIIRS	--	0.2
	<534.95	<4.18	1	
	534.95–1662.17	4.18–15.20	10	
	1662.17–3222.84	15.20–30.91	20	
	3222.84–4826.29	30.91–79.83	30	
	>4826.29	>79.83	50	

¹ The classification values shown in Table 2 are the average values of these 5 years of data. ² The classification columns of the nighttime light remote sensing data represent the values of DMSP/OLS and VIIRS, respectively. The DMSP/OLS values in the first column of the classification were used in 2000, 2005, and 2010, while the VIIRS/DNB values in the second column of the classification were used in 2015 and 2020.

The common methods used in determining the weights of ecological resistance factors are the analytic hierarchy process and the principal component analysis. The research focus of this paper is to construct and analyze time series ecological networks. The weights of different resistance factors at different times (2000–2020) are different. Therefore, in order to ensure the comparability of the construction of the time series resistance surfaces, this paper adopts the equal weight assignment method, where the weights of each resistance factor are the same (each weight is 0.2), to construct ecological resistance surfaces (Figure 3).

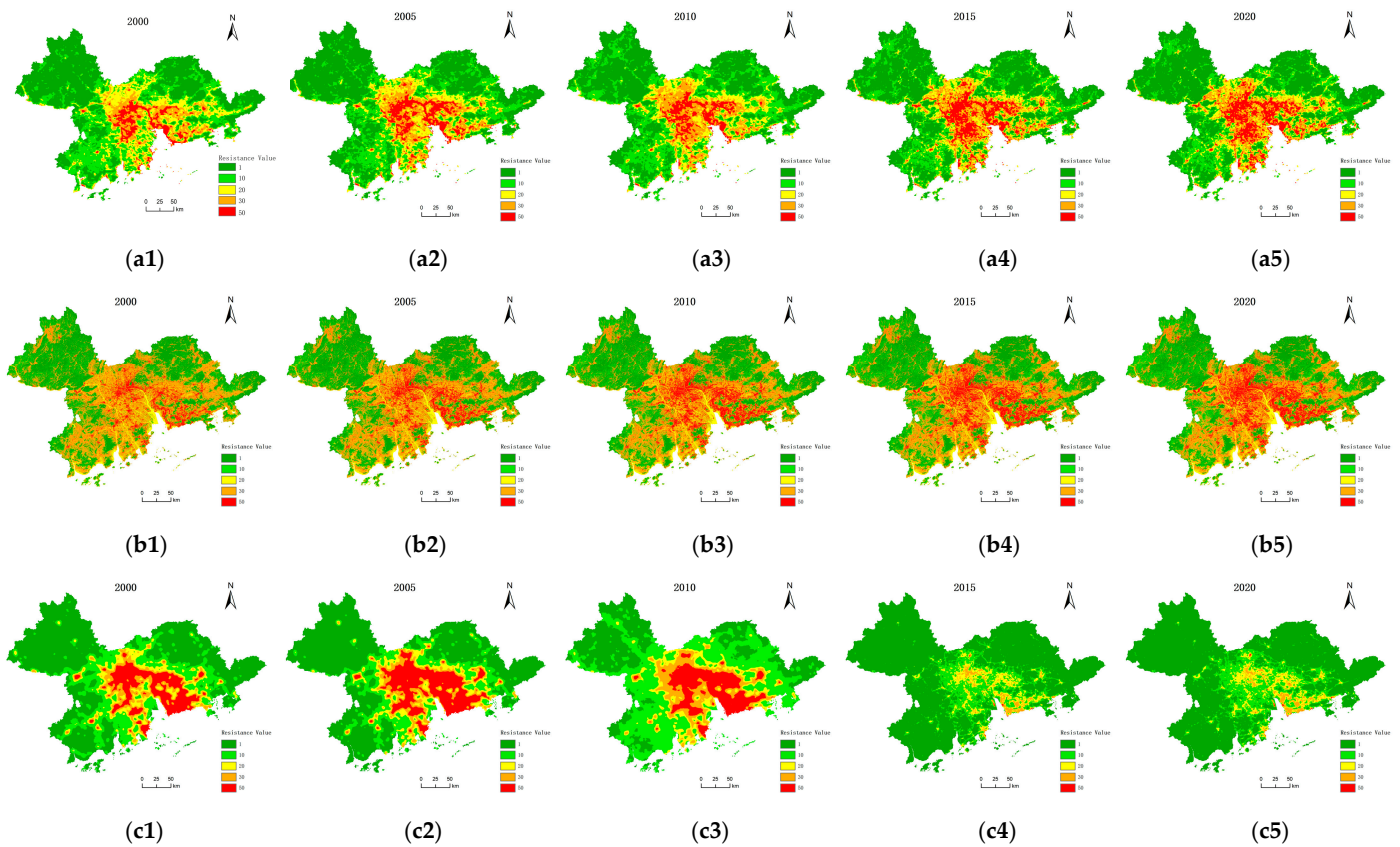


Figure 3. The resistance values of time series factors from 2000 to 2020. (a1–a5) represent the NDVI factors in 2000, 2005, 2010, 2015, and 2020, respectively. (b1–b5) represent the land-cover factors in 2000, 2005, 2010, 2015, and 2020, respectively. (c1–c5) represent the nighttime light factors in 2000, 2005, 2010, 2015, and 2020, respectively.

As can be seen in Figure 3a1–a5, the resistance value of the NDVI factor increased over time, indicating that the vegetation coverage area in the research area is decreasing. As can be seen in Figure 3b1–b5, the area of impervious surfaces in land-cover types increased,

resulting in an increase in the red area with high resistance values. In Figure 3c1–c5, due to the obvious oversaturation of the DMSP/OLS data used from 2000 to 2010, the red resistance value range is large, while the details are not as clear as in the VIIRS data of 2015 and 2020.

3. Results

3.1. Ecological Source Identification Based on the MSPA Method

The ArcGIS software was used to convert land-cover images of the Pearl River Delta region into binary images, with vegetation cover types such as forests and grasslands set as research foregrounds and other land-cover types as research backgrounds. The foregrounds are the ecological spaces that need to be analyzed, while the backgrounds are the urban and rural building land (impervious surfaces), water bodies, etc. The Guidos Toolbox software was used to perform a morphological spatial pattern analysis. The results of seven landscape types from 2000 to 2020 are shown in Table 3 and Figure 4.

