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FRAMEWORKS OF ECOLOGICAL CONNECTIVITY: SYSTEMATIC REVIEW ON GREEN INFRASTRUCTURE'S CASE STUDIES

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Abstract. Due to fast urbanisation, urban green space fragmentation has become a critical global concern. Nevertheless, understanding the planning and analysis of GI is deemed challenging. This paper examines the issue by focusing on Green Infrastructure (GI), a comprehensive strategy that provides viable answers. The foundation of the research relies on a methodical examination of existing literature, carried out with great attention to detail and adherence to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards. The Scopus and Elsevier databases yielded a total of 22 relevant articles. The study results provide insight into the existing GI planning and analysis approaches, specifically emphasising the utilisation of MSPA and the Landscape Connectivity Index. In addition, there are also other supplementary tools and resources for connectivity, such as minimum cumulative resistance model (MCR), Circuitscape, UNIversal CORridor network simulator (UNICOR), MatrixGreen, Zonation, FunConn, Fragstat and InVest. The review's outcome is a structured framework based on landscape ecology principles designed explicitly for urban green infrastructure planning and analysis. This framework is specifically developed to tackle and reverse the prevailing pattern of fragmentation of green spaces in urban settings.

Keywords: *Ecological network, green network, green space, landscape ecology framework, spatial planning.*

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1. Introduction

This study focuses on how Green Infrastructure (GI) can be leveraged to address these challenges, mainly through ecological networks and landscape connectivity. Landscape fragmentation is pervasive in places undergoing rapid urbanisation (Wanghe *et al*., 2019). Landscape fragmentation leads to habitat loss, causing ecosystems or land-use types to be surrounded by densely urbanised regions and alters the biological interrelationships within the affected areas (Jaeger, 2000; Kim, 2019). Ecological networks and greenways in Europe and America use landscape ecological principles in land use planning, which is a widely recognised concept in biological and landscape

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conservation among scientists, planners and policymakers (Jongman & Pungetti, 2004). Engaging in the implementation of GI during the planning and decision-making stage can effectively reduce the likelihood of losing ecosystem services (Skokanová *et al*., 2020) and promote stability in the urban ecosystem (Lee & Oh, 2019). Thus, it is reasonable to consider ecological networks 'GI' consisting of interconnected corridor and core area systems to maintain or restore ecological processes and functions and resultantly restore nature (Jongman & Pungetti, 2004).

Theoretically, landscape ecology principles suggest a hypothetical framework and investigative tools for understanding how multifaceted and varied landscapes, such as metropolitan spaces, operate specific ecological processes (Turner & Gardner, 2015). Furthermore, landscape ecology presents scientifically based landscape planning principles from a multi-scaled viewpoint (Ahern, 2007). Thus, landscape ecology principles provide a basis for this study.

This research hypothesises that enhancing landscape connectivity and optimising landscape patterns can significantly mitigate green space fragmentation. Landscape connectivity demonstrates how the landscape structure and function are interrelated (Ahern, 2007). Thus, it is crucial to investigate the role of corridors in ecological connectivity and assess how their compositional, structural and functional intricacy can be optimised. Connectivity references the extent to which a landscape promotes or obstructs the movements of materials, energy, species, nutrients and people across it (Ahern, 2007). The term 'corridor optimisation' refers to increasing corridor numbers and repairing corridor ecological breakpoints based on the extent of their connectedness (An *et al*., 2021). Corridor compositional and structural intricacy influences its role as an ecological connector (Cui *et al*., 2020); thus, functional and structural connections for better connectivity measurement should be addressed (Vogt *et al*., 2009).

The expected result is a deeper understanding and a practical framework for GI ecological connectivity-based planning and analysis. Landscape pattern optimisation is aimed at increasing landscape core patch connectivity (Wang *et al*., 2021b). The corridors potentially improve accessible habitats within the surrounding landscape and became an essential element of the European GI network, thus providing nationally and internationally significant biological fluctuations and corridors of conservation (Carlier *et al*., 2019). By preserving and developing ecological sources and artificial corridors, the landscape ecosystem's spatial interconnectedness protects biodiversity and increases urban restoration resilience (Dai *et al*., 2021). Thus, to solve the landscape fragmentation problem, understanding landscape ecological principles, landscape connectivity and optimisation is not enough. Furthormore, understanding how to develop GI for ecological connectivity is something to ponder upon. Yeo et al. (2022) mentioned that methodology and analysis tools should be chosen diligently for GI connectivity study.

