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Boundary green infrastructure: a green infrastructure connecting natural and artificial spaces

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As a naturally-based solution (NBS), green infrastructural network constructing can improve urban ecological resilience and support sustainable urban development. However, as the Frontier of urban expansion, the boundary of built-up areas has little research on the boundary green infrastructure (BGI) connecting natural and artificial spaces. In order to make up for the shortcomings of relevant research, we propose a method for identifying BGI and analyze its landscape pattern characteristics. We selected 15 European cities as cases to extract the boundaries of built-up areas. Moreover, we used morphological pattern analysis (MSPA) to identify the ecological source and select the best distance threshold for the landscape connectivity model to identify the BGI range. Through the gradient area method and MSPA, the BGI landscape pattern characteristics of the case cities were analyzed quantitatively. The BGI scale was affected by the area of the built-up area and the threshold of GI landscape connectivity distance. Additionally, the BGI space contained a small number of large ecological sources and many scattered and small fragmented patches. The best landscape model of BGI was the surrounding pattern, followed by the aggregation pattern, which had good landscape connectivity; however, the fragmentation of the scattered pattern was high. Lastly, the ecological core area in BGI was the main landscape type; it has a high landscape connection function for the GI network inside and outside the built-up area and promotes biological exchange inside and outside the built-up area. This study proves that BGI has an important ecological significance, can guarantee the scientific nature of the NBS method, and ensures the ecological security pattern of cities.

KEYWORDS

green infrastructure, BGI, boundary green infrastructure, urban development, ecological resilience, biodiversity

1 Introduction

The rapid development of urbanization has caused many ecological problems, severely degrading the city's and surrounding areas' environment (Peng et al., 2018a). The ecosystem has been unable to bear the ecological pressure brought by urban development, leading to the decline of the ecological resilience of the city (Jie Yi et al., 2022). Balancing ecological protection and urban construction and realizing sustainable urban development has become a pressing

Abbreviations: NBS, Naturally-Based Solution; BGI, Boundary Green Infrastructure; MSPA Morphological Spatial Pattern Analysis; UGI, Urban Green Infrastructure; RGI, Rregional Green Infrastructure; NL, Number of Links between patches; LC, Landscape omponent score.

problem worldwide (Kabisch et al., 2017; Su and Haonan, 2022). Naturally-based solutions (NBS) emerged as a new approach to social challenges in this context (Mackinnon, 2008; Eggermont et al., 2015). The green infrastructure (GI) network, as an NBS method (Nadja et al., 2016; Mabon, 2019), is an important strategy to enhance ecological resilience and achieve sustainable development (Panagopoulos et al., 2016; Song et al., 2018). As the Frontier of urban expansion, the contradiction between human activities and environmental protection is prominent (Manachini et al., 2013). Therefore, it is essential to study the GI located at the boundary of an urban built-up area for the research and practice of NBS.

GI is an ecological network formed by the interconnection of multi-functional natural areas and open green spaces (Tzoulas et al., 2007; Bartesaghi Koc et al., 2017). Landscape connectivity is the basis of species communication among ecological patches, and maintaining such connectivity is vital to ensure sustainable development (J. Peng et al., 2018b; Wimberly et al., 2018). Therefore, GI located at the boundary of urban built-up areas (BGI) must ensure the GI network structure's connectivity and functional transition inside and outside built-up areas. Chen et al. built GI networks in urban fringe areas to improve landscape patterns and enhance landscape connectivity (Cui et al., 2020; Zhong et al., 2020; Liang et al., 2022); however, few studies considered the multi-level landscape connectivity characteristics of GI in urban fringe areas. There are two main reasons for the fragmentation of GI networks inside and outside urban built-up areas. First, urban built-up areas are used as resistance surfaces for biological migration (Dong et al., 2020; Xindi Zhang, 2022). Second, the GI area in urban built-up areas is small; hence, they are not usually selected as ecological sources (Liuyang et al., 2018). Therefore, ignoring GI at the boundary of built-up urban areas negatively affects ecological processes, causing the separation of GI networks inside and outside built-up areas, and it is difficult to maintain the security and stability of the ecosystem. Therefore, a BGI range identification method can be established from the perspective of landscape connectivity characteristics to determine the GI space near the built-up area boundary that can generate effective landscape connections for internal and external GI networks.

BGI—an important connecting space of the GI network inside and outside built-up areas—comprises patches and corridors (Forman, 1995). Studies on GI patterns mostly focus on urban central areas and regional scales (Xiao Ran et al., 2015; Gu et al., 2017; Jiaxing et al., 2019; Jeong et al., 2020; Kan et al., 2021; Jiang et al., 2022). Additionally, analysis models, such as landscape pattern (Wang et al., 2019), landscape connectivity index, and landscape pattern index of GI (Huang et al., 2021; Modica et al., 2021), are usually applied to analyze and evaluate GI patterns based on specific scope and elements. However, studies on the spatial structure and landscape pattern characteristics of BGI are relatively weak. Studying the structural composition and landscape pattern characteristics of BGI helps reveal the GI network's structural characteristics and ecological processes, strengthen the connection degree of natural and artificial GI space, and improve the structural integrity.

As a part of the GI network, BGI is the NBS method for improving urban ecological resilience. Based on the landscape connectivity characteristics of BGI, we established the spatial identification method of BGI and analyzed its landscape pattern characteristics. Distance threshold is the maximum diffusion distance of biological flow used to determine the presence or strength of landscape connectivity between patches in the study area (Meng et al., 2016; Qinghe et al., 2017). As an important method to measure landscape patterns and function, the landscape connectivity model based on graph theory can obtain the optimal distance threshold (Almenar et al., 2019). In this study, we used PC, IIC, and other connectivity indexes to analyze and determine the optimal diffusion distance threshold. Based on this, the spatial range of BGI with landscape connectivity function for GI networks inside and outside the built-up area was defined. Moreover, we selected the gradient area and morphological spatial pattern analysis (MSPA) methods to evaluate the overall landscape pattern and structure of BGI. In this study, 15 United Kingdom, France, and German cities were selected as research objects. Based on ArcGIS, GuidosToolbox, and other software, MSPA and landscape connectivity model based on graph theory were adopted to identify the spatial scope of case BGI and analyze the landscape pattern. The results can provide a reference and basis for urban BGI spatial identification and pattern optimization.

2 Material and methods

The city is a complex system (Bonnes et al., 1990). Due to the high degree of human intervention inside the built-up area, urban green infrastructure (UGI) is mainly artificial green space integrating various ecosystem service functions (Chengcheng et al., 2021). The primary function of regional green infrastructure (RGI) outside built-up areas is to maintain ecosystem stability and protect biodiversity, including natural ecological spaces, such as woodland and grassland (Tang Xiaolan, 2011).

In this study, BGI is the GI located at the boundary of the urban built-up area, including a certain range of UGI and RGI on both sides of the boundary, which plays a role of landscape connection for the GI network between the built-up area and the region (Figure 1). In the BGI space, BGI connects the GI network inside and outside the built-up area, ensures multi-level landscape connectivity, and maintains the stability and biodiversity of the urban ecosystem. The primary functions of GI inside and outside the built-up area transition are to ensure that the biological flow in the regional GI network can move to the built-up area and extend the composite functionality of GI in the built-up area outward.

The study of BGI space in the cases is divided into two parts (Figure 2). First, delineating the BGI space scope, which involves two steps. a) Identifying the built-up area boundary of the case city. b) Determining the most suitable landscape connection distance threshold between the built-up area and the regional GI network of the case according to BGI's landscape connection characteristics. Second, analyzing the case cities' BGI spatial landscape pattern and structure.

The data in this study is mainly the land cover data of case cities in Germany, the United Kingdom, and France in 2020 (spatial resolution 30 m, data source: http://www.globallandcover.com/).

