

Article

Exploratory Vulnerability Assessment of the Urban Ecological Security Pattern in Bogotá: Static and Dynamic Attack Simulations and Cascading-Failure Modelling in a Global South City

Jose David Martinez Otalora ¹, Jie Shen ^{1,2,*} and Anyela Piedad Rojas Celis ¹

¹ College of Civil Engineering and Architecture, Zhejiang University, Hangzhou 310058, China; jdmartinezo@unal.edu.co (J.D.M.O.); 12212173@zju.edu.cn (A.P.R.C.)

² Center for Balance Architecture, Zhejiang University, Hangzhou 310058, China

* Correspondence: jshen@zju.edu.cn

Abstract

The Ecological Security Pattern (ESP), composed of ecological sources, resistance surfaces, and corridors, provides a spatial basis for mitigating urban landscape fragmentation and sustaining ecological security. However, most urban ESP studies have focused on its spatial delimitation, while the assessment of network vulnerability under disturbance remains limited. This study applies an integrated, exploratory, and model-based methodological framework that combines ESP mapping, ecological network analysis, attack simulation, and load–capacity cascading failure modelling to generate simulated indications of the potential vulnerability of the urban ecological network of Bogota. The results identified 58 ecological sources with a combined area of 123.02 km² (19.58% of the study area) and 107 active corridors. In the simulations, sources N540, N433, and N847 showed the highest topological relevance, whereas sources N933, N337, and N847 concentrated the greatest functional importance. In the disturbance simulations, the network showed greater relative robustness to random removals; in contrast, degree- and betweenness-targeted removals produced a more accelerated loss of the connected component, whereas degree- and PageRank-based perturbations accelerated simulated functional degradation. In the dynamic scenario analyzed, the model organized the network into four risk levels and suggested indirect and multi-stage trajectories of simulated potential failure propagation. These findings contribute to the exploratory diagnosis of ESP functional vulnerability and provide preliminary, simulation-based spatial criteria to guide exploratory ecological prioritization analyses and scenario assessment in Bogotá and dense Global South metropolises.

Keywords: ecological security pattern; network vulnerability; structural connectivity; cascading failures; urban ecological vulnerability

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1. Introduction

Urban expansion constitutes a major land-use change process that transforms landscape ecological structure [1,2]. This process increases fragmentation, reduces habitat continuity, and reorganizes ecological spaces, affecting ecosystem services and urban re-

sponses to environmental pressures such as climate change, biodiversity loss, and thermal stress [3–5]. In densely urbanized metropolises, these transformations reduce the amount of available ecological space, fragment the functional continuity of the landscape, and limit potential connectivity among ecological areas within heterogeneous built matrices. The key analytical problem is how connectivity is organized, how it responds to perturbations, and which components produce disproportionate losses in the modelled functioning of the system.

The Ecological Security Pattern (ESP) provides a framework for addressing this problem by integrating ecological sources, resistance surfaces, and corridors into a spatial structure that supports territorial ecological security [6–8]. In this study, the ESP is interpreted as a spatial network whose potential connectivity depends both on patch arrangement and on the resistance of the urban matrix [9–11]. Ecological flow is operationally represented as the potential connectivity of ecosystem functions among ecological sources, rather than as direct species movement, observed hydrological flow, or demographic connectivity. This interpretation follows graph-based connectivity approaches, in which potential connectivity represents the capacity of landscape elements to remain connected under defined spatial or resistance assumptions [12–14]. For the cascade model, the relative functional contribution of each ecological source is represented through a synthetic functional load assigned to each node, defined from a nodal functional-importance index that integrates normalized components of cooling capacity, land-use suitability, habitat quality, and carbon storage [15,16]. This synthetic functional load is used as a modelling construct to approximate the relative functional contribution of ecological sources within the cascade simulation; it does not represent a direct measurement of observed ecological flow or empirical ecosystem-function transfer. Consequently, the identification of ecological sources cannot rely solely on patch size or visual continuity, but requires the integration of complementary dimensions, including the provision of ecosystem services, landscape spatial morphology, and graph-based structural connectivity [17–19].

