Proceedings of the 4th International Conference on Software Engineering and Machine Learning
DOI: 10.54254/2755-2721/2026.34269

Research on Evaluation Method of Urban Landscape Ecological Connectivity Based on Multi-Source Spatial Data Fusion

Yulu Zhou

The University of New South Wales, Sydney, Australia
wellington589125@gmail.com

Abstract. Rapid urbanization has promoted the continuous expansion of urban built-up space. Green spaces, water bodies, woodlands, and open spaces have been increasingly divided by roads, residential areas, commercial land, and high-intensity functional zones. This process has caused ecological patch fragmentation, blocked ecological flows, and reduced the accuracy of corridor identification. To support the optimization of urban landscape ecological networks, this study takes the central urban area of Guangzhou as the case area. It integrates Sentinel-2 remote sensing imagery, 30 m land-use data, POI data, and road data from 2020 to 2024. A multi-source spatial data-driven method is developed to evaluate urban landscape ecological connectivity. NDVI and MNDWI are used to extract vegetation and water information. MSPA is combined to identify ecological sources. Land-use resistance, road proximity resistance, built-up intensity, POI kernel density, and the inverse NDVI indicator are integrated into a comprehensive ecological resistance surface. The MCR model, circuit theory, and graph-theoretic indicators are then used to extract potential ecological corridors and identify pinch points, barrier points, and key restoration nodes. The results show that ecological spaces in central Guangzhou present a pattern of relative continuity in peripheral areas and clear fragmentation in the urban core. The Pearl River green belts, Haizhu Wetland, the southern edge of Baiyun Mountain, and large parks form the main ecological connection framework. Road intersections, high-density commercial areas, and hardened riverbanks still create significant barriers. The study provides a computational basis for green-space restoration, ecological corridor planning, and landscape spatial optimization.

Keywords: Urban landscape ecological connectivity, Multi-source spatial data fusion, Remote sensing imagery, Ecological corridor identification, Minimum cumulative resistance model

1. Introduction

Rapid urbanization has continuously reshaped the spatial composition of urban green spaces, water bodies, woodlands, and open spaces. Road construction, commercial development, and high-intensity residential expansion have divided formerly continuous ecological spaces into dispersed

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2755-2721/2026.34269

patches, thereby constraining ecological flows within dense urban areas [1]. Existing evaluations of urban landscape ecology have often focused on static pattern indicators, such as patch area, patch number, patch shape, and fragmentation degree. These indicators help reveal the spatial distribution of green spaces, yet they provide limited explanation of the combined effects of vegetation quality, land development intensity, human activity density, and road barriers on ecological connectivity [2]. With the growing availability of Sentinel-2 imagery, 30 m land-use data, POI data, and road-network data, ecological connectivity evaluation is shifting toward multi-source spatial data fusion, comprehensive resistance surface construction, and refined ecological corridor identification [3]. To address ecological patch fragmentation and insufficient corridor identification accuracy, a computational framework is developed through data preprocessing, ecological source identification, resistance surface modeling, corridor extraction, and key node diagnosis.

2. Literature review

2.1. Evaluation of urban landscape ecological connectivity

The evaluation of urban landscape ecological connectivity focuses on whether ecological patches can form stable spatial relationships and whether ecological processes can move continuously through complex urban environments [4]. Early studies commonly used landscape metrics to describe green-space fragmentation, including patch area, edge density, aggregation, and connectivity. These indicators are useful for identifying changes in spatial patterns and explaining whether ecological patches are becoming isolated. As mixed urban functions and spatial barriers increase, judging connectivity only by patch distance may underestimate the resistance caused by roads, viaducts, commercial complexes, and high-density built-up areas [5]. Ecological connectivity evaluation has therefore moved toward an integrated logic of pattern, process, and node analysis. Ecological sources, resistance paths, bottleneck areas, and priority restoration locations are gradually incorporated into the same network structure, allowing landscape ecological evaluation to support corridor layout, node restoration, and green-space system reorganization in urban renewal.