2.1 BGI spatial identification

2.1.1 Built-up area boundary extraction

The entropy analysis of land use types is an information model that expresses the richness and orderliness of land use types through the number of land use types and the proportion of the unit area

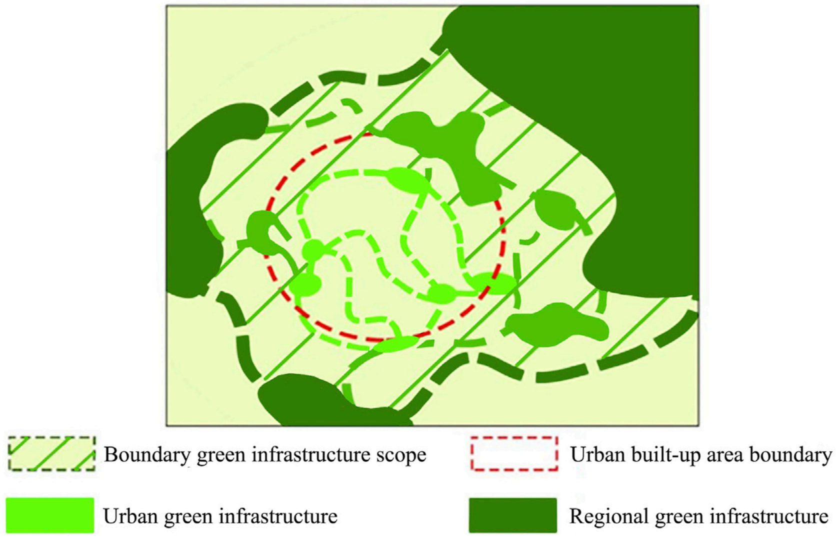

FIGURE 1
BGI location diagram.

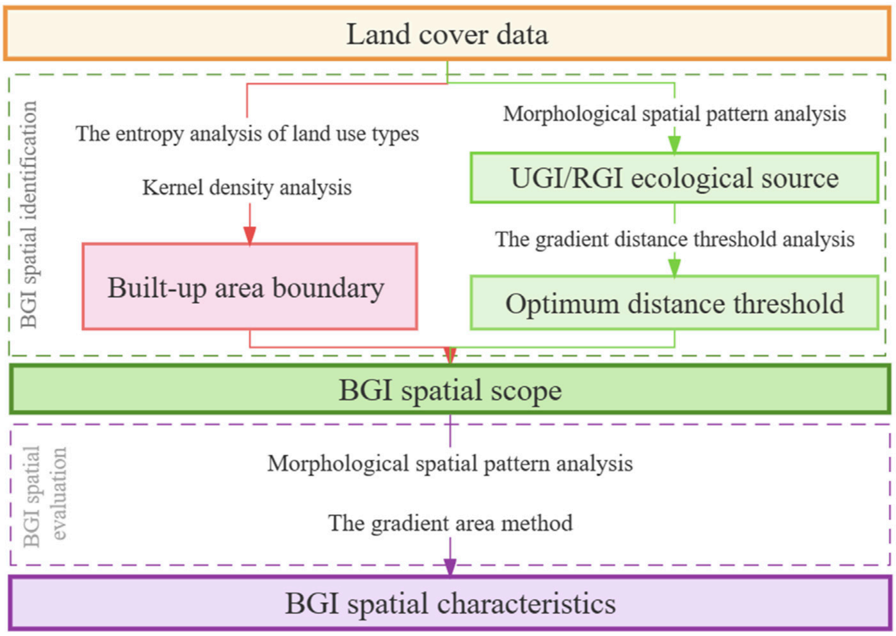

FIGURE 2
The methodological framework used in this study.

occupied by the types (Figure 3). Its principle is similar to that of thermodynamics, in which entropy represents the degree of molecular disorder in a thermodynamic system (Prunkl, 2018). We selected the standard deviation (S) of a simple statistical variable to represent the richness of land use type information. The formula is as follows:

$$S = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - u)^2} \quad (3\text{–}1)$$

Where S is the standard deviation; N is the number of land use types; x_i is the area percentage of a certain land type; u is the average area of land use type in the unit. The land cover raster data is reclassified into Built-up and Non-built-up lands. Notably, on both sides of the built-up area boundary, the land use type is single, and the information entropy is very low. However, the boundary of the built-up area, land use type changes, and information entropy increase. In this study, the standard deviation threshold of land use was set between 0.3 and 0.4, and the boundary of land use type

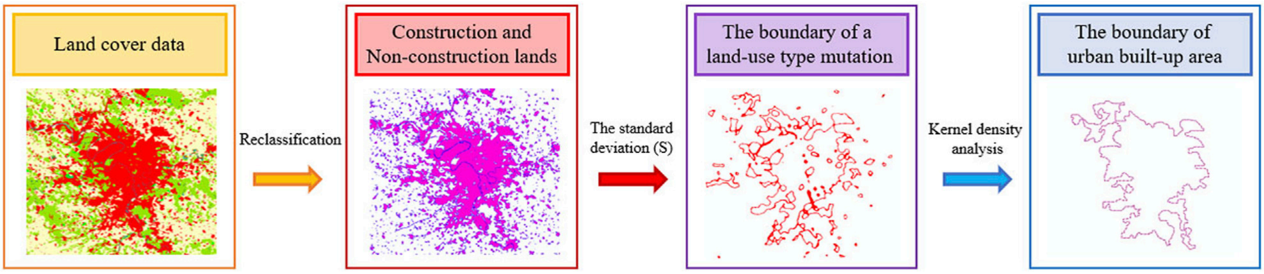

FIGURE 3
Urban built-up boundary extraction process.

with sudden change was selected and identified as the boundary of urban built-up area (Liuyang et al., 2018). However, this method gives the "salt and pepper particles" phenomenon and cannot extract a stable and clear built-up area boundary line; therefore, it requires correction.

Through kernel density analysis of the binary raster data of land type, the raster data is converted into vector point elements, and the result of boundary extraction of the built-up area is optimized. When the land type changes, the point density of a single attribute decreases rapidly, and the kernel density value drops sharply. Therefore, kernel density analysis can reflect the spatial boundary of a sudden change in land use type, and it is calculated as follows (Zhang and Lu, 2009):

$$f(x) = \sum_{i=1}^{n} \frac{1}{\pi r^2} \varphi\left(\frac{d_{ix}}{r}\right) \tag{3–2}$$

Where $f(x)$ is the comprehensive index value of core density per unit area; r is the search radius in km; n is the number of samples; d_{ix} is the distance between elements i and x in km; φ is the distance weight.

2.1.2 Ecological source selection

MSPA can identify ecological patches that significantly impact the ecological connectivity of the study area (Soille and Vogt, 2009). Notably, the MSPA method can only identify patches and corridors with ecological protection significance using land use raster data (Julien Carlier, 2019). According to morphology, spatial pattern, impact on the overall landscape connectivity, and other factors, the ecological land raster data is divided into seven non-overlapping landscape types (Nan-nan et al., 2021). The ecological core and bridging areas have high ecological connectivity and can protect regional biological diversity. This method has important significance in improving the scientific nature of ecological source selection.

Within the boundaries of built-up areas, the GI primarily enhances the function of recreation service, biodiversity protection is relatively weak, and the ecological land area is small. In this study, ecological patches with an area of ≥0.5 km^2 were selected as the ecological source area at the built-up area scale (He et al., 2019). At the regional scale, the ecological land within 50 km outside the built-up area boundary was selected for MSPA analysis based on the reachable range of species diffusion (Meng et al., 2016). As an important ecology for regional biodiversity conservation, the biological habitat must have sufficient scale. Therefore, the core area of ≥5 km^2 was selected as the ecological source area at the regional scale (MT et al., 2017).

2.1.3 Distance threshold selection

The gradient distance threshold analysis can identify the study area's most suitable landscape connection distance threshold (Baranyi et al., 2011; DU et al., 2019). We selected the threshold range of landscape diffusion distance in the built-up area and regional scale based on the study area and biological migration characteristics.

There are few tracks of large wildlife activities in urban built-up areas, and the study scale is relatively small (Wei al. 2009). Therefore, 15 distance threshholds at 200 m interval from 200 to 3,000, plus 4,000, 5,000 and 10000 selected to analyze of the built-up area scale. Outside the built-up area, combined with the characteristics of biological migration (Meng et al., 2016), we selected 1,000, 2,000, 2,500, 3,000, 3,500, 4,000, 4,500, 5,000, 5,500, 6,000, 6,500, 7,000, 7500, 8000, 8500, 9,000, 9500, 10000, 15000, 20000 m; therefore, 20 distance thresholds were used for regional scale analysis.

The stable range of landscape connectivity can be preliminarily determined using the number of links between patches (NL) and landscape component score (NC) as the indicators of landscape connectivity (Montis et al., 2019). Furthermore, the importance index of each BGI patch is calculated within the stable distance threshold range of landscape connection (Table 1). Moreover, by comparing the importance index of each patch, the most suitable threshold of landscape connection distance is determined. The higher the consistency of the index change trend of each patch, the more effective the selection of distance threshold (DU Zhibo al. 2019).