To achieve these objectives, our methodology involves a detailed literature review on morphological spatial pattern analysis (MSPA) and the landscape connectivity index as tools to address green space fragmentation. Thus, the following questions were investigated:

1. How should GI ecological connectivity-based planning and analysis be performed in a case study?
2. How can a GI ecological connectivity-based framework be established?

Hence, the study objective is to systematically review case studies on how interconnected corridors and core areas within GI can maintain or restore ecological processes and functions, ultimately aiding in nature restoration of landscape fragmentation.

2. Methodology

Case studies were analysed using a systematic literature review (SLR) protocol. Article sources were identified, articles were screened and their eligibility was evaluated using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2009) process.

2.1. The PRISMA Process

The PRISMA 2009 guides an SLR by describing a precise research question, ascertaining the criteria for exclusion and inclusion and evaluating the pertinent scientific articles (Sierra-Correa & Kintz, 2015). The PRISMA flowchart presents data on article screening, eligibility assessment and whether the article should be excluded from the review or included (Pati & Lorusso, 2018).Thus, the PRISMA 2009 is clear and credible.

2.2. Resources

The Scopus and ScienceDirect journal databases were searched in this SLR. The Scopus database features approximately 7000 publishers and 23,452 peer-reviewed journals and displays citations and abstracts, while ScienceDirect contains 2,350 peer-reviewed journals and 19 million articles. Both databases feature peer-reviewed and wide-ranging environmental science topics; therefore, they are reliable.

2.3. The SLR Article Selection Process

SLR is a stepwise structured methodological literature review. Figure 1 depicts the SLR process, where articles were selected based on identification, screening and eligibility.

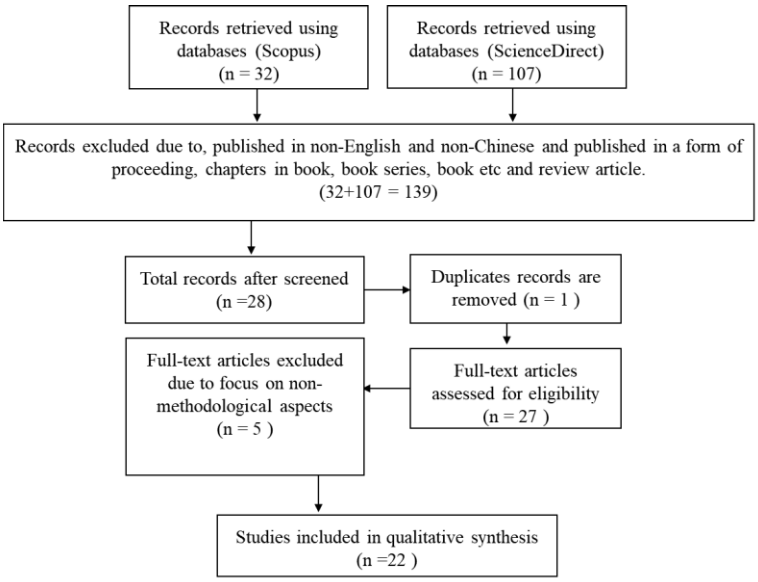

Figure 1. Selection of relevant articles

The study subject was based on the findings of Yeo et al. (2022), who reported that GuidosToolbox and Conefor are the two most frequently used tools in environmental science.

GuidosToolbox and Conefor can be paired where the GuidosToolbox MSPA is used to understand structural connectivity while the Conefor connectivity index can determine functional connectivity.

Conefor is a software programme used to measure the importance of habitat patches for maintaining and improving landscape connectivity (Saura & Rubio, 2010; Yu *et al*., 2016). Conefor is built on solid habitat accessibility and a graph-based model that combines many habitat patch functions in the landscape network (dispersion flux sources, stepping stones) into one indicator (Saura *et al*., 2011). The graph model is a powerful and effective technique for overcoming computing constraints when dealing with large data sets and conducting detailed forest connectivity research (Saura, 2006). Using the MSPA together with graph-based indicators enables constant and correct assessment of digital raster map morphological patterns and ecological significance (Saura *et al*., 2011). Hence, the MSPA is compatible with the landscape connectivity index.