2.2. Application of multi-source spatial data in landscape evaluation

Multi-source spatial data provide a more detailed spatial basis for evaluating urban landscape ecology. Remote sensing imagery can identify vegetation, water bodies, built-up land, and bare land, while NDVI and water indices help represent ecological patch quality [6]. Land-use data further reveal functional differences among residential, commercial, industrial, transport, and public green spaces, making it possible to quantify the resistance effects of different urban land types on ecological movement. POI data supplement traditional ecological data from the perspective of human activity. Higher densities of commercial, transport, catering, office, and public-service facilities usually indicate stronger population concentration and development disturbance [7]. These three data types form complementary ecological, functional, and activity-based meanings. After coordinate unification, resampling, classification coding, kernel density estimation, and rasterization, they can jointly support the construction of a comprehensive ecological resistance surface and reduce spatial judgment bias caused by reliance on a single data source.

DOI: 10.54254/2755-2721/2026.34269

2.3. Ecological corridor identification and resistance modeling

Ecological corridor identification depends on the joint support of ecological sources and resistance surfaces. Ecological sources are usually composed of woodlands, water bodies, wetlands, mountain parks, and large urban parks with large areas, high ecological quality, and strong connectivity value [8]. The MCR model calculates the minimum cumulative resistance paths between sources and can identify potential low-resistance corridors. It is suitable for judging whether riverfront green belts, roadside green spaces, and continuous green areas can connect fragmented patches. Graph-theoretic indicators transform ecological sources into network nodes and ecological corridors into connecting edges. Node degree, betweenness centrality, probability of connectivity, and overall connectivity index are then used to evaluate network structure. Circuit theory interprets the resistance surface as an electrical resistance system and identifies multi-path diffusion, high-flow pinch points, and barrier points through current density [9]. Resistance modeling that relies only on empirical land-use assignment may weaken the effects of POI activity density, road proximity, and construction intensity on ecological movement, while multi-source fusion improves the precision of corridor identification.

3. Experimental methods

3.1. Multi-source spatial data collection and preprocessing

Data collection uses the central urban area of Guangzhou as the case area, covering Yuexiu, Tianhe, Haizhu, Liwan, southern Baiyun, and key ecological connection zones along the Pearl River. The area includes dense old urban districts, urban park clusters, river green belts, and peripheral mountain green spaces. The study period is 2020–2024. Sentinel-2 MSI images are obtained from Google Earth Engine, with April–October images selected under cloud cover below 20%. Public 30 m land-cover data, POI data from Amap, Baidu Maps, or OpenStreetMap, and road-network data are also collected. Land cover is reclassified into woodland, grassland, water bodies, built-up land, transport land, and other land. POI and road data are cleaned, classified, corrected, and rasterized. All datasets are unified by projection, resolution, and boundary to support ecological patch identification, resistance surface construction, and corridor extraction.

3.2. Ecological patch identification and comprehensive resistance surface construction

Ecological patch identification is first completed based on remote sensing indices and land-use types [10]. Vegetation areas are extracted using the normalized difference vegetation index, as shown in Formula (1):

$$NDVI=\frac{NIR-Red}{NIR+Red} \tag{1}$$

Water bodies are identified using the modified normalized difference water index, as shown in Formula (2):

$$MNDWI=\frac{Green-SWIR}{Green+SWIR} \tag{2}$$

space. GIS patch analysis is used to remove scattered patches with small areas, fragmented forms, and weak ecological functions. MSPA further classifies ecological space into core areas, edge areas,

DOI: 10.54254/2755-2721/2026.34269

bridge areas, islets, and branches. Ecological sources are selected from patches with larger areas, higher mean NDVI values, and higher proportions of core areas. The comprehensive ecological resistance surface is constructed based on the results of ecological source identification. The resistance factors include land-use resistance, road proximity resistance, built-up intensity, POI kernel density, and the inverse NDVI indicator. Woodland, water bodies, and large parks are assigned low resistance values. Commercially dense areas, areas near main roads, high-POI-density zones, and continuous built-up land are assigned high resistance values. After standardization and weighted overlay, a rasterized resistance surface is generated for the following MCR model and circuit theory analysis.