2.1.4 BGI spatial scoping

Using the boundary of the urban built-up area as the baseline, the best distance threshold for buffering UGI inward and outward of the boundary was determined. Additionally, the combination of the inner and outer buffer zones constitutes the BGI spatial range of the case city. This scope can ensure that BGI space has an effective landscape connection between the area and the GI of the built-up area and can identify the GI connection and transition space between the built-up area and the area.

TABLE 1 The interpretation of landscape connectivity indices.

Type	Index	Interpretation
Overall indices	Number of Links (NL)	Refers to the number of connections between habitat nodes in the landscape, i.e., between any two patches. If the distance is less than the set distance threshold, the number of links between the two patches is considered to exist
	Number of Components (NC)	It refers to a whole composed of patches connected functionally or structurally. An isolated node or plaque will form a component, and there is no functional relationship between different components
Patches importance indices	Patch comprehensive connectivity index (dIIC)	Calculate the index change value after removing a single patch to determine the importance of the integrated connectivity of the patch. The higher the integrated connectivity value, the higher the importance of the patch in the landscape
	Patch connectivity probability index (dPC)	It describes the probability of species moving between any two patches. The higher the index value, the higher the connectivity of patches in the landscape
	Patch coincidence pobability Index (dLCP)	The probability of patches being randomly connected as habitats represents the coherent role of patches in the landscape

TABLE 2 Definition of landscape type based on MSPA.

Landscape type	Ecological significance
Core	Larger habitat patches in foreground pixels, providing relatively larger habitats space for species; represents ecological sources of importance for protecting biodiversity
Bridge	Narrow area connected the cores, representing a corridor that connects patches in an ecological network; essential for biological migration and landscape connectivity
Edge	Similar to the Bridge, but only represents the corridors that communicate within the same core for the migration of internal species
Loop	Transitional zone between the core zone and the external non-green space, its width varies according to the migration characteristics of different species
Perforation	Transitional zone between the core zone and the internal non-green space, its width varies according to the migration characteristics of different species
Branch	Extending area of green space; only one end is connected to the green space
Islet	Isolated, broken small patches that are not connected to each other, with low connectivity

2.2 BGI spatial feature quantification

2.2.1 BGI landscape composition analysis

To ensure the stable development of ecological functions, ecological patches should have a specific scale (Urban, 2001; Baguette et al., 2013). The purpose of the gradient area method is to retain the habitat patches of great significance for biodiversity conservation and remove a large number of fragmented, isolated patches. Setting the area threshold by comprehensively considering the number of patches, patch area, and the proportion of screened patches to the total area of the ecological space can ensure that the basic ecological functions and processes are unaffected (Xiaolin et al., 2021). We extracted the continuously distributed forest land, grassland, and other vegetation cover land included in the BGI space as the BGI patch and calculated the patch area. Additionally, we selected 16 area thresholds between 0 and 3 km^2 in steps of 0.2 km^2 (Mao Quan et al., 2019). Next, we analyzed the changing trend of patch number, area, and proportion of total ecological land area with the area threshold to determine the patch size and composition in the landscape.

2.2.2 BGI landscape pattern quantification

The MSPA method can divide the grid data of patches into core, island, perforation, edge, loop, bridge, and branch (Table 2). The core area and bridge are the landscape types with the connectivity of the landscape structure (Yong Zheng et al., 2022).

3 Results

3.1 BGI space identification

3.1.1 Extraction results of the built-up area boundary

The extraction results are presented in Figure 4 and Table 3. The built-up areas of the case cities were >100 km^2. London and Paris had the highest built-up area, 1174.16 km^2 and 1521.5629 km^2, respectively. However, Nuremberg and Toulouse had the smallest built-up area, 100.1155 km^2 and 100.0332 km^2, respectively The size of the built-up area reflects the construction scale of the city. Moreover, the differences in the built-up areas of the case cities were large. It can analyze cities with different built-up areas scales and better study the BGI characteristics of cities with different sizes.

3.1.2 Ecological source identification

Figure 4 shows the case cities' UGI and RGI ecological sources, and each city's ecological source area and quantity are listed in Table 3. London had the highest number of UGI ecological sources,

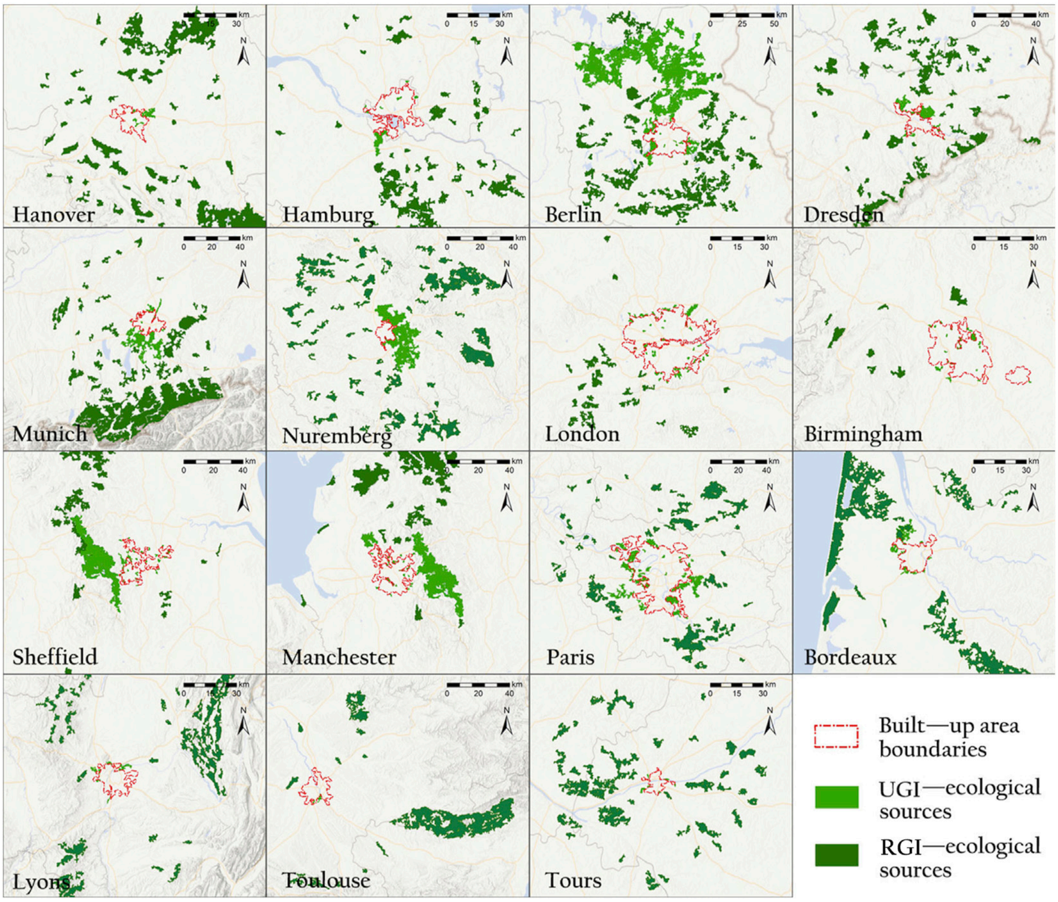

FIGURE 4
Distribution of UGI and RGI ecological sources.

with 45 patches, mainly small parks and greenbelts. However, the UGI ecological source area in the built-up area of Berlin was the largest, with strong ecological functions. Notably, there were only 4 UGI ecological sources in the built-up area of Toulouse, with a total area of only 3.328 km^2; therefore, biodiversity protection was relatively weak. Berlin had the highest number of regional ecological sources outside the built-up area, with 66 patches. However, the total area of regional ecological sources in Sheffield, Manchester, and Berlin was >3,000 km^2, which can maintain regional ecological security (Ma et al., 2004) and biodiversity. The GI inside and outside the built-up area of the case cities had certain ecological and landscape connectivity functions, which can provide a good basis for identifying and analyzing BGI.