This interpretation of the ESP frames a resilience problem assessed through simulation. If the ESP is conceived as an ecological network, its performance depends not only on the presence of ecological sources and ecological corridors, but also on the system's capacity to absorb perturbations. In this study, ESP resilience is defined operationally as a modelled capacity to maintain network structure and modelled functional-load distribution, redistribute load, and avoid disproportionate losses under explicit assumptions of failure and redistribution. A resilience assessment framework for the ESP therefore integrates at least three dimensions: the structural organization of the network, the functional importance of nodes, and the simulated response of the system to perturbations [20,21].

Although the literature on ESP has advanced in the identification of ecological sources, the construction of resistance surfaces, and the delineation of ecological corridors, these studies have focused on the cartographic representation of spatial patterns [22,23]. In parallel, the literature on ecological network resilience has developed topological metrics and perturbation models that allow structural robustness to be evaluated under random and targeted disturbances [19,24], while cascading failure models have shown that failure propagation cannot be fully captured through static analyses [25]. However, these bodies of literature have remained disconnected: ESP studies rarely examine the simulated vulnerability of the networks they delineate, whereas ecological network resilience models often represent load and propagation more abstractly, without fully incorporating the functional heterogeneity that distinguishes the ESP—sources with differentiated ecosystem-service loads, spatially explicit resistance, and corridors with variable viability—as attributes that condition both failure propagation and the differential criticality of nodes. This disconnection is relevant in metropolitan contexts of the Global South, where network analyses applied to ecosystem services remain scarce [26,27].

The specific contribution of this study lies in the exploratory adaptation of a load–capacity cascading–failure model to the functional structure of the ESP: an architecture in which the initial load of each node is neither homogeneous nor arbitrary, but reflects its differentiated ecosystem-service-based functional load; failure propagation, in turn, is modelled according to the resistance geometry of the landscape. This approach allows us to explore, in simulated terms, the distinction between structural importance and functional importance of nodes, trace modelled cascade-propagation trajectories under explicit load–capacity assumptions, and establish prioritization criteria based on functional criticality under perturbation—advances that do not derive from simply adding existing methods together, but from their joint reformulation within the logic of the ESP [28].

Bogotá represents a relevant case for examining the resilience of the ESP because it combines a dense urban matrix, marked topographic heterogeneity, and a fragmented ecological structure with non-uniform connectivity [29,30]. Under these conditions, the simulated response of the ESP depends on a limited subset of ecological sources, corridors, and nodes capable of sustaining connectivity and buffering functional degradation under perturbations. Bogotá therefore provides an analytical case for evaluating how simulated ESP vulnerability is shaped by three linked dimensions: the structural and functional organization of ecological sources, the response of the network to targeted and random perturbations, and the spatial orientation of cascade-propagation trajectories along the mountain–city transition.

Based on this framework, the study is guided by three theoretical expectations, each linked to a specific objective. First, because structural position and ecosystem-service-based functional load are not assumed to be fully coincident dimensions of node importance, simulated node criticality is expected to reflect both network position and nodal functional load rather than structural centrality alone [31,32]; the corresponding objective is to identify and characterize the ecological sources and the structural organization of Bogotá's ESP by integrating ecosystem services, landscape morphology, and structural connectivity. Second, because heterogeneous networks are typically more vulnerable to targeted removals than to random failures, centrality-targeted perturbations are expected to produce faster losses of efficiency and connectivity than random attacks [13,33]; the corresponding objective is to evaluate the simulated response of the network by comparing multiple attack strategies in terms of scale and efficiency. Third, given Bogotá's mountain–city topographic polarization, cascading propagation is expected to follow spatially anisotropic trajectories shaped by edge corridors and resistance geometry, an expectation derived from the structural conditions of the study area [29,30]. The corresponding objective is to identify critical nodes, risk levels, propagation trajectories, and preliminary spatial-prioritization criteria based on cascading–failure simulation.