3.3. Ecological corridor extraction and connectivity evaluation model

Ecological corridor extraction uses the ecological sources and comprehensive resistance surface obtained in Section 3.2 as inputs. The Cost Distance and Cost Path tools in ArcGIS Pro are first used to run the minimum cumulative resistance model. The model calculates low-resistance connection paths among different ecological sources [11]. Its basic expression is shown in Formula (3):

$$MCR=f_{min}\sum_{j=1}^{m}(D_{ij}\times R_j) \tag{3}$$

In this formula, D_{ij} represents the spatial distance or cost distance from source i to raster cell j, while R_j represents the resistance value of raster cell j. Paths with low MCR values are extracted as potential ecological corridors. To avoid overly narrow corridor identification caused by a single-path result, Circuitscape or Omniscape is further used to run the circuit theory model. Ecological sources are set as electrodes, and the comprehensive resistance surface is converted into a resistance surface. Current density is then used to identify high-current areas, pinch points, and barrier points. Finally, ecological sources are abstracted as network nodes, while potential corridors are abstracted as network edges. Graph-theoretic indicators are used to evaluate the network structure. The probability of connectivity is calculated as shown in Formula (4):

$$PC=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}a_i a_j p_{ij}^{*}}{A_L^2} \tag{4}$$

In Formula (4), a_i and a_j represent the areas of ecological sources, p_{ij}^{*} represents the maximum connection probability between sources, and A_L represents the total area of the study region. This process forms a continuous workflow of source identification, resistance modeling, corridor extraction, bottleneck diagnosis, and network evaluation.

4. Results

4.1. Identification results of urban ecological patch fragmentation

Based on the processed multi-source spatial data from 2020 to 2024, about 860 ecological patches were identified in the central urban area of Guangzhou, covering a total ecological space of approximately 215.4 km². Among them, 36 core ecological patches larger than 20 ha were mainly distributed around Baiyun Mountain, Haizhu Wetland, the Pearl River green belts, peripheral mountain green spaces, and large urban parks. Although the number of patches was high, their area distribution was uneven. Patches smaller than 5 ha accounted for about 67.8%, showing that central

DOI: 10.54254/2755-2721/2026.34269

urban green spaces were strongly fragmented by roads, residential areas, and commercial land. MSPA results showed that core areas covered about 132.6 km², accounting for 61.6% of ecological space, while edge areas covered 38.7 km², accounting for 18.0%. Bridge areas covered only 17.2 km², accounting for 8.0%, and islets and branches together covered 26.9 km², accounting for 12.4%. These results indicate a spatial pattern of relatively continuous peripheral ecological spaces and fragmented central patches, with insufficient bridge spaces and weak transitional interfaces among ecological patches. As shown in Table 1.

Table 1. Identification results of urban ecological patches and MSPA structure

Indicator type	Identification result	Spatial interpretation
Total number of ecological patches	About 860	The central urban area had many green spaces, but small-scale patches accounted for a high proportion.
Total ecological space area	About 215.4 km²	Ecological spaces mainly relied on mountains, parks, water bodies, and riverfront green belts.
Core patches larger than 20 ha	About 36	They were concentrated around Baiyun Mountain, Haizhu Wetland, Pearl River green belts, and large parks.
Proportion of patches below 5 ha	About 67.8%	Roads, residential areas, and commercial land caused obvious patch fragmentation.
MSPA core areas	About 132.6 km², 61.6%	Large peripheral ecological spaces still maintained relatively high stability.
MSPA edge areas	About 38.7 km², 18.0%	Many green spaces were compressed by built-up space, showing clear edge effects.
MSPA bridge areas	About 17.2 km², 8.0%	Connecting green spaces were insufficient, and ecological corridor continuity was weak.
MSPA islets and branches	About 26.9 km², 12.4%	Some green spaces in the central urban area were isolated, and network integration was insufficient.