3.1.3 Determination of optimum distance threshold

Berlin—the city with the best UGI landscape connectivity in German case cities—had many ecological patches, and a relatively close distance between patches is superior to the other five case cities (Figure 5). Additionally, the landscape connectivity of four United Kingdom cities was good in the built-up area. At the 10,000 m distance threshold, all the landscape elements were connected into a landscape component, and the NC value reached 1. According to the NL value, the UGI landscape connectivity in London's built-up area was the strongest, and that in Birmingham was relatively weak. Among the French cities, Paris had many UGI patches, high NL value, and a small and stable increase trend. However, the number of UGI patches in other cities was <10, and the patch distribution was relatively discrete. The overall NC and NL values changed step wisely with the distance threshold in a stepwise manner.

In the RGI analysis result shown in Figure 6, London, Manchester, and Sheffield in the United Kingdom had good connectivity. With the change of distance threshold, there were stages of a small change rate of NC and NL and stable value. Furthermore, the number of RGI patches in Birmingham was relatively small, and the distribution was relatively discrete; therefore, the NC and NL values changed stepwise with the increased distance threshold. Moreover, the number of RGI patches in German case cities was large and closely distributed. With the change in distance threshold, the change in NC and NL values was relatively stable. Excluding Dresden, other cases could be connected into a landscape component when the distance reached 20000 m, indicating that the regional ecological source can meet the needs of biological migration and diffusion. Furthermore, the number of RGI patches in Toulouse, France, was relatively small, and the distribution was relatively sparse, resulting in the NC and NL change curves showing a constant interval with the increase of the distance threshold.

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TABLE 3 Ecological source extraction results of UGI, RGI.

Case Country	Case city	Built-up area (km^2)	UGI		RGI	
			Quantity	Area (km^2)	Quantity	Area (km^2)
United Kingdom	London	1174.1600	45	64.9450	23	271.7972
	Birmingham	651.6437	20	28.2266	8	113.2634
	Sheffield	302.2855	29	543.8582	18	3,359.5077
	Manchester	459.4656	25	581.6185	19	3,535.1707
Germany	Hanover	187.3413	5	25.5083	46	2420.0632
	Hamburg	418.4669	10	48.2607	43	1256.6128
	Berlin	593.4302	22	2196.1155	66	3,394.8261
	Dresden	200.2891	11	101.1098	51	1227.2470
	Munich	225.4226	9	208.4119	47	2338.0627
	Nuremberg	100.1155	3	367.8156	63	1672.9128
France	Paris	1521.5629	34	329.2047	57	1308.1500
	Bordeaux	262.8390	9	76.6908	21	1807.7616
	Lyons	252.6015	7	15.1362	38	1055.3337
	Toulouse	241.4913	4	3.3282	16	1001.3949
	Tours	100.0332	6	8.1909	40	869.9130

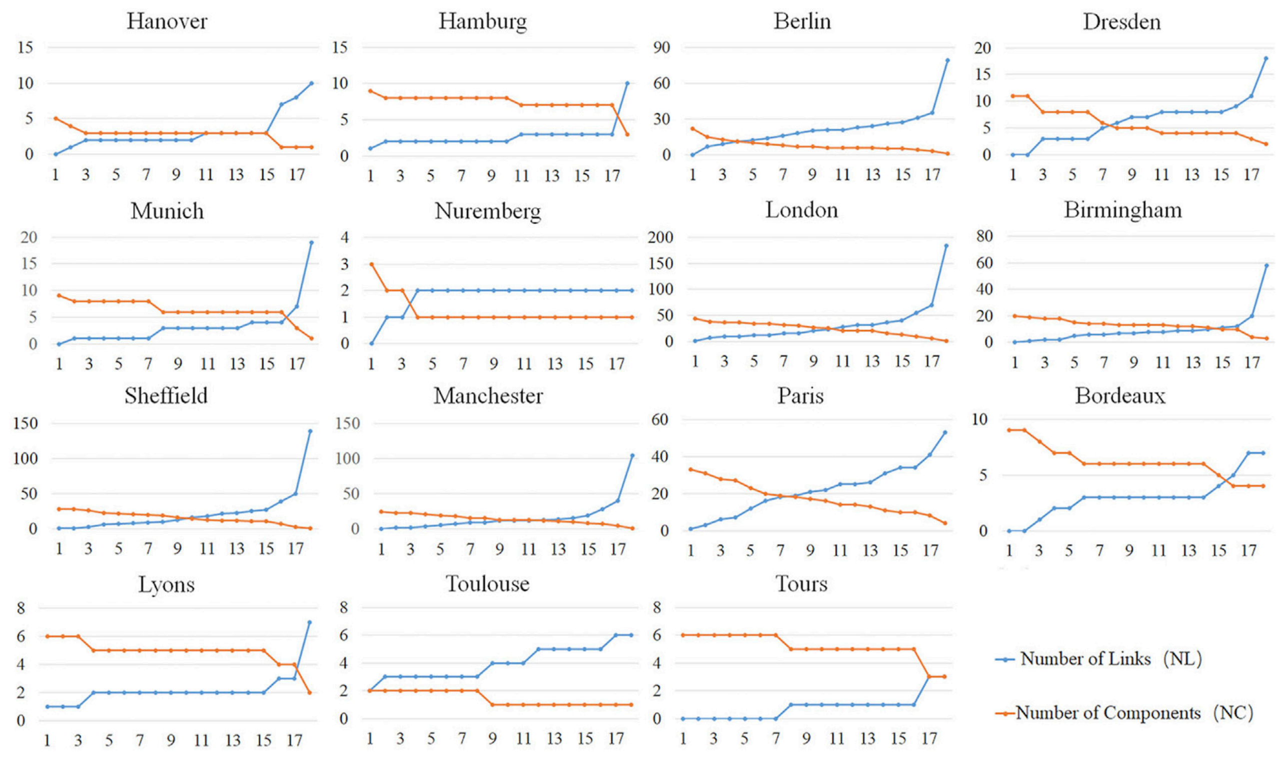

FIGURE 5
Changes in the distance threshold of UGI NL and NC.

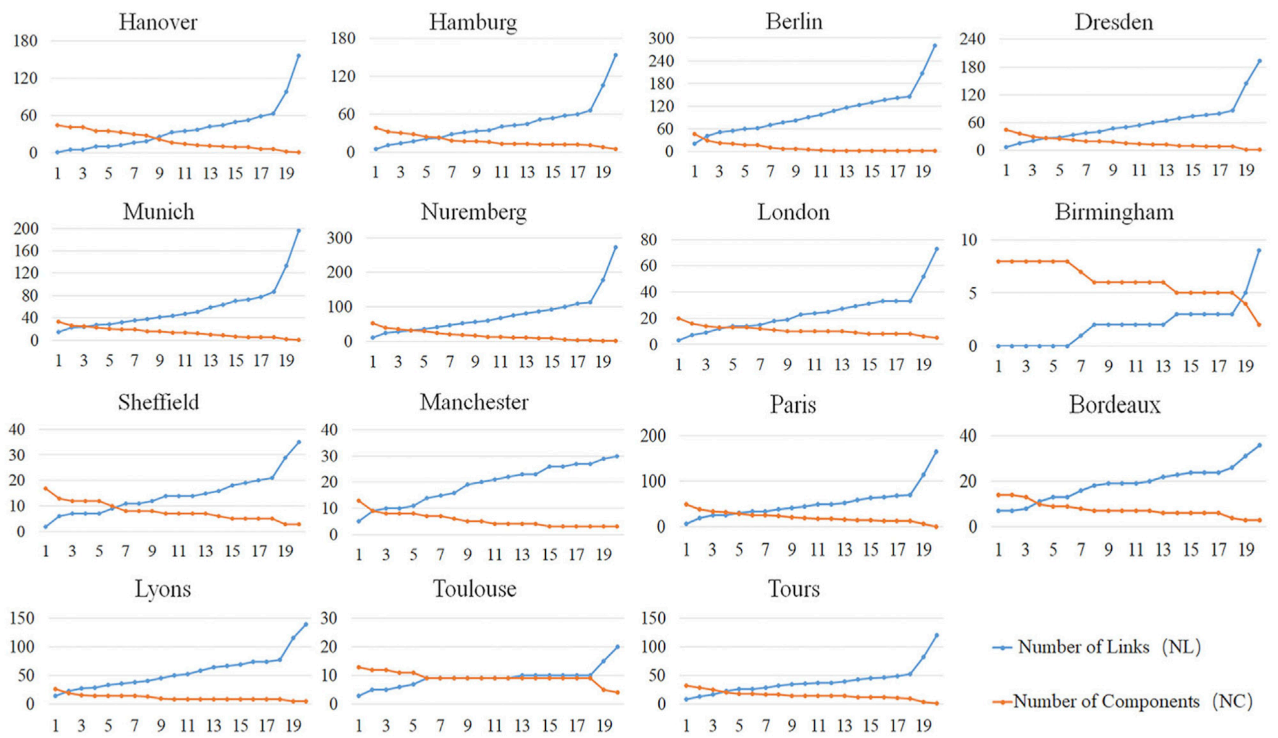

FIGURE 6
Changes in the distance threshold of RGI NL and NC.