Table 3. The results of landscape types based on the MSPA model.

Year	2000	2005	2010	2015	2020
Landscape Types	FG/Data (%) ¹	FG/Data (%)	FG/Data (%)	FG/Data (%)	FG/Data (%)
Core	75.07/64.63	74.42/62.27	74.10/60.40	73.79/59.03	73.58/58.13
Islet	0.74/0.64	1.10/0.92	1.42/1.16	1.70/1.36	1.78/1.41
Perforation	7.05/6.07	6.84/5.73	6.74/5.50	6.57/5.25	6.37/5.03
Edge	8.99/7.74	8.91/7.45	8.79/7.17	8.87/7.10	9.09/7.18
Loop	0.93/0.80	0.97/0.81	1.05/0.85	1.10/0.88	1.11/0.88
Bridge	6.13/5.28	6.47/5.41	6.44/5.25	6.41/5.13	6.44/5.09
Branch	1.10/0.95	1.29/1.08	1.45/1.18	1.56/1.25	1.64/1.29
Background	--/13.90	--/16.32	--/18.49	--/20.01	--/21.00
Total	100/100	100/100	100/100	100/100	100/100

¹ The first column in Table 3 is the proportion of this type to the foreground area (FG), and the second column is the proportion of this type to the entire image area (Data).

It can be seen that from 2000 to 2020, the proportion of core areas in the entire Pearl River Delta region decreased from 64.63% to 58.13%, and the proportion of background areas (built-up areas and water systems) increased from 13.90% to 21.00% (Table 3). Due to the acceleration of urbanization, the number of built-up areas increased rapidly from 2000 to 2010 [46–48]. With the advancement of ecological construction and forest urban agglomeration construction, the urbanization process has slowed down since 2010, and the background area growth from 2010 to 2020 was slow and stable. Table 3 shows that the proportion of the islet area increased rapidly from 2000 to 2010, which means that small, isolated green patches increased rapidly, while the islet area increased slowly from 2015 to 2020, that is, small, fragmented patches increased slowly. The overall trend of the perforation and edge areas slowly decreased from 2000 to 2020. These two landscape indices are related to the edge of the foreground, which indicates that the edge effect is reduced. The proportion of the loop area in both the foreground and the background showed an upward trend, which showed that the area with a low correlation with the surrounding natural patches increased and the ecological connectivity tended to decrease. The bridge area increased rapidly from 2000 to 2005 and remained relatively stable from 2005 to 2020. This is related to the complexity and activity of the corridors and is conducive to promoting the energy flow between core areas. The area of branch gradually increased from 2000 to 2020, indicating a decreasing trend in landscape.