In line with these expectations and objectives, the study makes three exploratory contributions, articulated within an integrated ESP–network–cascade framework for a dense metropolis in the Global South. First, it proposes and applies a scheme that integrates multisource data to approximate, exploratorily and without empirical validation of the underlying ecological processes, the structural organization and functional load of the ESP. Second, it articulates complex-network methods with landscape ecology to examine, in an exploratory manner, the dynamic vulnerability of the network under simulated perturbations, beyond static cartographic representation. Third, it applies this approach in Bogotá, generating preliminary model-based indications of how mountain–city topographic polarization may shape the vulnerability of metropolitan ecological networks in the Global South, without treating these indications as empirically validated ecological responses or planning-ready prescriptions.

2. Materials and Methods

2.1. Study Area

Bogotá, the capital of Colombia, is located on a high-altitude plateau in the Eastern Cordillera of the Andes, with elevations ranging from 2650 to 3750 m above sea level. It has a tropical highland climate, with mean annual temperatures between 7 and 14.5 °C. Its territorial structure is shaped by a contrasting physical setting: mountainous formations dominate the eastern and southern sectors, while the Bogotá River defines the western boundary and part of the northern edge of the urban system. This configuration establishes topographic and environmental gradients that influence the distribution of natural land covers, urbanized areas, and infrastructure.

The city covers a total area of 1774.8 km², of which 307.36 km² correspond to urban land, 170.45 km² to suburban land, and 1298.15 km² to rural land, according to the Territorial Land-Use Plan (POT) and the Spatial Data Infrastructure of the Capital District (IDECA). It hosts approximately 7,929,539 inhabitants and 703,523 residential buildings. For this study, the analysis was limited to the urban footprint of 628.4 km², which encompasses the urban and suburban land of Bogotá (Figure 1a). This delimitation concentrates the area where anthropogenic pressure, landscape fragmentation, and constraints on ecological flow are most intense.

Land use and land cover within this urban footprint form a highly heterogeneous spatial mosaic (Figure 1b). Urbanized areas occupy approximately 267.9 km², forests 153.9 km², grasslands 89.4 km², and croplands 27.7 km², while road infrastructure covers 51.3 km². Strategic ecosystems, including wetlands and water bodies, account for 20.86 km², and areas associated with mining activities represent 17.07 km².