The Scopus and ScienceDirect databases were searched using the keywords listed in Table 1. The keywords were chosen according to the subject topic and search efforts in the identification stage, which revealed that the synonym search included varied studies outside the study scope. Accordingly, the search results were limited using exact terms and Boolean search keywords.

Table 1. The search string

Database	search string
Scopus	All fields (“GuidosToolbox” OR “MSPA” OR “Morphological Spatial Pattern Analysis” AND “Conefor” OR “Conefor Sensinode”)
ScienceDirect	(“GuidosToolbox” OR “MSPA” OR “Morphological Spatial Pattern Analysis” AND “Conefor” OR “Conefor Sensinode”)

Table 2. Criteria for exclusion and inclusion

Criterion	Inclusion	Exclusion
Publication timeline	No exact date to understand the research time frame	
Document type	Peer-reviewed articles that used landscape ecology as the GI theory and used GuidosToolbox and Conefor	Conference proceedings, book chapters, book series
Language	English and Chinese	Not in English or Chinese
Study type	Case study focused on MSPA and landscape connectivity	Not focused on planning methodology, GI analysis, case study, MSPA, Conefor

The two databases were searched on 10 September 2021, from which a total of 139 articles met the criteria listed in Table 2. No publication timeline was excluded to ensure understanding of the progressive studies included in this review according to year. The quality of the selected articles was assessed by examining whether the main objectives and aims of the article were connected to MSPA and Conefor. One article was removed due to duplication.

In the eligibility assessment, the titles, abstracts and contents of 27 articles were judiciously reviewed to ensure that they fulfilled the inclusion requirements and achieved the study objective. In total, five articles were excluded as they did not focus on the non-methodological quality; therefore, 22 qualified articles remained for the analysis.

3. Results and Discussion

The key findings presented in Table 3 (see at the end of the paper) demonstrate the data sources and processing, MSPA and landscape connectivity index. A few other functional connectivity tools were also identified.

3.1. Data Source and Processing

The data sources were mainly determined based on the purpose of the included study. Most studies included the data source where remote sensing (RS and land cover) and land use data were the primary data sources for GI connectivity research. Lin et al. (2021) utilised land use data from planning agencies and Chinese Academy of Sciences land cover data. Nonetheless, additional data were needed when the study objective required a resistance layer, such as physical land characteristics (topography, digital elevation model [DEM]) and human interference (night-time light image and human population). Ecological data, such as the normalised difference vegetation index (NDVI), soil data, climate data (precipitation data, precipitation, perennial average evapotranspiration) and habitat data were also studied to derive a better ecological understanding of the site. For example, Dai et al. (2021) used NDVI, chlorophyll concentration and sample enterprise data to construct an ecological network together with land use and land cover.

Regarding RS data, satellite resolutions ranged from medium to high. The factors influencing the RS data type used were largely based on the study problem and objective, which determined the RS image's spatial, spectral, radiometric and temporal resolution. Moreover, financial support determined whether free or paid RS images were used in the study. The RS image preparation is crucial to ensure accurate data. Only seven studies described pre-processing, such as atmospheric correction, radiometric calibration, mosaic and clipping. Guo et al. (2018) used ENVI software with object-based image analysis (OBIA) to obtain agricultural land, green space, transportation area, built-up area and water land cover categories. Land use and land cover were classified mainly to distinguish between non-greenery and greenery areas. Castro et al. (2020b) studied the Belém area of endemism, the Amazon and soil cover as non-habitat (other than natural forest) and habitat (natural forest). Thus, the research objectives determined their classification.

The RS images use and interpretation are considered with insufficient weight in GI ecological connectivity studies, as depicted in Table 3. Seven studies described image pre-processing (Chen *et al*., 2019; Guo *et al*., 2018; He *et al*., 2021; Li *et al*., 2020; Tao *et al*., 2021; Wang *et al*., 2021a; Zhang & Wu, 2018), six studies mentioned land use and land cover classification methods (Chen *et al*., 2019; Guo *et al*., 2018; He *et al*., 2021; Hernando *et al*., 2017; Tao *et al*., 2021; Wang *et al*., 2021a) and 10 studies validated their data (Chen *et al*., 2019; Guo *et al*., 2018; Gutiérrez *et al*., 2021; Hernando *et al*., 2017; Tao *et al*., 2021; Valeri *et al*., 2021; Wang *et al*., 2021a; 2021b; Zhang *et al*., 2020; Zhang & Wu, 2018). Thus, future research should seriously consider RS applications and explanations to ensure that other researchers understand, replicate or enhance the data collection methodology to establish GI.