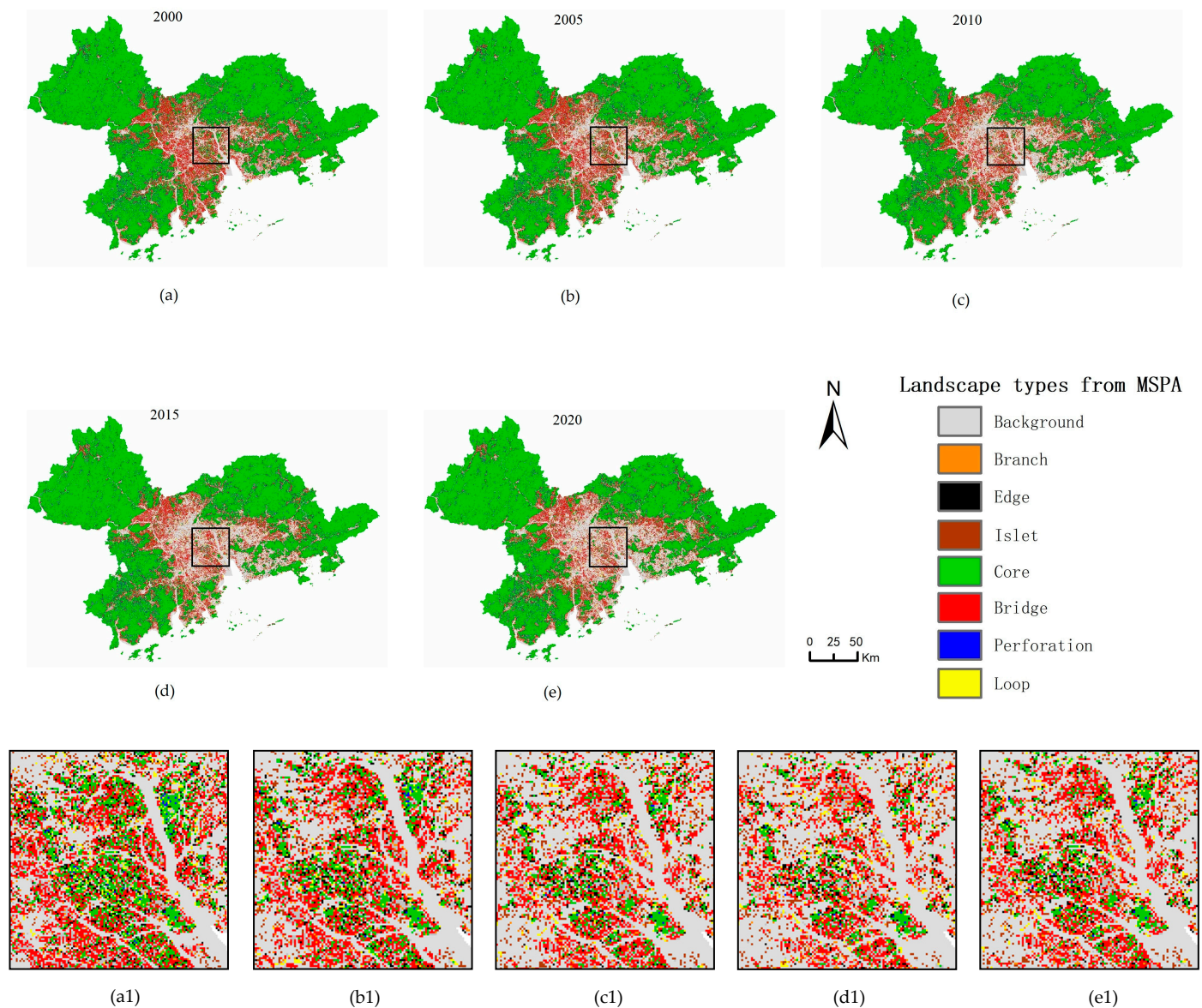


Figure 4. Landscape types based on the MSPA method. (a–e) represent the MSPA type of the global image of the Pearl River Delta from 2000 to 2020, and (a1–e1) represent the MSPA type (highlighted in the black block) of the local image of the Pearl River Delta from 2000 to 2020.