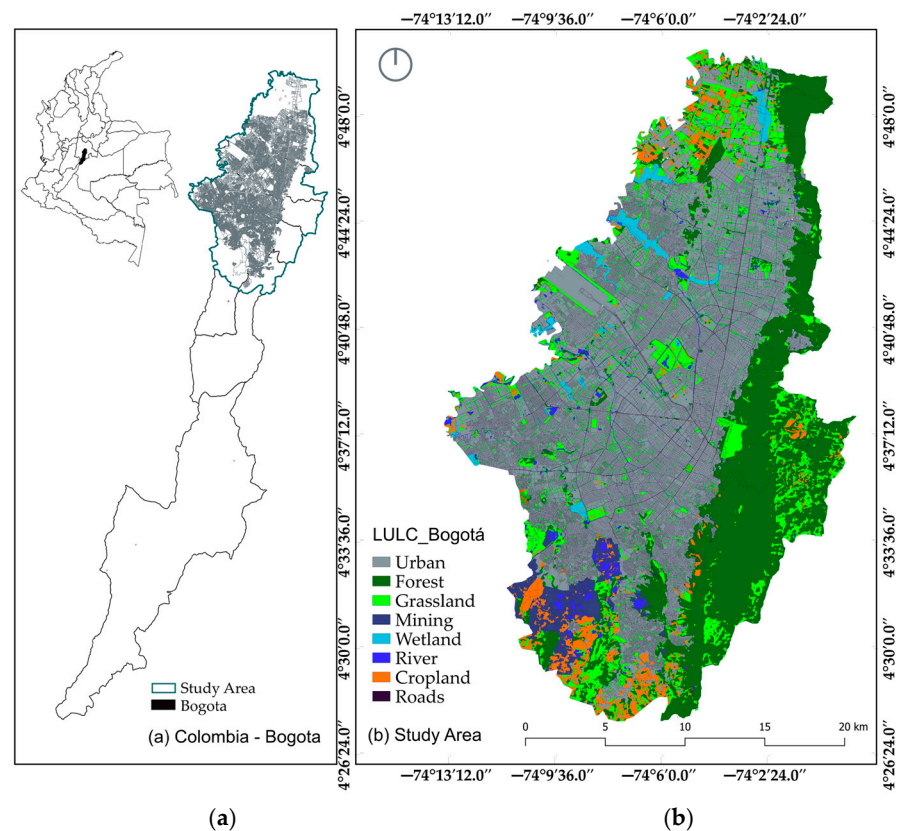


Figure 1. Geographic context and land use and land cover (LULC) characteristics of Bogotá, Colombia. (a) Location of Bogotá and the study area within Colombia. (b) Spatial distribution of land use and land cover categories used in the ecological security pattern assessment. The map was generated using the WGS 84/UTM Zone 18N coordinate reference system (EPSG:32618). The LULC cate-

gories include Urban areas, Forest, Grassland, Mining areas, Wetlands, Rivers, Croplands, and Roads. The scale bar indicates distances in kilometers (km).

Within this urban footprint, natural and semi-natural land covers exhibit greater continuity along the eastern and southeastern edges, whereas the central and western sectors are characterized by denser built cover, infrastructure, and fragmented open spaces.

2.2. Data Sources

The database was constructed from geospatial information obtained from official sources and global platforms, integrating biophysical variables and anthropogenic factors for the characterization of the ESP. Table 1 summarizes the datasets used in terms of variable type, year, and spatial resolution, while the complete sources and access URLs are provided in Supplementary Table S1. The layers were selected based on their contribution to the identification of ecological sources, the construction of resistance surfaces, and the extraction of ecological corridors. To address differences in dataset acquisition years, the study was structured as a cross-sectional diagnostic of the current ESP configuration. The 2025 Dynamic World land-use and land-cover layer was used as the main spatial reference for ecological source identification, ecosystem-service assessment, MSPA reclassification, and resistance modelling. Earlier layers were incorporated according to their analytical role and expected temporal stability: the DEM was used as a stable topographic variable; potential evapotranspiration as a bioclimatic baseline; the World Settlement Footprint and road network as proxies of relatively stable anthropogenic structure; and precipitation and population layers as the most recent official records available for Bogotá. Processing was conducted across multiple platforms: land use and land cover were processed in Google Earth Engine; spatial integration of ESP layers was performed in ArcGIS Pro (v. 3.3.2); ecological corridor extraction and the identification of pinch points and barriers were carried out using Linkage Mapper 3.1.0 and Circuitscape 4.0.5 within ArcGIS Pro; and topological, resilience, and cascading analyses were conducted in RStudio 2023.06.0 Build 421.

Biophysical data included land use and land cover derived from Dynamic World V1, processed in Google Earth Engine using the most recent data at a spatial resolution of 10 m. Natural and semi-natural ecosystems were obtained from the official cartography of the Spatial Data Infrastructure of the Capital District (IDECA) for the identification of core areas and the morphological characterization of the landscape. Additional biophysical variables included the Digital Elevation Model (DEM) of Bogotá (IDECA, 2022), mean annual accumulated precipitation (IDECA, 2023), and potential evapotranspiration derived from the Global Aridity Index v3 [34], which were used both in ecosystem service assessment and in the construction of the resistance surface.