3.2. Identification of Ecological Sources

An ecological source is a critical patch that stimulates ecological processes, maintains the integrity of the ecosystem and delivers high-quality or extensive ecosystem services (Peng *et al*., 2018). Thus, identifying ecological sources is a crucial phase in ecological corridor construction (Cui *et al*., 2020).

3.2.1. The MSPA

This section presents crucial information on using MSPA as a structural connectivity method. All studies in this SLR used MSPA, but some only mentioned it briefly (Carlier *et al*., 2019; Dai *et al*., 2021; Hernando *et al*., 2017; Li *et al*., 2020; Wang *et al*., 2021a; Zhang *et al*., 2020). It is important to have detailed explanation of the methods that can guide novice researchers. Some researchers used conventionally ecological sources, such as large-scale forest parks or nature reserves. Nevertheless, the MSPA approach differentiates the types of landscape and extracts core regions as ecological sources and avoids the partiality of artificially selected ecological sources (Tao *et al*., 2021). Consequently, conservationists should focus on safeguarding core habitat sizes, enhancing connectivity and recognising the minor-habitat value (Lin *et al*., 2021). The MSPA is a raster image classification approach that accurately classifies the spatial pattern function classes (Tao *et al*., 2021) via the measurement, identification and segmentation of digital raster map morphological patterns according to mathematical morphological principles, such as dilation, erosion, opening and closure processes (Vogt *et al*., 2007). Table 4 lists the pattern classes that can be extracted from MSPA and provide meaningful spatial information on fragmented green spaces.

Table 4. The MSPA pattern classes and their ecological implications (An *et al*., 2021; Vogt *et al*., 2009)

Pattern classes	Ecological implications
Core	Large habitat patches serve as vital source areas, facilitating migration and supporting diverse wildlife habitats.
Islet	Small and weakly connected patches act as hubs for species communication, dispersal, energy and matter flow.
Perforation	Internal patch between core and non-green area transition zone, generating crucial exerts edge effects on core patch ecology.
Edge	Transition zones between the core area and non-green landscape area, safeguarding the core area ecological process through edge effects.
Bridge	Connecting corridors linking adjacent core areas essential for species diffusion and energy exchange.
Loop	Corridors within the same core area enable species and energy exchange in the core patch.
Branch	A pattern that links with only one side to a bridge, perforation, edge or loop.

The MSPA is sensitive to pixel size and edge width (Wang *et al*., 2021c) where smaller grain sizes and edge widths yield a more detailed spatial pattern (Chen *et al*., 2019). The resolution range used in this review was 4–120 m. For example, Saura and Pascual-Hortal (2007) studied a relatively small total area in the research region. Resultantly, the 30 m × 30 m cell size preserved the primary landscape components of the study area while meeting research data accuracy standards. Nonetheless, sustained discussion of the rationale of the MSPA scale in future studies is vital (He *et al*., 2021). The MSPA segmentation can be refined using a user-defined edge width parameter (Velázquez *et al*., 2017). The edge width defines the patch edge effect size and may influence the number of cells demarcated as the core area (An *et al*., 2021).

The core and background area transition zone has an edge impact and preserves the core area biological processes (Tao *et al*., 2021). In a multi-scale study (10, 20, 30, 60, 100, 120 m), Hernando et al. (2017) reported that increasing edge width converted a small core into an islet and a narrow core into a bridge. Thus, the edge width should be established considering the protected species, research area form and appropriateness (Wickham *et al*., 2010). In this review, the edge width varied with the species or study objective and ranged from 15–300 m.

Only nine studies reported the neighbourhood rule (An *et al*., 2021; Cui *et al*., 2020; Guo *et al*., 2018; He *et al*., 2021; Modica *et al*., 2021; Tao *et al*., 2021; Valeri *et al*., 2021; Wang *et al*., 2021b; Zhang & Wu, 2018). All nine studies used the eight-neighbour rule instead of the four-neighbour rule, where the former increased core area connectivity (Wickham *et al*., 2010).