From the spatial distribution of the landscape pattern elements over these five years, it can be seen that the ecological core areas are mainly located in the periphery of the Pearl River Delta region, concentrated in high-altitude mountains and hills (Figure 4). High-altitude mountains and hills generally have higher vegetation coverage, so the core areas are concentrated in these areas. Compared with the other four years, the core areas in 2000 were larger, and it can be clearly seen from Figure 4(a1–e1) that the core areas have decreased over time. The bridge areas, as narrow and elongated areas connecting the core areas, represent the corridor-connecting patches in the ecological network and are of great significance for biological migration and landscape connectivity. From the local images in Figure 4(a1–e1), the bridges (red regions) were the highest in 2005. From 2000 to 2020, branch (orange regions) gradually increased, edge (black regions) showed a downward trend, and loop (yellow regions) showed an increasing trend.

Ecological source areas are large ecological patches with high connectivity and ecological service value. From 2000 to 2020, there was almost no change in the spatial distribution of ecological sources. From the perspective of space, the ecological source areas are mainly distributed in the northwest, southwest, and northeast of the Pearl River Delta, and the large ecological source areas are concentrated in the northwest. This research combined *IIC*, *PC*, and *dPC* to measure the patch connectivity and importance, and comprehensively considered the patch area and its spatial distribution to extract important ecological sources and general ecological sources (Figure 5). The core is the most important landscape type in MSPA, which is used to extract ecological sources and ecological corridors. This research adopted the minimum area threshold method [15] to select ecological source areas, excluding small and scattered patches with limited impact, and finally selected 15 core area patches with an area greater than 100 hm² as important ecological sources.

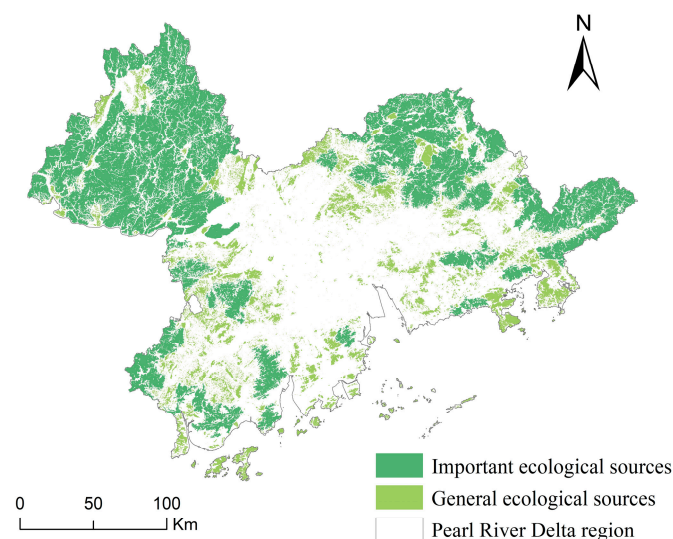


Figure 5. Important and general ecological sources of the Pearl River Delta.

3.2. Ecological Resistance Surface Construction Based on the MCR Model

The ecological resistance surface is the resistance that species need to overcome when moving between ecological sources. According to previous studies [43,49], natural conditions and human activities jointly affect the resistance level of the ecological resistance surface. This research combined the availability of time series data from 2000 to 2020 and selected elevation, slope, normalized vegetation index (NDVI), land-cover type, and nighttime light remote sensing data as ecological resistance factors from three aspects—terrain, land-use type, and human activity impact—to construct ecological resistance surfaces. By referring to the research of relevant scholars, the appropriate resistance factor grading and resistance values of the Pearl River Delta research area were determined [50–52]. The results of the reclassification and weight assignment of each factor were performed using a band calculation to obtain the resistance surfaces from 2000 to 2020, as shown in Figure 6.

It can be seen from the time series resistance surface results that the highest resistance value of the resistance surface in 2015 and 2020 has decreased. From Figure 6, it can also be seen that the areas with high resistance values in 2015 and 2020 were relatively small (red areas), while the areas with low resistance values from 2000 to 2015 were relatively large (blue areas). The resistance surface details are more obvious in 2015 and 2020. This is because the VIIRS nighttime light remote sensing data used in 2015 and 2020 have a higher resolution than the data used in other years.