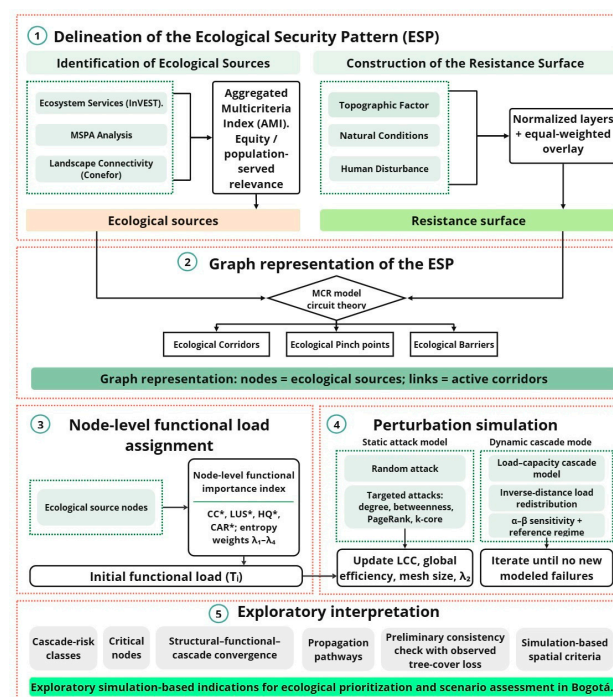
Table 1. Data types and sources used in this study.

Category	Variable/Dataset	Data Year	Spatial Resolution/Format
Ecological factors (natural)	Land use and land cover	2025	10 m
	Digital Elevation Model (DEM)	2022	Raster (GeoTIFF)
	Mean annual accumulated precipitation	2023	Vector (shapefile)
	Potential evapotranspiration	2019	30 arc-seconds
	NDVI (Normalized Difference Vegetation Index)	2025	10 m
Social factors	World Settlement Footprint	2019	10 m
	Population density	2022	Vector (shapefile)
	Distance to roads	2022	Vector (shapefile)
	Distance to rivers	2022	Vector (shapefile)

Anthropogenic factors were represented by the urban footprint, delineated from the World Settlement Footprint product, urban land-use categories obtained from IDECA, population density, distance to roads, and distance to rivers, integrated as spatial proxies of anthropogenic disturbance, fragmentation, accessibility, hydrological proximity, and spatial friction. Prior to analysis, all layers were reprojected to the WGS 84/UTM Zone 18N coordinate system (EPSG:32618), harmonized into a common spatial reference, and adjusted to the working resolution required for each methodological stage through clipping, resampling, or rasterization, when necessary, in ArcGIS Pro.

2.3. Research Methodology

This study applied an integrated methodological framework to characterize the ESP of Bogotá and to evaluate its simulated network response under perturbations (Figure 2). The analysis was structured as an inferential sequence linking ESP delineation, graph representation, nodal functional-load assignment, perturbation modelling, and exploratory interpretation. Ecological-source selection and resistance-surface construction define the ESP as a spatial structure by integrating ecosystem-service indicators, landscape morphology, structural connectivity, and spatial resistance. Corridor extraction, pinch-point and barrier diagnostics, and graph construction then translate this spatial structure into a network representation, in which ecological sources are represented as nodes and active corridors as edges. A node-level functional-importance index subsequently assigns the initial functional load to each source node. Static and dynamic attack simulations, together with the load–capacity cascading-failure model, evaluate structural and functional perturbation under explicit graph, load, tolerance, and redistribution assumptions. Finally, diagnostic screening, preliminary comparison with observed tree-cover loss, and planning prioritization draw on the resulting cascade-risk classification but are interpreted as exploratory, model-derived indications rather than validated ecological outcomes. Table S2 provides a concise audit trail of the main indices, variables, diagnostic outputs, and simulation rules used in this inferential sequence, from ESP delineation to exploratory interpretation, including their source or input, role in the workflow, weighting or parameterization, and calibration or methodological status.



Abbreviations: ESP, Ecological Security Pattern; InVEST, Integrated Valuation of Ecosystem Services and Tradeoffs; MSPA, Morphological Spatial Pattern Analysis; Conefor, connectivity analysis based on graph theory; AMI, Aggregated Multicriteria Index; MCR, Minimum Cumulative Resistance; LCC, Largest Connected Component; CC, cooling capacity; LUS, land-use suitability; HQ, habitat quality; CAR, carbon storage; α , load redistribution coefficient; β , nodal tolerance coefficient; λ , weighting parameter.