3.3. Potential Important Ecological Sources

3.3.1. Conefor

This section presents Conefor as landscape patch ranking tool. All included studies used Conefor but did not document the details well. Fourteen studies discussed the distance threshold value (An *et al*., 2021; Carlier *et al*., 2019; Castro *et al*., 2020a; 2020b; Chen *et al*., 2019; Cui *et al*., 2020; Guo *et al*., 2018; He *et al*., 2021; Lin *et al*., 2021; Tao *et al*., 2021; Valeri *et al*., 2021; Velázquez *et al*., 2017; Wang *et al*., 2021a; Zhang & Wu, 2018), six studies mentioned the dispersal probability and three studies reported on connectivity classification (Chen *et al*., 2019; Cui *et al*., 2020; Guo *et al*., 2018; Lin *et al*., 2021; Tao *et al*., 2021; Zhang & Wu, 2018).

Saura and Pascual-Hortal (2007) defined the probability of connectivity (PC) as the possibility of two individuals distributed randomly in the landscape, which fall into interconnected (passable) habitat areas assuming a set *n* of habitat fragments and connections (P_{ij}) between them. Saura and Pascual-Hortal (2007) The PC concept relies on interpatch dispersion probabilities, habitat availability and graph structure as foundation (Saura & Pascual-Hortal, 2007) The PC concept, as recommended by Saura (2006) provides a more precise and comprehensive portrayal of connectivity, rendering it a superior option for planning applications of forest landscapes compared to integral index of connectivity (IIC). Thus, the extensively used PC (Wang *et al*., 2021b; Wei *et al*., 2018) is the best index for assessing connectivity (Li *et al*., 2020). The PC may be used to measure landscape connectivity and identify areas with significant connectivity. The PC is determined using the following formula: where a_i and a_j denote habitat areas *i* and *j*, P_{ij}denotes the strength of connection between any pair of patches *i* and *j* and A_L denotes the area of study, which includes all land cover types (Wei *et al*., 2018). The PC increases from zero to one as the connection improves. The PC equation is stated as follows:

$$PC = \frac{\sum_{i=1}^{n} \sum_{j=1, i \neq j}^{n} P_{ij}^{*} \ a_i a_j}{A_L^2}.$$

The dPC value (%) quantifies the significance nodes to sustain connectivity across the landscape (Guo *et al*., 2018; Saura & Torné, 2012). Thus, utilising dPC serves as a valuable tool for practising conservation efforts, focusing on patches crucial for maintaining network connectivity. The dPC is calculated with the following equation:

$$dPC(\%) = 100.\frac{PC - PC_{remove}}{PC},$$

where PC indicate the patch's overall landscape connection, while PC_{remove} reflects the the overall landscape connectivity after a patch removal (Cui *et al*., 2020). The critical value of the deleted patch is determined by the change in overall landscape connectedness (Guo *et al*., 2018).

The IIC measures the distance between patches to the threshold dispersion distance of a species (Saura & Torné, 2009). A binary dispersion model in which two forest patches are either linked or not, without intermediate alteration of the connection strength or feasibility, is the basis of the IIC (Saura, 2006). The IIC is divided into the IIC-Intra, IIC-Flux and IIC-Conn sub-indices, which each considers the unique contribution of a fragment to total landscape connectivity. The IIC-Intra calculates the internal contribution of a fragment according to its area, the IIC-Flux calculates dispersion flow based on the placement of a fragment within a fragmented network and the IIC-Conn calculates the contribution of a fragment to a connecting element based on its topology (Saura & Rubio, 2010). When the IIC = 1, the whole area included in the computation is considered a habitat patch (Cui *et al*., 2020).

Based on the impact on overall landscape connectivity according to the IIC and PC, the relative patch ranking can be determined by calculating the percentage of importance of the patch delta IIC (dIIC) and dPC, which equals the index per cent decrease if the specific patch is removed (Pascual-Hortal & Saura, 2006; 2007). Using IIC instead of PC is only acceptable in circumstances of data unavailability (in which P_{ij} cannot be determined) or for ease of interpretation and analysis (Saura & Pascual-Hortal, 2007).

The dIIC is the relative significance calculated for each node based on the IIC fluctuation (Castro *et al*., 2020a). The dPC and dIIC can be integrated. For example, Dai et al. (2021) selected core patches with dPC and dIIC values > 1 as the source of biological species reproduction and development. Lin et al. (2021) indicated patch size and the degree of connectivity as two key markers for ecological function measurement. Accordingly, the authors classified core patches into extremely important, important and common core areas according to a combined assessment of dI (the average of dPC and dIIC and patch size).