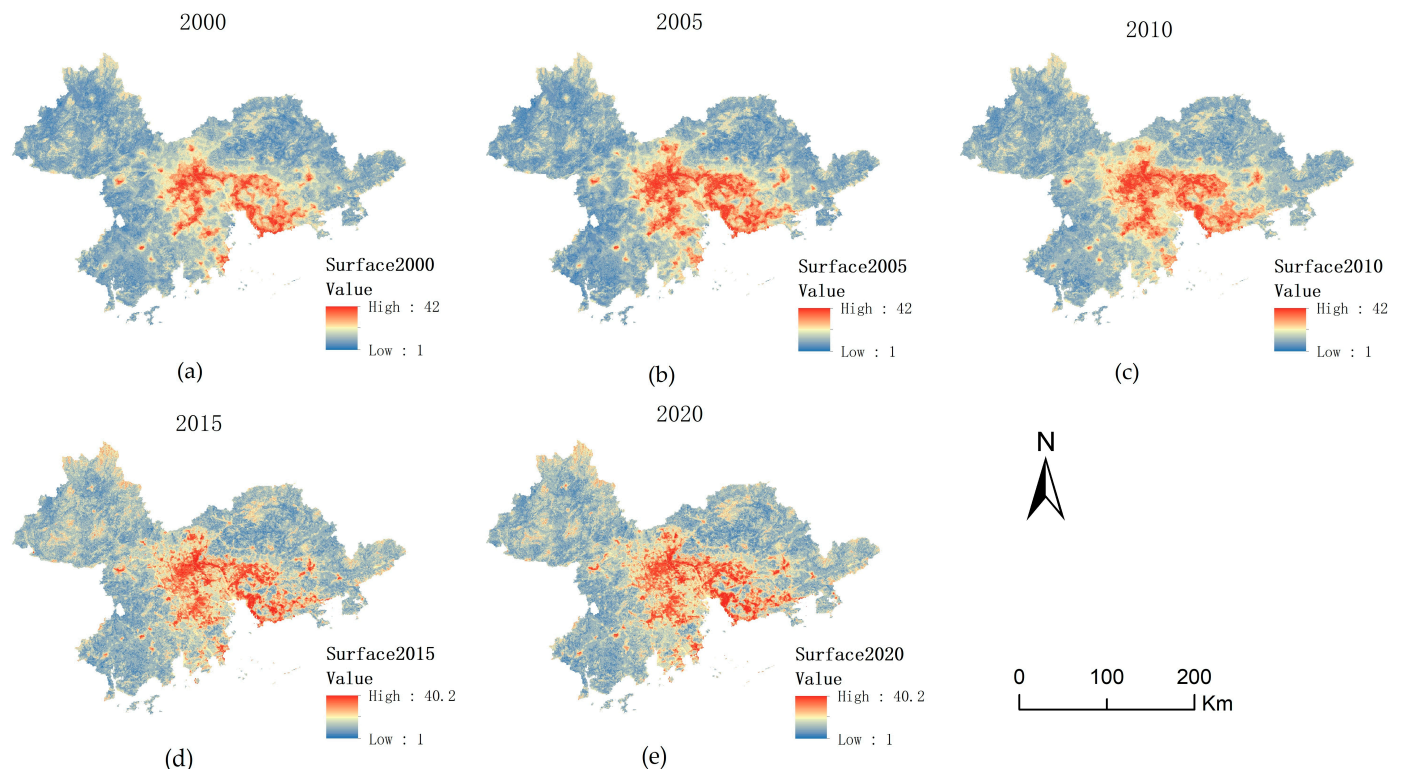


Figure 6. Ecological resistance surfaces construction based on the MCR model. (a) 2000; (b) 2005; (c) 2010; (d) 2015; (e) 2020.

3.3. Time Series Ecological Networks Construction Based on the MSPA and MCR Methods

Ecological corridors refer to the narrow and continuous strip areas between ecological sources, which can improve the migration efficiency of organisms and promote gene exchange between local populations, thereby reducing the negative impact of habitat patch fragmentation [53]. They not only enable sustainable landscape ecological processes, but also help to enrich the biodiversity of the local area. The ecological corridor connects two ecological sources, making it the minimum resistance channel between the two sources. In the MCR model, the ecological corridor is established on the path with the lowest cost connecting the ecological sources [54]. The shortest path was calculated to form ecological corridors between the source and source areas based on the important ecological source points and ecological resistance surfaces. The ecological corridors of the Pearl River Delta region from 2000 to 2020 were extracted from the least cost path (LCP) using the ArcGIS Linkage Mapper 2.0 software, consisting of active and inactive ecological corridors. The number and length of the ecological corridors vary from year to year. As shown in Figure 7, active and inactive ecological corridors together form the ecological network.