The trend of curve change in Figure 5, Figure 6 can be divided into several stages.

(a) The NC value decreased rapidly, and the NL value increased rapidly. The increase in landscape connectivity indicates that it promotes ecosystem stability. When the change of distance threshold causes a drastic change in landscape connectivity, it indicates that the landscape connectivity is unstable, and this interval distance threshold is unsuitable for the correlation analysis of landscape connectivity in the study area.
(b) The NC value gradually decreased or remained unchanged, and the NL value slowly increased or remained stable. In this interval, the landscape component fraction changes slightly, and the number of connections increases steadily, indicating that the landscape connection stability is less affected by the change in distance threshold. Therefore, the landscape connection in this section is in a relatively stable state, which is suitable for studying landscape connectivity.
(c) The NC curve changes slightly; however, the NL curve significantly increases. The landscape connection between patches becomes increasingly strong with the increased diffusion distance. However, the NL value changes significantly, which cannot reflect the study area's landscape pattern and ecological process, and it is unsuitable to be selected as the stable distance threshold range.
(d) The NC value is = 1. This means that all ecological sources are connected and can be considered biological habitats. However, this situation does not conform to the actual landscape pattern in the study area and cannot be used as the stable distance threshold range for the landscape connectivity study.

The selected stable distance threshold ranges are listed in Table 4. The NL curve of RGI in Bordeaux showed a staged growth, and the NC curve showed a fluctuating stable state; therefore, two stable distance threshold intervals were selected. Since the number of UGI patches in Nuremberg, Toulouse, and Toure was very small, when the diffusion distance reached a fixed value, the NC and NL values did not change; therefore, there was no threshold range to maintain the stable connection of the landscape.

For example, in Berlin, 20 RGI patches were screened, and the distance thresholds of 7,000, 7,500, and 8000 m were set. Additionally, the changes in plaque importance index dLCP, dIIC, and dPC were analyzed, and the results are shown in Figure 7. Moreover, when the distance threshold is set to 8,000 m, the difference in plaque importance index is the smallest, and the index trend of each patch is the most consistent, so it is selected as the optimal distance threshold. Notably, when the distance threshold was 8,000 m, the difference in plaque importance index was the smallest, making it the best distance threshold. The appropriate distance threshold between each case city's RGI and UGI ecological source was determined similarly, and the results are presented in Table 4.

The appropriate distance threshold between patches is affected by the distance between patches. The closer the patch distribution, the more stable the landscape pattern, and the lower the appropriate distance threshold. Sheffield's UGI pattern was good, with many patches, a large total area, and a relatively close distribution. Moreover, Munich's RGI pattern was good, and the area and quantity of ecological sources were large and close, which is conducive to biological diffusion.

TABLE 4 The result of the optimal distance threshold selection.

Case Country	Case city	UGI		RGI	
		Range (m)	Distance threshold (m)	Range (m)	Distance threshold (m)
United Kingdom	London	2200–2600	2600	6000–7000	7000
	Birmingham	1800–2200	2200	6500–7500	8000
	Sheffield	800–1600	1200	6000–7000	7000
	Manchester	1600–2200	2200	8000–10000	6500
Germany	Hanover	2200–5,000	2800	4,500–6000	6000
	Hamburg	2000–2200	2800	7000–8000	6000
	Berlin	2200–3,000	2200	6000–7000	8000
	Dresden	1800–3,000	3,000	5,000–5,500	9500
	Munich	2200–3,000	2000	8500–9500	5,500
	Nuremberg	800	800	7500–8500	8500
France	Paris	2200–2400	2200	6500–7000	6500
	Bordeaux	1200–2800	3,200	5,500–6500, 8500–9500	8500
	Lyons	800–3,000	2800	7500–8500	8500
	Toulouse	1800	1800	4,000–10000	10000
	Tours	1600	1600	5,500–7000	6500

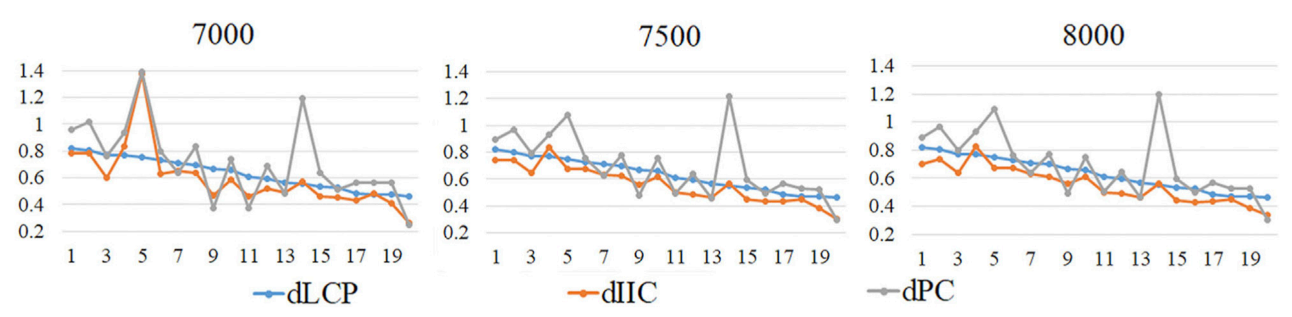

FIGURE 7
Changes in the distance threshold of Berlin patch importance indices.

3.1.4 BGI width determination

The width and area of BGI in each case city are shown in Figure 8, and the spatial distribution of BGI is shown in Figure 10. BGI scope is affected by the appropriate distance threshold of GI and the scale of the built-up area. The closer the distribution of ecological patches inside and outside the built-up area, the stronger the landscape connection and the smaller the coverage width of BGI.

3.2 BGI spatial evaluation

3.2.1 Differences in the characteristics of BGI pattern

The total ecological land area of case BGI was >100 km^{2}, and the number of BGI patches was >100 (Table 5). In the BGI space, the ecological land has a certain scale. The larger the ecological source area, the better the ecological function. At the urban boundary, the intensity of human activities was gradually weakened. Additionally, the total ecological area and the number of patches increased, higher than those in the urban built-up areas. Within the scope of BGI, the increase in the number of patches indicates that the number of nodes in the GI network has increased, and the landscape connection has improved.

Among the numerous patches, a large area of ecological core could provide habitats for organisms, and small and scattered serve patches as stepping stone patches. Using the gradient area threshold analysis of the BGI patches in the case cities, the composition of the BGI patches in each case was analyzed according to the inflection point of the curve in Figure 9. The results are presented in Table 5.

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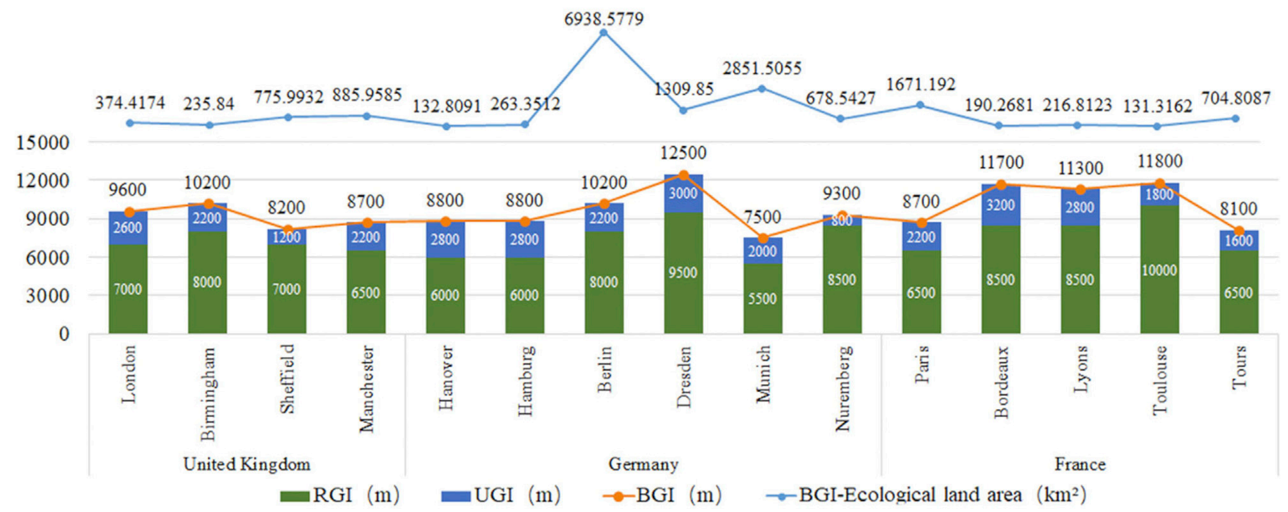

FIGURE 8
Case city BGI width and area.