4.2. Identification results of ecological corridors and key restoration nodes

Based on the integrated results of the MCR model, circuit theory, and graph-theoretic indicators, about 24 potential ecological corridors were extracted in the study area, with a total length of approximately 138.2 km. Among them, 8 low-resistance main corridors were mainly distributed along the Pearl River system, green belts around Haizhu Wetland, transitional green spaces from Baiyun Mountain to the central urban area, and continuous open spaces between large parks. Circuit theory results showed that high-current-density areas were concentrated between Haizhu Wetland and the Pearl River green belts, in the transition zone from southern Baiyun Mountain to Yuexiu and Tianhe, near arterial road intersections, and at park boundary breakpoints. The model further identified about 18 pinch points and 12 barrier points. Pinch points were mainly located in narrow riverfront green belts, contracted roadside green spaces, and narrow park connections. Barrier points were mostly related to expressway crossings, viaduct nodes, hardened riverbanks, and high-POI commercial areas. These results indicate that ecological restoration should prioritize corridor breakpoints, cross-road connections, and high-resistance built-up gaps.As shown in Figure 1.

DOI: 10.54254/2755-2721/2026.34269

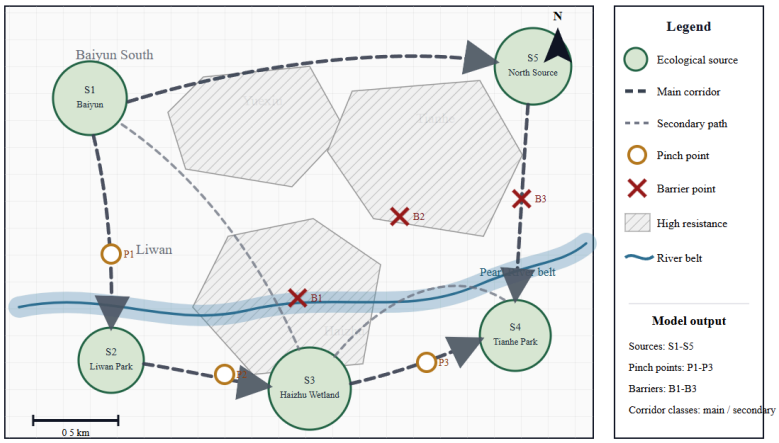

Figure 1. Identification diagram of ecological corridors and key restoration nodes in the central urban area of Guangzhou

5. Discussion

Multi-source spatial data fusion improves the precision of urban landscape ecological connectivity evaluation. It allows ecological network analysis to move beyond green-space area and patch distance. It also supports the integrated identification of vegetation quality, spatial function, human activity intensity, and road barriers. The results show that the key ecological problem in the central urban area is not only the limited scale of green space. It also lies in the lack of continuous transitional spaces among core patches. Local pinch points and barrier points weaken the stability of ecological flows. The MCR model is suitable for identifying low-resistance connection paths. Circuit theory reveals multi-path diffusion and areas with concentrated ecological flows. Graph-theoretic indicators help judge the structural value of sources and corridors in the whole network. When these methods are combined, ecological connectivity differences can be explained from the levels of path, node, and network. Planning optimization should focus on Pearl River green belts, road intersections, park boundaries, and high-POI-density areas. Continuous green-belt planting, ecological bridge construction, road-buffer greening, and park-boundary connection can improve network connectivity.