Figure 2. Research framework and technical workflow. Arrows indicate the sequential analytical flow and the transfer of outputs from one methodological stage to the next. The superscript asterisk (*) indicates normalized variable values.

2.3.1. Identification of Ecological Sources

Ecosystem service assessment using InVEST

Three ecosystem services—habitat quality, carbon storage and sequestration, and water yield—were evaluated using InVEST 3.15.0 due to their capacity to represent ecological functions in the identification of source areas, following approaches applied in ecological network and ESP studies [35,36]. InVEST parameterization was based on the 2025 land-use and land-cover map, spatially explicit threat layers, habitat-suitability values, land-cover sensitivity matrices, and biophysical parameters assigned by land-cover class. In the Habitat Quality model, the threat factors included urban built-up areas, road infrastructure, intensive agriculture, mining extraction, water pollution, and solid-waste/soil pollution. For each threat, a relative weight, maximum effect distance, and decay function were defined, as reported in Table S3. Habitat suitability and the sensitivity of each land-cover type to these threats were assigned through a land-cover-specific matrix including forests, wetlands, rivers, grasslands, croplands, urban areas, mining areas, roads, and no-data areas; these values are provided in Table S4.

Habitat quality was estimated based on the suitability of each land-cover type and its level of degradation; carbon was derived from aboveground carbon stocks; and water yield was calculated from the balance among precipitation, evapotranspiration, and retention capacity. Carbon storage and sequestration were parameterized using carbon-pool values assigned to each land-cover class, including aboveground carbon, below-ground carbon, soil carbon, and dead organic matter, as shown in Table S5. Water yield was estimated using the InVEST water-balance model, incorporating accumulated annual precipitation, potential evapotranspiration, and land-cover-specific biophysical parameters, including root depth and crop evapotranspiration coefficients, as reported in Table S5. The InVEST parameters were not locally calibrated with field measurements. Therefore, the resulting outputs were interpreted as relative and normalized ecosystem-service indicators for ecological-source selection, rather than as locally validated estimates of absolute ecosystem-service supply. In the source-selection stage, the three InVEST outputs—habitat quality, carbon storage, and water yield—contributed to the ecosystem-service component of the AMI. After ecological sources were selected, the cascade model used a separate node-level functional-importance index to assign the initial functional load to each source node, as described in Section 2.3.3. Water yield was used only in the source-selection stage and was not included as a functional-load component. The input data used for the InVEST assessment are reported in Tables S3–S6, while the corresponding equations, variables, and operational parameters are summarized in Table S7.

Assessment of landscape geometric structure

The geometric structure of the landscape was characterized using Morphological Spatial Pattern Analysis (MSPA) [37] in Guidos Toolbox 3.1. Land-cover maps of Bogotá were reclassified into a binary raster, considering forests, wetlands, grasslands, and water bodies as foreground, and urban areas, mining zones, croplands, and roads as background. MSPA was executed using an 8-neighbor connectivity rule and an edge width of 1, equivalent to one cell at the working resolution of 10 m (Section 2.2), a configuration widely used in urban applications to detect fine patches, riparian elements, and narrow linear connectors in fragmented urban landscapes [38,39]. The procedure classified the foreground into seven morphological classes: core, islet, loop, bridge, perforation, edge, and branch.

Assessment of structural connectivity

The structural relevance of candidate patches was evaluated using Conefor Sensinode 2.6 through the Probability of Connectivity (*PC*) index and its derivative delta Probability of Connectivity (*dPC*) [14]. The 1000 m threshold was used as an operational distance to construct a generic approximation of structural connectivity among patches within Bogotá's urban ESP. Therefore, the resulting *PC* and *dPC* values are interpreted as indicators of potential structural connectivity, rather than as a functional connectivity assessment validated for a focal taxon, observed hydrological flow, or specific demographic process [40]. Connection probabilities (p_{ij}) were modeled using a negative exponential function of the distance between patches, adjusting α such that $p_{ij} = 0.5$ when $d_{ij} = 1000$ m ($\alpha = 1000/\ln(2) \approx 1443$ m), following the conceptual framework of probabilistic connectivity metrics [14]. The expressions of *dPC* and *PC* are presented in Equations (1) and (2), respectively. The operational definition and ecological significance of both indices in the context of the urban ESP of Bogotá are summarized in Table 2.