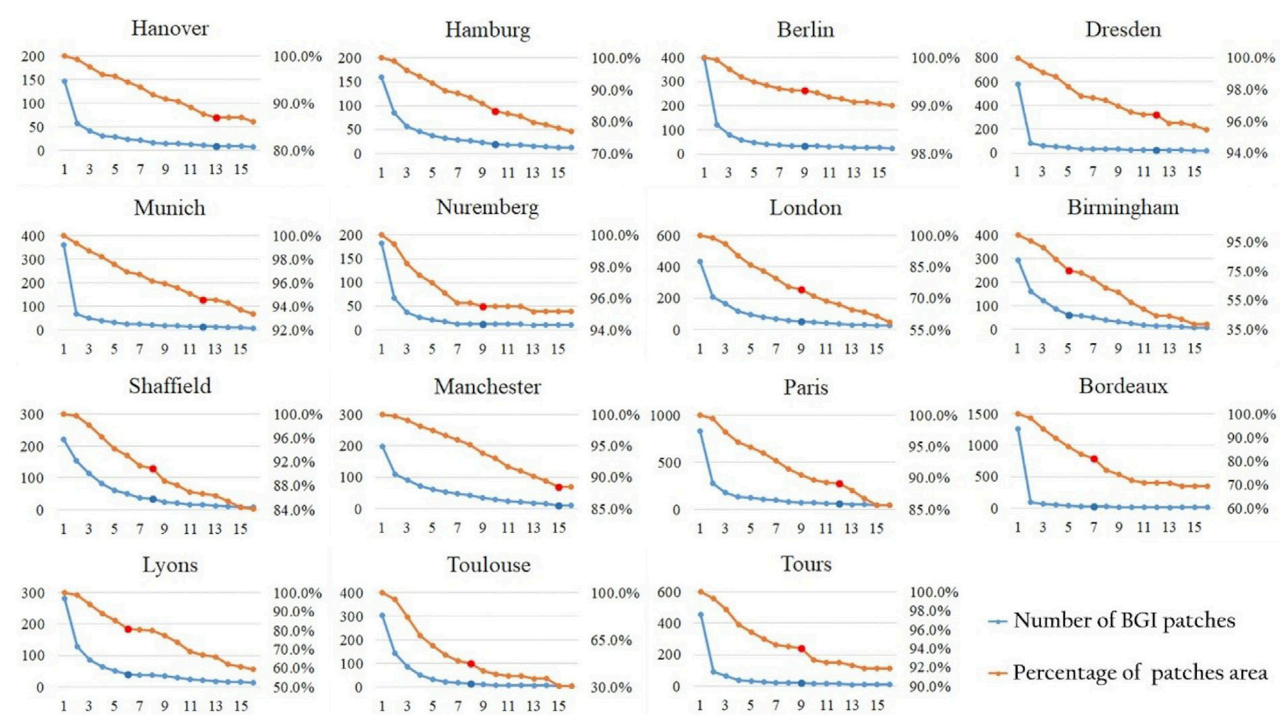

FIGURE 9
Changes in the minimum area threshold of the patch.

The number of scattered small patches in Birmingham's BGI was large, accounting for about 25% of the total area. Moreover, the BGI was relatively broken, and the proportion of large patches was relatively low. Furthermore, the BGI in Toulouse contains many small ecological patches, and the landscape pattern was severely fragmented. Hanover's BGI had a high proportion of medium and large patch areas, a complete overall ecological pattern, and stable function. In all cases, the BGI space contained a large area of ecological sources to ensure biodiversity and ecological security, and many small patches were stepping stones in the biological migration and diffusion path.

According to the distribution location and spatial pattern of BGI in Figure 10, the BGI model of the case cities can be divided into three types.

1) Surrounding pattern: The patches can be closely surrounded by the urban built-up area, forming a circular or semi-circular structure conducive to biological flow between GI networks

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TABLE 5 Analysis results of gradient area threshold.

Case Country	Case city	BGI-ecological land area (km^2)	Number of all patches	Number of selected patches	Area of remaining patches (km^2)	Proportion of area (%)	Proportion of quantity (%)
United Kingdom	London	374.4174	432	54	1.6	74.395	12.500
	Birmingham	235.84	295	61	0.8	75.527	20.678
	Sheffield	775.9932	220	35	1.4	90.887	15.909
	Manchester	885.9585	198	12	2.8	88.478	6.061
Germany	Hanover	132.8091	147	10	1.4	99.313	6.803
	Hamburg	263.3512	159	19	1.8	83.226	11.950
	Berlin	6938.5779	397	35	2.2	87.719	8.816
	Dresden	1309.85	580	23	2.4	95.916	3.966
	Munich	2851.5055	363	13	2.2	94.613	3.581
	Nuremberg	678.5427	183	13	1.2	95.705	7.104
France	Paris	1671.192	829	64	2.2	89.144	7.720
	Bordeaux	190.2681	1259	30	1.2	81.263	2.383
	Lyons	216.8123	282	40	1	81.011	14.184
	Toulouse	131.3162	303	15	1.4	47.805	4.950
	Tours	704.8087	456	20	1.6	93.993	4.386

and the biological migration and diffusion in BGI space. There are two types of surrounding patterns. First, a large ecological source outside the built-up area with a very high landscape structure and functional connection seen in Berlin and Paris. Second, many small artificial green spaces clustered to form a green ring structure surrounding the built-up area seen in London. This type of BGI has a high overall structural connectivity; however, the functional connectivity of the patch is weaker than that of the large regional ecological source.

2) Aggregation pattern. Local patches are clustered and distributed around the built-up area, and multiple clustered and distributed GI network nodes connect the GI landscape. For example, in Hamburg, Bordeaux, and Sheffield, the ecological patches were clustered and distributed and had a certain scale without forming a semi-ring or ring structure. The more the number and area of patches, the stronger the landscape connection function between the two ecological networks and the better the landscape stability.
3) Scattered pattern. The patches are scattered in the BGI space, and the patch area is generally small. The landscape connection function of BGI was relatively weak in Birmingham and Toulouse. Small-area ecological patches are suitable stepping stones in the biological migration path and play a relatively weak role in biodiversity protection. The scattered distribution pattern can easily cause landscape fragmentation.

3.2.2 BGI landscape pattern analysis

Figure 11 and Table 6 present the analysis results of MSPA. The proportion of core in BGI was the highest (>30%) in all case cities. Munich had the highest proportion of BGI core area, and Berlin had the largest BGI core area. As a landscape type with high structure connectivity function and less disturbance, the core mainly serves as the habitat of organisms and protects diversity. Therefore, the case cities' BGI can protect biodiversity, of which Berlin and Munich had the strongest biodiversity protection function, and Toulouse had a relatively weak ecological function.

The edge area comes after the core area. In all cases, the proportion of marginal areas in BGI was >10%. Moreover, the area of BGI edge in Berlin and Munich was large; however, the proportion was small, 13.22% and 12.73%, respectively. This situation is because the edge area usually surrounds the ecological core area, and the patch's size, quantity, and geometric shape can significantly affect the area and proportion of the edge area.

The third area is the branch, which can promote the material and energy exchange between the core area and the outside world. The area of branch lines in Berlin BGI was the largest; however, the proportion was the lowest due to the huge total area of Berlin BGI. Additionally, the branch has certain landscape connectivity, which enhances landscape connectivity and biodiversity protection by establishing ecological corridors.