From the spatial distribution of the ecological corridors from 2000 to 2020 (Figure 7), it can be seen that the ecological corridors within the northwest, southwest, and northeast of the Pearl River Delta are relatively abundant, while the ecological corridors connecting the three regions are relatively simple. The ecological corridors in the central built-up area of the Pearl River Delta are missing. These are all related to the urbanization process in the Pearl River Delta. The Pearl River Delta experienced rapid urban expansion at the beginning of the 21st century, leading to ecological destruction and the reduction of green space. With the advancement of the construction of the forest city cluster in the Pearl River Delta, the ecological resources within the Pearl River Delta are more closely connected, and the spatial structure of the ecological network is also increasing in complexity. From Figure 7d,e, it can be seen that in 2015 and 2020, the construction of forest urban agglomerations achieved results, and the forest ecological network pattern in the Pearl River Delta gradually recovered.

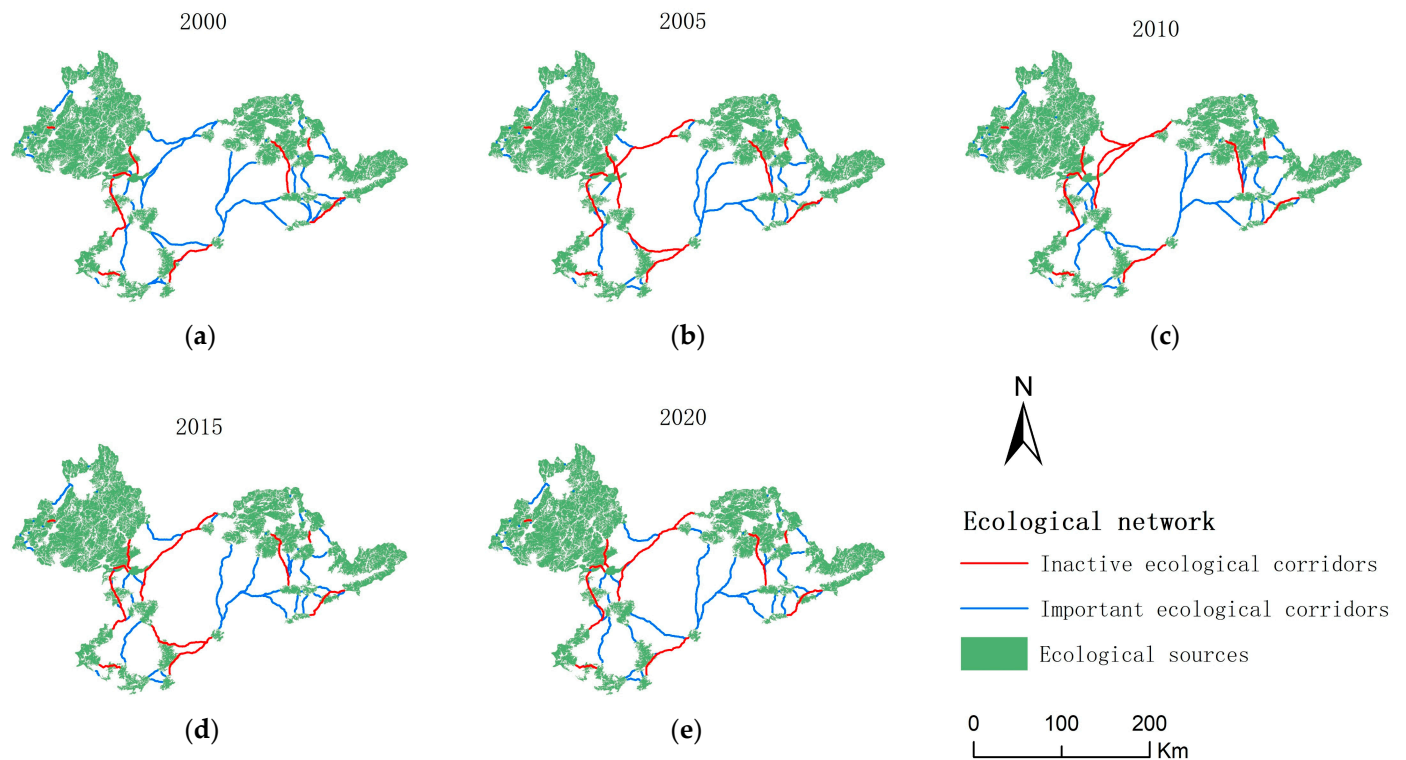


Figure 7. Ecological network pattern of the Pearl River Delta from 2000 to 2020. (a) 2000; (b) 2005; (c) 2010; (d) 2015; (e) 2020.