In Conefor, the associated threshold value varies and relies on biological diffusion and migration parameters (Cui *et al*., 2020). An et al. (2021) stated that the threshold value was established at 500 m, which may ensure successful migration by the Asian elephant (*Elephas maximus* Linnaeus). The direct dispersion probabilities (P_{ij}) that typified the linkages were determined by altering the dispersal ability of a hypothetical focus species living in the environment (Saura & Rubio, 2010). Subsequently, each inter-patch connection was defined by a dispersal probability, obtained as a function of distance (Velázquez *et al*., 2017).

The core area is classified to establish management measures. Size, dPC values, or natural breaks (or Jenks natural breaks optimisation) determine the classification method. For example, An et al. (2021) identified the 10 highest dPC core patches as biological species reproduction and growth source sites. Nevertheless, Li et al. (2020) identified the most significant ecological patches with dPC > 0.5 as ecological sources. Ecological sources were divided into three grades according to area size (Dai *et al*., 2021). Furthermore, the classification can be integrated by using area size and dPC value (Cui *et al*., 2020). The forest pieces were classified into five hierarchical groupings using Jenks natural breaks optimisation where class one and five were the most and least important, respectively (Zhang *et al*., 2020). Thus, the classification category depends on the author's judgment.

The selection of focal species and their dispersion distance is critical for a more comprehensive assessment of landscape connectivity (Guo *et al*., 2018). Focal species can be chosen based on the literature, expert opinions, models of species distribution, or information from radio tracking (Bergès *et al*., 2020). Only four studies mentioned the focal species, namely the Asian elephant, bats (*Pipistrellus pygmaeus*, *Nyctalus leisleri*, *P. pipistrellus*, *Myotis mystacinus*, *M. nattereri*, *M. daubentoniid*, *Plecotus auratus*, *P. nathusii*), raccoon dogs (*Nyctereutes procyonoides*), ring-necked pheasants (*Phasianus colchius*) and the Cantabrian capercaillie (*Tetrao urogallus cantabricus*). For example, Weber and Allen (2010) selected keystone, umbrella and other focal species local to the region to determine GI connectivity, size and other thresholds.

Guo et al. (2018) allocated dispersion distances for focal species based on existing research publications, but the dispersal distances of most species have not been investigated. Modica et al. (2021) used each CORINE Land Cover (CLC) class suitability score and 66 terrestrial faunal focal species and reported a comprehensive finding. Nonetheless, data reliability must be relevant to describe the ecological characteristics (Modica *et al*., 2021). Consequently, species with the greatest exigencies on habitat quality and dispersion (those with the lowest dispersal ability) should be favoured over generalist or highly migratory species (Baguette *et al*., 2013). Guo et al. (2018)suggested that the focal species chosen should display the following traits: (1) dependent on green spaces; (2) endangered by city growth; (3) average dispersion capacity. Thus, species under exigencies and non-highly dispersed species are preferred as focal species.

3.4. Other Supportive Connectivity Tools

This section outlines the frequently used methods for identifying ecological corridor connectivity. Landscape connectivity is crucial in landscape ecological integrity; hence, it is critical to reflect landscape connectivity correctly and define the degree of ecological corridor importance. Castro et al. (2020) reported that the significance of fragments in protecting biodiversity was better understood by quantitative rankings of possible corridors.

The minimum cumulative resistance (MCR) obtained minimal resistance surface to determine species migration corridor (Tang *et al*., 2021). In this review, eight of the included studies used the MCR model. The MCR model utilised a geographical information system (GIS) platform to incorporate geomorphology, geography, human activities and related variables, enabling the simulation of the least cost path between the ecological sources (Tao *et al*., 2021). The formula for the MCR model is as follows:

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

where D_{ij} denotes the spatial distance between the source point j and the space unit I and R_i denotes the space unit i resistance coefficient. Simplifying the MCR model into an assessment factor instead of a geographical pattern reduced the influence of human development activity on the natural environment (Dai *et al*., 2021). Thus, Wang et al. (2021c) recommended incorporating field surveys and expert advice to express theoretical optimisation into reality. For example, Tao et al. (2021) determined individual resistance factor categorisation and score by engaging experts, researching relevant literature and calculating the each resistance component weights using analytic hierarchy to derive the comprehensive ecological resistance surface, thus determining the MCR model cost data.