As a narrow and long area connecting the ecological core areas, the bridge can serve as a corridor for biological migration and diffusion, which is essential for biodiversity protection. In the MSPA analysis of the case cities, Toulouse and Lyon BGI had the highest proportion of bridging areas. Notably, insufficient bridging area leads to a lack of connectivity between BGI patches and limited species migration and gene exchange, which is unconducive for maintaining biodiversity.

Furthermore, the loop is a shortcut for species migration within the patch, which is conducive to species migration within the same patch. In these cases, the area of the BGI loop in Lyon accounted for 1.739%; however, that of other cities was <1%, indicating that there are few patches in the BGI core area.

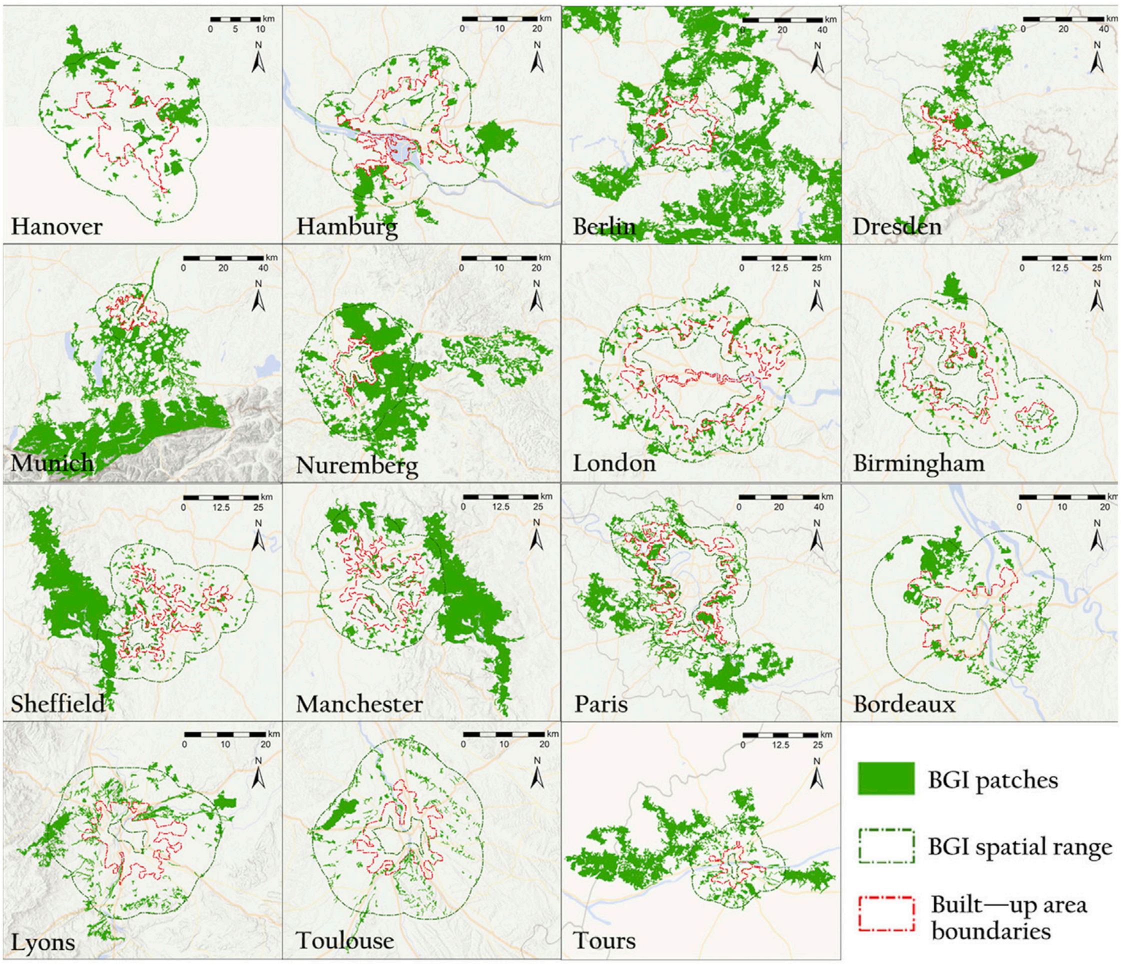

FIGURE 10
Spatial distribution of BGI in case cities.

The perforation and the edge are the transition areas between the core and other land types; however, the perforation is located in the core of the patch, which easily affects the ecological process in the core. The low proportion of perforation area in BGI indicates that the impact on the interior of the BGI patch is small, and the ecological process in the core area can be well protected.

The landscape connectivity of islands is relatively low, and the possibility of internal material and energy exchange and transmission is relatively small. The BGI of the case cities contained a small number of islands, and the proportion of isolated patches in the BGI was small. This indicates that BGI had a relatively low landscape fragmentation degree, good landscape connectivity, and small stepping-stone ecological patches to ensure the activity and diffusion of organisms.

According to the MSPA analysis results, the core in BGI space was the most important landscape type, with the highest proportion and the largest area. This suggests that BGI' primarily protects the normal migration and organism diffusion, maintains of ecosystem's stability, and ensures the GI network's landscape connectivity. Furthermore, the high proportion of edge was due to the weakening of the development intensity at the boundary of urban built-up areas compared with that in the built-up areas; however, there were still human activities around the edge of BGI patches. Moreover, the extremely low proportion of perforation indicates that human development and construction of GI patches are usually not in the core areas to prevent interference with ecological processes in the core areas. Additionally, the branch, bridge, and loop area all had certain proportions, indicating that BGI can provide corridors for the migration and diffusion of species, which is conducive to GI network connectivity and biodiversity protection.

4 Discussion

In the BGI space of the case, cities such as Berlin, Paris, and Bordeaux have large ecological sources, while cities such as Birmingham, Toulouse, and London only have small-area ecological patches (Figure 10). Among them, the BGI space in Berlin contains many large ecological sources with the highest total ecological area, and ecological patches are interconnected to form a surrounding pattern. The BGI space in Bordeaux also contains large ecological sources, but the patches are only locally clustered and cannot form a circular structure. The BGI of Birmingham is composed of many small patches, and the patches are scattered, with poor landscape connectivity and serious fragmentation. Similarly, there is no large

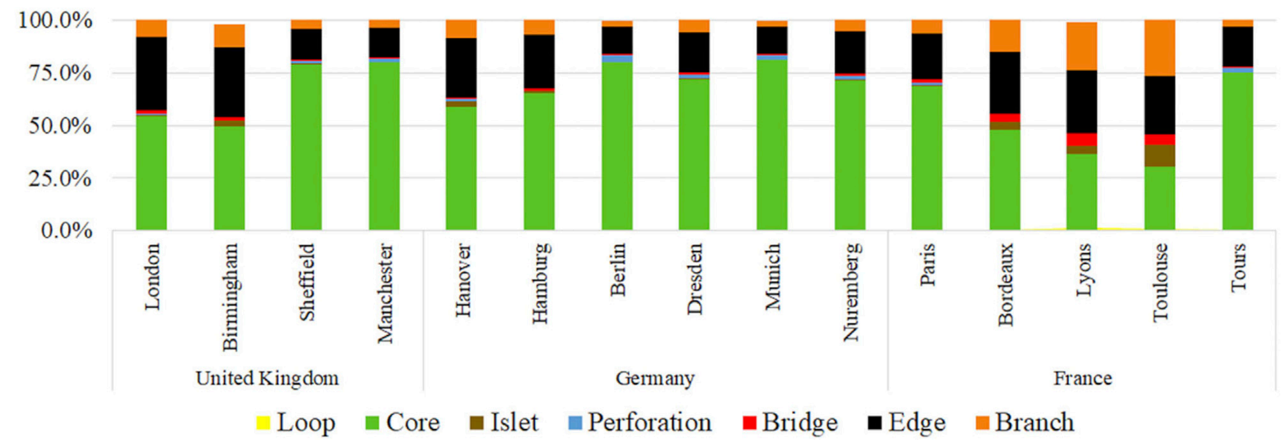

FIGURE 11
Case City MSPA landscape type scale.

TABLE 6 The area of MSPA landscape type in the case city.