$$dPC_i = \frac{PC - PC_{remove,i}}{PC} \times 100 \quad (1)$$

where *PC* represents the global Probability of Connectivity index and *PC_{remove,i}* is the recalculated value after the removal of node *i*. The *PC* index is expressed as

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

where *A* is the total landscape area, a_i and a_j are the areas of patches *i* and *j*, respectively, and p_{ij} is the maximum probability of connection between them.

Table 2. Ecological significance of the *PC* and *dPC* indices in the context of the urban ESP of Bogotá.

Index	Operational Definition	Ecological Significance in the ESP of Bogotá
<i>PC</i> (Probability of Connectivity)	Global index that estimates the probability of connection between patches by integrating patch area and dispersal probability among them.	Represents the overall connectivity of the ecological system and allows comparison of changes in the overall state of the network.
<i>dPC</i> (delta <i>PC</i>)	Change in <i>PC</i> after the removal of a patch <i>i</i> . It is decomposed into the fractions <i>dPC_{intra}</i> , <i>dPC_{flux}</i> , and <i>dPC_{connector}</i> .	Quantifies the individual contribution of each patch to maintaining connectivity. In this study, <i>dPC_{connector}</i> was used to identify patches with an articulating (bridging) function within the network.

2.3.2. Selection of Ecological Sources

Ecological sources were identified through the integration of three complementary dimensions: ecosystem services, landscape spatial morphology, and structural connectivity. Patches derived from the core areas delineated by MSPA were classified using an Aggregated Multicriteria Index (AMI), composed of three normalized variables: equity relevance in service provision to the population (*Crit_Equity_PopServed*), contribution to structural connectivity (*dpc_connector*), and normalized ecosystem service value (*ESI_Norm*). The AMI weighting was structured to balance social relevance, structural-connectivity function, and ecosystem-service performance in source selection: equity relevance and *dPC* connector value received comparable weights, 0.35 each, whereas ecosystem-service value retained a slightly lower but substantial weight, 0.30, within the multicriteria index. The index was calculated as

$$AMI_i = (0.35 \times Crit_Equity_PopServed_i) + (0.35 \times dPC_connector_i) + (0.30 \times ESI_Norm_i) \quad (3)$$

where *i* corresponds to each patch. Patches with $AMI > 0.14$ were retained as ecological sources. This value corresponds to the Jenks natural break in the AMI distribution (0.1391)

and was used as an operational selection criterion, not as an independently calibrated ecological threshold. From an ecological-planning perspective, the cutoff identifies candidate patches with higher composite multicriteria performance by integrating contribution to structural connectivity, ecosystem-service value, and equity relevance. However, it should not be interpreted as a minimum viable area for a focal taxon, a minimum functional-connectivity value, or an observed demographic or hydrological threshold. To assess selection sensitivity, two checks were conducted: component weights were varied by $\pm 10\%$, renormalized, and evaluated with the threshold fixed; and fixed-weight threshold scenarios of 0.12, 0.14, and 0.16 were tested using the same candidate-patch set and index formulation. The retained patches defined the source-node set used in subsequent resistance, corridor, and vulnerability analyses.

Construction of resistance surfaces

The resistance surface represents spatial friction associated with potential ecological connectivity, conditioned by anthropogenic and natural factors [41]. It was constructed from seven normalized and directionally standardized layers so that higher values represented greater resistance: human population density, NDVI, distance to roads, distance to rivers, digital elevation model (DEM), slope, and land use. The seven layers were assigned equal weights $w = 1/7$ for each layer to derive a parsimonious, transparent, and reproducible baseline resistance surface, consistent with previous ecological connectivity and corridor studies that used equal-weight superposition or identical weighting across resistance layers to construct operational resistance surfaces [42–45]. Corridor extraction, network topology, network metrics, node rankings, cascade behaviour, and reinforcement candidates derived from this surface are interpreted as conditional on this resistance parameterization.