Only one study used Circuitscape, which is based on circuit theory (describes the movement behaviour of wild animals via the random walk theory and may reveal several viable pathways) (An *et al*., 2021). Migratory paths and the possibility of successful population dispersal can be determined with circuit theory (McRae & Beier, 2007). Therefore, the theory is crucial in landscape connectivity assessment and facilitating biological habitat conservation (McRae *et al*., 2008). Circuit theory identifies ecological networks through associating ecological meanings with physical variables, such as conductivity, current, resistance and voltage, without requiring new formats of data and using the benefits of the random migration and graph theory (McRae, 2006). The novel approach of combining MSPA and circuit theory in landscape connectivity research may be a model for developing and optimising ecological networks in other domains (An *et al*., 2021).

The other tools that were mentioned once in the included articles were UNICOR (UNIversal CORridor network simulator), MatrixGreen, Zonation model and FunConn. The UNICOR predicts resistant kernel and factorial least-cost route networks for each dispersion ability threshold (Wang *et al*., 2021a). Wang et al. (2021a) performed supervised classification on Landsat 8 data followed by MSPA and Conefor to identify critical core biodiversity regions. The factorial least-cost path connectivity networks and the resistant kernel were simulated with UNICOR, where resistant kernel analysis predicted the dispersion movement density over the terrain, which indicated that kernel connection was highly dependent on dispersal ability (Wang *et al*., 2021a). MatrixGreen uses patch distance analysis to analyse the core patches in GI landscape networks and the largest landscape network under different connection distances (Chen *et al*., 2019).

The significance of corridors in ecological networks was assessed with the Zonation model (An *et al*., 2021), where the top 10% of the grids ranked by the model were recognised as significant corridor areas. The Zonation model performs ranking at the pixel level based on the minimal marginal loss principal, which iteratively subtracts grids from existing density maps to describe the landscape connectivity state better and determine the relative biological corridor relevance (Moilanen *et al*., 2005).

FunConn is a toolkit that combines graph theory and least-cost path analysis to generate a topological and spatial ecological network model (Modica *et al*., 2021). The FunConn model uses land cover surface with additional predictor variables and inputs, such as minimum patch size and resource quality threshold, which the user must define and weight (Evangelista *et al*., 2012). Hence, expert habitat knowledge is crucial for spatial model integration (Evangelista *et al*., 2012). The authors selected FunConn for its flexibility and reliability, which resulted in a considerably more knowledgeable identification of the most suitable habitats of a species (Evangelista *et al*., 2012). For example, Modica et al. (2021) used FunConn to determine faunal species migration patterns and land cover characteristics.

Fragstat also supports connectivity and can be used to understand landscape patterns before or after modelling. Cui et al. (2020) used Fragstat before modelling, while Lin et al. (2021) used it to understand the landscape pattern using the landscape shape index after modelling. The included studies also used other supporting tools and methods, such as InVEST, spatial buffer analysis and kernel density analysis, which are not discussed here as it was not significant (only one study used each of the aforementioned tools).

Conclusively, the MCR model remains relevant in connectivity analysis, given its wide acceptance in most studies. Furthermore, the MCR model can be integrated with other tools for comparison and validation, which presents a compromise among the methods. Nevertheless, other tools can also be considered based on the study objectives, data requirement, expertise and compromise between generalisation and details. Thus, improvements are expected to result in an improved understanding of the compatibility and result reliability of the integrated tools.

4. The GI Connectivity Provision Framework

An urban green space network with strong ecological connectivity requires a thorough understanding of landscape ecology and resistant-surface design (Cui *et al*., 2020). Thus, landscape ecological principle, graph theory and the MCR model provided a theoretical and methodological basis for establishing a GI connectivity framework.

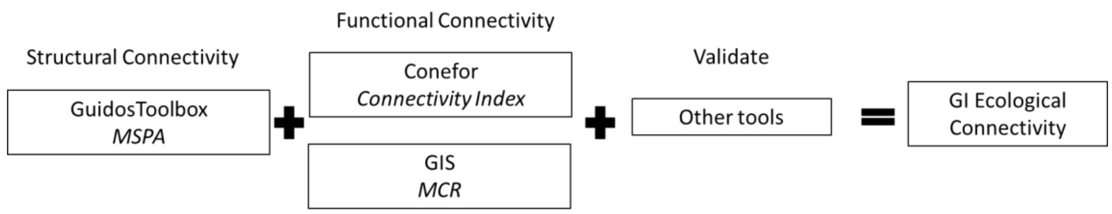

Figure 2. Summary of structural and functional connectivity integration to achieve GI ecological connectivity

The study flow is summarised in Figure 2. An understanding of structural connectivity was established using MSPA; subsequently, functional connectivity was clarified using the connectivity index and MCR model. The structural and functional connectivity results were validated with Circuitscape. The following section describes the proposed framework.