Case Country	Case city	Area (km^2)	Core (km^2)	Islet (km^2)	Perforation (km^2)	Loop (km^2)	Bridge (km^2)	Edge (km^2)	Branch (km^2)
United Kingdom	London	374.42	204.10	2.53	1.42	1.69	5.89	130.60	33.69
	Birmingham	235.84	116.90	6.10	0.46	1.05	3.70	79.35	24.78
	Sheffield	775.99	614.30	2.19	10.14	1.39	4.69	115.10	32.01
	Manchester	885.96	709.90	2.37	11.84	2.34	5.039	126.80	32.15
Germany	Hanover	132.80	78.26	3.69	1.21	0.74	1.06	37.83	12.38
	Hamburg	263.35	172.40	3.39	0.14	0.47	2.60	67.44	20.33
	Berlin	6938.58	5,554.00	6.87	231.1	22.1	43.03	917.60	189.5
	Dresden	1309.85	944.20	8.94	20.54	5.16	16.11	249.90	72.97
	Munich	2851.50	2319.00	3.10	56.57	8.42	22.26	363.00	87.66
	Nuremberg	678.54	485.40	4.18	9.27	2.10	8.39	136.00	36.51
France	Paris	1671.19	1153.0	5.93	14.11	7.45	27.24	367.2	107.00
	Bordeaux	190.27	91.46	6.93	0.50	0.67	7.10	56.20	31.20
	Lyons	216.81	79.28	7.73	0	3.77	13.38	65.08	50.45
	Toulouse	131.32	40.14	13.3	0.08	1.28	6.85	36.68	34.82
	Tours	704.80	529.20	2.31	14.88	1.47	5.32	134.18	25.14

ecological source in BGI space in London, but the patches are closely distributed and the landscape connectivity is high, forming a circular structure composed of many small-area patches. Therefore, in the BGI space, the larger the area of the ecological source and the stronger the connection function, the better the ecological function can be played. Moreover, the landscape pattern of BGI also plays a crucial role, the closer the distribution between the patches, the stronger the landscape connectivity, and the more conducive to the connection between the urban and the regional GI network.

In this study, BGI can play an important role in ensuring the integrity and connectivity of urban and regional GI network structures, which is consistent with other studies on the strengthening of urban-rural ecological connections between urban and rural GI at urban and rural margins (Zhong et al., 2020). The connectivity of urban and rural ecological networks is limited by the lack of ecological areas and the lack of stepping stone patches in some urban marginal areas (Cui et al., 2020; Zhong et al., 2020; Liang et al., 2022). In contrast, the border green infrastructure of European case cities can better maintain the biological flow between GI networks. By summarizing the pattern of case BGI and identifying different spatial pattern characteristics, the BGI of European case cities can support the

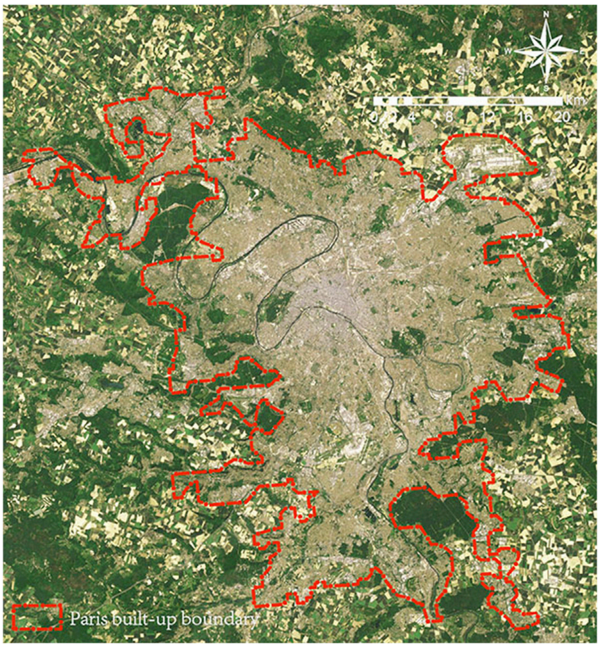

FIGURE 12
Results of boundary extraction of Paris urban built-up area.

connection between cities and regional GI networks. In addition, the results of the MSPA analysis showed that the BGI plaque of the case could provide services for human activities and also had a high biodiversity conservation function. In summary, BGI contains the composite functions of urban green infrastructure and regional green infrastructure and is an important part of the GI network.

When extracting ecological sources, MSPA considers the area factor and the structural characteristics and connectivity functions of landscape elements, preventing the subjectivity of source extraction and improving accuracy. However, MSPA analysis has a strong scale and edge effects, and the analysis results at different research scales are quite different (Ya-Ping et al., 2016). Therefore, it is important to select the appropriate analysis scale when using MSPA to analyze the characteristics of landscape patterns. To retain the small but important landscape elements in the built-up area and ensure the accuracy of the results, the grid size of the built-up area scale was set to 30 m, and the grid size outside the built-up area was set to 90 m (Tanner and Fuhlendorf, 2018). However, the reasonable selection of grid data granularity and edge width for different research areas still needs further research.

When extracting the boundaries of urban built-up areas, the edges of built-up areas extracted using the land-use entropy method were severely fragmented and showed an obvious sawtooth shape. Moreover, many holes were observed in the built-up area extracted by the POI kernel density analysis method, and the POI category was inconsistent with the land type (Jinhua et al., 2021). Notably, the boundary of the built-up area extracted in this study was accurate and can overcome the information-missing phenomenon of the extracted results. The comparison between the extraction results of the built-up area in Paris obtained by this method and the remote sensing satellite images is shown in Figure 12. The built-up area was close to the actual boundary, improving the “salt and pepper particles” phenomenon of the boundary of the built-up area determined using the land-use entropy method to extract the built-up area. Therefore, this method reflects the boundary details of urban built-up areas and has good applicability. Moreover, the extraction effect of built-up area boundaries in cities of different sizes had good accuracy.

The distance threshold needs to be determined when analyzing the landscape connectivity between the built-up area and the regional GI using Conefor software. However, the selection of distance threshold requires careful consideration of many factors, among which the diffusion range of species is the key factor, which varies widely for different species. Furthermore, when the landscape connectivity index is used to screen the landscape distance threshold, the appropriate distance threshold is closely related to the current distribution of BGI landscape patches. In this study, IIC, PC, and other landscape connectivity indexes were used to screen the appropriate distance threshold of the study area, and the selection index was small. Lastly, when selecting the distance threshold, the rationality of landscape connectivity and the ecological process of different scales should be considered to determine the most suitable distance threshold for the case city.

5 Conclusion

In conclusion, high-intensity urban development has led to the isolation of built-up areas and natural ecological space. GI network planning–has been ignored at the boundary of built-up areas, and its scientific and rational nature has been questioned. The innovation of this study lies in identifying the scope of BGI and analyzing its landscape pattern characteristics using the GI network’s continuity, transition, and systematic characteristics at the boundary of urban built-up areas. Based on the landscape connectivity model, MSPA, and other methods, this method can effectively analyze the best landscape distance threshold of UGI and RGI and delimit the scope of BGI. Additionally, we analyzed and summarized the landscape pattern and structural characteristics of BGI space, providing reference and guidance for planners and decision-makers. By studying the European case cities, we proved that BGI is a vital in the GI network under the context of rapid urbanization.

Overall, a BGI with a landscape connection between UGI and RGI at the boundary of the urban built-up area was observed, and its scope was affected by the scale of the built-up area and the optimum distance threshold of UGI and RGI. Moreover, the BGI contained many small ecological patches and a small number of large ecological patches. Moreover, the proportion of large patches in the BGI area was high, and the total area of broken small patches was small. Additionally, large-scale ecological patches in BGI spaces performed major ecological functions. Patch distribution in BGI space can be divided into the surrounding, aggregation, and scattered patterns. The BGI of the surrounding pattern can improve the landscape connection between UGI and RGI and enable the migration and diffusion of organisms inside and outside the built-up area. The best landscape model of BGI was the surrounding pattern, followed by the aggregation pattern; however, the fragmentation of the scattered pattern was high. Lastly, The ecological core area in BGI is the main landscape type, followed by the marginal area. Therefore, BGI can promote the habitat and migration of organisms, maintain biodiversity and ensure ecological security, and is an important part of the NBS method in the context of rapid urbanization.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JY Conceptualization, Methodology, Resources, Writing–original draft, Writing–review and editing. BW Methodology, Vali-dation, Investigation. XL Validation, Visualization, Resources. ML Writing–review and editing, Visualization. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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