As shown in Table 4, the number of ecological corridors between large core areas decreased from 57 in 2000 to 53 in 2010, and increased to 55 in 2020. The total length of the ecological corridors did not change significantly between 2000 and 2020, but the lengths of the active and inactive ecological corridors showed significant changes (Figure 8). The changes in the active ecological corridors showed a trend of first decreasing and then increasing. The length of the active ecological corridors was the longest in 2000. From 2000 to 2010, the length of the active ecological corridors decreased from 1763.60 km to 1248.59 km, a decrease of 29.20%. The length of the active ecological corridors gradually increased to 1526.65 km from 2010 to 2020. The length variation trend of the inactive ecological corridors was opposite to that of the active ecological corridors. The length of the inactive ecological corridors increased from 421.77 km in 2000 to a peak of 892.80 km in 2010. From 2010 to 2020, there was a slight decrease in the length of the inactive ecological corridors, indicating an improvement in the material and energy exchange capabilities between the large core areas of the Pearl River Delta.

Table 4. The count and length of the ecological corridors from 2000 to 2020.

Year	Active Corridors		Inactive Corridors		Total Length/km
	Count	Length/km	Count	Length/km	
2000	57	1763.60	10	421.77	2185.37
2005	54	1456.50	13	805.63	2262.13
2010	53	1248.59	14	892.80	2141.39
2015	54	1458.22	13	803.78	2262.00
2020	55	1526.65	12	708.35	2235.00

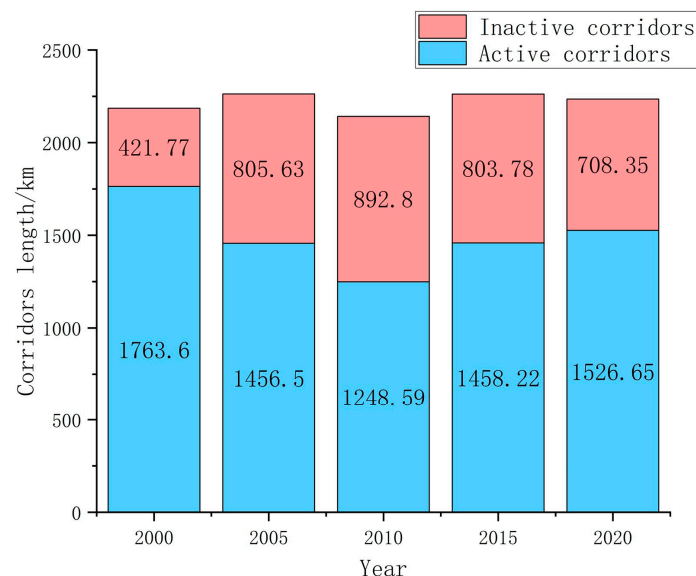


Figure 8. Change in the ecological corridor length of the Pearl River Delta from 2000 to 2020.

4. Discussion

From 2000 to 2020, inactive ecological corridors in the overall ecological network of the Pearl River Delta first increased and then converted into active ecological corridors. The proportion of inactive ecological corridors increased from 19.30% in 2000 to 41.69% in 2010 due to accelerated urbanization, and then decreased to 31.69% in 2020 after ecological restoration. The connectivity of the corridors in the centers of urban agglomerations has significantly improved, reducing the ecological pattern risks in the centers of urban agglomerations. The connectivity potential of forest ecological barriers in the northwest and northeast, as well as the ecological protection belt along the southern coast, has significantly increased.

Identifying ecological corridors and ecological protected areas is crucial for optimizing ecological networks and achieving optimal ecological, economic, and social benefits [49,55]. Based on the theory of the “patch–corridor–matrix” in the principles of landscape ecology, the priority protected areas and restoration areas of the research area were determined by extracting ecologically fragile areas and ecological break points. Ecologically fragile areas can be used as priority protected areas, and the ecologically fragile areas in urban agglomerations are mainly distributed in the ecological source areas outside the cities. The distribution of ecological break points is opposite to the distribution of ecologically fragile areas, which are mainly distributed in the central areas of urban agglomerations.

Priority protected areas are mainly the backbone of the ecological network composed of ecological source areas with high importance, ecological corridors with high activity, and ecologically fragile areas, which need priority protection. Priority restoration areas are mainly distributed in the centers of urban agglomerations and coastal shelterbelts (Figure 9). Ecological break points and inactive ecological corridors play a key role in the ecological connectivity between the east and west of the Pearl River Delta and the coastal areas, and need to be repaired. Through the construction of national forest urban agglomerations, the ecological sources in the Pearl River Delta have increased significantly, and the ecological corridor paths have changed, forming a new ecological fracture point aggregation. To protect and repair the ecological break points, we can take effective measures such as increasing the greening of roads, building ecological bridges, improving the connectivity of ecological corridors, and reducing the ecological flow of channels.