6. Conclusion

This study constructs an urban landscape ecological connectivity evaluation method based on multi-source spatial data fusion. It forms a complete workflow from data collection, remote sensing index calculation, ecological patch identification, ecological source selection, and comprehensive resistance surface construction to corridor extraction and key node diagnosis. Taking the central urban area of Guangzhou as the case area, the results show that ecological patch fragmentation is mainly concentrated in high-density built-up areas and spaces strongly divided by roads. The main ecological corridors rely on river systems, large parks, and peripheral mountain green spaces. Pinch points and barrier points are mostly distributed in road-crossing areas, hardened riverbanks, and areas with intensive commercial activities. The method integrates remote sensing imagery, land-use data, POI data, and road data into a unified model framework. It can more accurately reflect urban ecological movement costs and spatial connection relationships. The results can support ecological security pattern construction, green-space restoration in urban renewal, and landscape planning

DOI: 10.54254/2755-2721/2026.34269

decisions. Future studies may combine higher-resolution imagery and multi-period dynamic monitoring to further improve evaluation accuracy.

References

[1] Jiang, Jiawen, et al. "Establishment and Optimization of Urban Ecological Network Based on Ecological Regulation Services Aiming at Stability and Connectivity." Ecological Indicators, vol. 165, 2024, article 112217, doi: 10.1016/j.ecolind.2024.112217.

[2] Wei, Wenyu, et al. "Identification and Analysis of Ecological Corridors in the Central Urban Area of Xuchang Based on Multi-Source Geospatial Data." ISPRS International Journal of Geo-Information, vol. 13, no. 9, 2024, article 322, doi: 10.3390/ijgi13090322.

[3] Zhang, Shunmin, et al. "Construction of Urban-Rural Ecological Networks with Multi-Scale Nesting and Composite Functions Based on the 'Red-Green-Blue' Spatial Perspective: A Case Study of Dali City, China." Heliyon, vol. 10, no. 18, 2024, article e37870, doi: 10.1016/j.heliyon.2024.e37870.

[4] Qin, Ji-zheng, et al. "Construction of Ecological Network in Qujing City Based on MSPA and MCR Models." Scientific Reports, vol. 14, 2024, article 9800, doi: 10.1038/s41598-024-60048-z.

[5] Zhang, Xifeng, Xiaowei Cui, and Shuiming Liang. "Evolution and Optimization of an Ecological Network in an Arid Region Based on MSPA-MCR: A Case Study of the Hexi Corridor." Sustainability, vol. 16, no. 4, 2024, article 1704, doi: 10.3390/su16041704.

[6] Liu, Shaobo, et al. "Balancing Urban Expansion and Ecological Connectivity through Ecological Network Optimization: A Case Study of ChangSha County." Land, vol. 12, no. 7, 2023, article 1379, doi: 10.3390/land12071379.

[7] Zhou, Yuan, et al. "Optimizing an Urban Green Space Ecological Network by Coupling Structural and Functional Connectivity: A Case for Biodiversity Conservation Planning." Sustainability, vol. 15, no. 22, 2023, article 15818, doi: 10.3390/su152215818.

[8] Lu, Jie, Sheng Jiao, Zongwei Han, and Jingwen Yin. "Promoting Ecological Restoration of Deeply Urbanized Hilly Areas: A Multi-Scale Ecological Networks Approach." Ecological Indicators, vol. 154, 2023, article 110655, doi: 10.1016/j.ecolind.2023.110655.

[9] Tong, An, Yan Zhou, Tao Chen, and Zihan Qu. "Constructing an Ecological Spatial Network Optimization Framework from the Pattern–Process–Function Perspective: A Case Study in Wuhan." Remote Sensing, vol. 17, no. 15, 2025, article 2548, doi: 10.3390/rs17152548.

[10] Zhang, Yan, et al. "Urban Multi-Scale Ecological Network Sequence and Spatial Structure Optimization: A Case Study in Nanjing City, China." Ecological Indicators, vol. 167, 2024, article 112622, doi: 10.1016/j.ecolind.2024.112622.

[11] Zhang, Shuhan, et al. "Construction of Landscape Ecological Network Based on MCR Risk Assessment Model: A Case Study of Liaoning Province, China." Ecological Indicators, vol. 166, 2024, article 112549, doi: 10.1016/j.ecolind.2024.112549.