4.1. Example of Proposed GI Ecological Connectivity Framework

Land use-derived data must be categorised systematically. The land use data was adapted from (Ahern, 1995) planning strategies to obtain the information needed to aid decision-making and GI development as a mainstream urban infrastructure mechanism. The planning framework contained four measures (protective, defensive, offensive and opportunistic). Land cover data should be systematically informed, pre-processed, classified and validated. Nonetheless, the application of this framework is subject to data availability and the methods or software can be selected according to the available data type. Thus, MSPA (GuidosToolbox), PC (Conefor) and the MCR model were used.

In the proposed framework, the MSPA foreground was the land cover and land use data that contribute to GI connectivity. Opportunistic green spaces were identified with 30-m resolution Landsat images. The edge width was set to 15 m and connectivity was maximised with the neighbourhood rule of eight. The Conefor threshold value was 1000 m according to the indicator species Eurasian tree sparrow (*Passer montanus*), which is a dispersal species constantly present in urban tropical areas that can be a patch distance parameter (seed dispersal) (Nor *et al*., 2017). The probability of dispersal was 0.5. The PC was chosen as it yielded better quantitative results than the IIC. The result was classified according to area size and dPC to identify the critical patches. Finally, the least-cost path for the most suitable corridor was determined using the MCR model and validated via Circuitscape.

5. Conclusion

The GI ecological connectivity can solve landscape fragmentation problem in highly fragmented urban green spaces. A suggested framework was formulated to guide any study that employs GI ecological connectivity as landscape fragmentation solution. The GI ecological connectivity is vital in highly fragmented urban green spaces and requires investigation. Structural (MSPA) and functional connectivity (connectivity index, PC) should be paired as an ecological connectivity solution. The SLR enabled a clearer understanding of the study details involving MSPA and the connectivity index. Data sources should be selected systematically and RS can aid in identifying potential green spaces that are not in land use. Furthermore, focal species that determine the dispersal distance are vital to ecological connectivity studies. The SLR revealed a few ecological corridor methods where the MCR model was used most frequently; thus, MSPA, the connectivity index and the MCR model were used to propose a GI connectivity framework. Other tools could be used for comparison or validation. For example, Circuitscape could be used to validate the least cost path produced in the MCR model. Nevertheless, tool and data selection are dependent on the study area's availability and complexity. In future research, the study's findings can be utilised to address the issue of landscape fragmentation by understanding the details of structural and functional connectivity.

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Table 3. Overall SLR findings

Author	Data source	Pre-processing-atmospheric correction	RS Analysis	Data validation	MSPA					Conefor			Indicator species
					Pixel	Edge width	Format	Neighbourhood rule	Moving window	Threshold value of distance	Probability of dispersal	Classification of importance	
An et al. (2021)	/				/	/	/	/		/			/
Carlier et al. (2019)										/			/
Castro et al. (2020)	/					/				/		/	
Castro et al. (2020)	/					/				/		/	
Chen et al. (2019)	/	/	/	/	/	/	/			/	/		
Cui et al. (2020)	/				/		/	/		/	/	/	
Dai et al. (2021)	/												
Guo et al. (2018)	/	/	/	/	/	/		/		/	/		/
Gutiérrez et al. (2021)	/			/		/							
He et al. (2021)	/	/	/		/	/	/	/		/			
Hernando et al. (2017)	/		/	/									
Li et al. (2020)	/	/											
Lin et al. (2021)	/					/				/	/		
Modica et al. (2021)	/				/			/	/				
Tao et al. (2021)	/	/	/	/	/		/	/		/	/		
Valeri et al. (2021)	/			/	/	/		/		/			
Velázquez et al. (2017)	/					/				/			/
Wang G. et al. (2021)	/	/	/	/						/			
Wang N.et al. (2021)	/			/	/	/		/					
Wang S. et al. (2021)	/				/	/							
Zhang et al. (2020)	/			/									
Zhang & Wu (2018)	/	/		/	/	/		/		/	/		