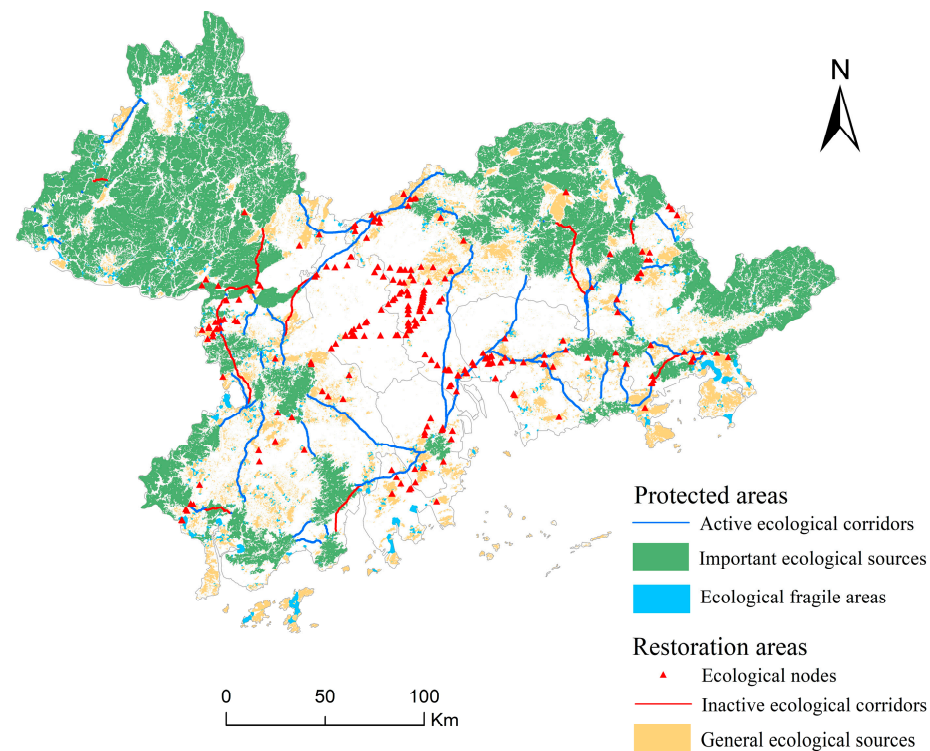


Figure 9. Priority protected areas and restoration areas in the Pearl River Delta.

5. Conclusions

The purpose of constructing and analyzing the time series ecological network model is to improve the stability and sustainability of the ecosystem and provide a scientific basis for the sustainable development of modern cities. In this paper, the ecological network of the Pearl River Delta National Forest Urban Agglomeration of China was constructed in a time series from 2000 to 2020, the process of ecological corridor change was analyzed, and the ecological priority protected areas and restoration areas in the research area were identified, which is of great significance in protecting the ecological environment in the rapidly urbanized area and maintaining the stability of the regional ecosystem.

With the tight flow of elements in the Pearl River Delta urban agglomeration and the continuous development of urban space, the trend of spatial integration is increasingly evident. The ecological security pattern in the Pearl River Delta region has been significantly optimized, and the linkage and connectivity between regions were effectively strengthened from 2015 to 2020. The distribution characteristics of ecological sources and ecological corridors have obvious spatial heterogeneity, which is mainly distributed in the peripheral areas of urban agglomerations. From 2000 to 2020, the length of the active ecological corridor first decreased and then increased, while the length of the inactive ecological corridor first increased and then decreased. The connectivity of the western and eastern forest ecological barriers and the southern coastal ecological protection forest belts in the Pearl River Delta urban agglomerations has increased significantly, effectively strengthening the ecological links between regions. Although the construction of forest urban agglomerations has effectively strengthened the ecological links between regional green cores and between natural “patches”, the ecological links in urban core built-up areas are still relatively weak, and it is necessary to strengthen the restoration and protection of ecological sources and corridors in the core built-up areas. This paper combines the MSPA and MCR methods to construct the time series ecological networks of the Pearl River Delta urban agglomeration, which has certain practical significance and practical value in coordinating the relationship between its rapid urban development and ecological environment construction and can also provide a reference for the construction of ecological security patterns and the optimization and restoration of ecosystems in other rapid urbanization regions.

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