2.3.3. Extraction of Ecological Corridors

Potential ecological connectivity was modeled using the MCR model and circuit theory [46,47]. The MCR model estimates the minimum accumulated resistance required to connect ecological sources, whereas circuit theory characterizes multiple potential pathways and zones of flow concentration across the resistance surface. Corridor extraction was conducted in Linkage Mapper 3.1.0 and Circuitscape 4.0.5 using three modules: Linkage Pathways, to map least-cost connections between ecological sources; Pinchpoint Mapper, to identify zones of current-density concentration; and Barrier Mapper, to locate areas with greater constraints on connectivity.

The Linkage Mapper adjacency procedure identified 166 candidate source-pair links. Active corridors were defined as least-cost paths that directly connect two ecological sources without crossing an intermediate core. Inactive corridors were defined as indirect potential connections whose least-cost paths cross an intermediate core; these routes were interpreted in this study as conditional connectivity information but were not represented as direct links in the final corridor network. The term ‘inactive’ is used here only in a graph-construction sense and does not imply ecological irrelevance or connection impossibility. These routes may still represent potential connectivity between core areas, including redundant or secondary linkages whose relevance may vary under alternative parameterizations or future landscape change [48,49]. This procedure retained 107 active corridors and classified 59 links as inactive indirect connections. A cost-weighted distance threshold of 200,000 units was applied to truncate and normalize the least-cost corridor rasters, defining the maximum spatial extent of each mapped corridor surface. The resulting corridor network is interpreted as a reference operational configuration conditioned by the adopted resistance surface, the intermediate-core rule, and the raster-truncation threshold.

Topological and resilience metrics

The ecological network of the ESP was represented as an undirected graph, with ecological sources as nodes and active corridors as links. For the topological metrics and static attack simulations, this graph was treated as unweighted; edge weights based on corridor length, accumulated resistance, current density, pinch points, or barrier exposure were not used to compute degree centrality, betweenness centrality, PageRank, k-core, or static removal sequences. These metrics were calculated from the binary adjacency matrix of active corridors and therefore characterized the relational position of nodes in terms of direct connectivity, intermediary role, relational importance, and hierarchical embedding [13,50].

Spatial information from corridor modelling entered the analysis in two specific ways. First, edge presence was defined by the resistance-based extraction of active corridors using the MCR model and circuit theory. Second, in the dynamic cascading-failure model, load redistribution among neighboring nodes was weighted by the inverse Euclidean distance of the connecting link. Thus, static attack simulations were topology-based, whereas the dynamic simulation incorporated a spatially explicit redistribution rule.

Simulated network vulnerability and robustness under perturbation were evaluated using a set of complementary performance metrics. Largest Connected Component (LCC) quantified the size of the largest connected subgraph after the sequential removal of nodes, whereas global efficiency measured the efficiency of connections between nodes through shortest paths under perturbation [51]. Complementarily, area-weighted effective mesh size was used to evaluate the spatial fragmentation of the remaining ecological sources within connected components, and algebraic connectivity, defined as the second-smallest eigenvalue of the graph Laplacian, λ_2 , was used as a spectral indicator of global structural cohesion and as an operational equivalent of the Laplacian spectral gap (Table S8). Together, these metrics allowed comparison of changes in connected scale, path efficiency, area-weighted spatial fragmentation, and spectral cohesion under perturbation.

Static attack mode

The static attack mode was used to evaluate network robustness under perturbations without adaptive feedback between successive steps. Two scenarios were considered: random attack and targeted attack [25,31]. In the random attack, nodes were removed with equal probability, simulating non-selective disturbances. In the targeted attack, nodes were sequentially removed according to descending rankings of degree centrality, betweenness, PageRank, and k-core. In both cases, after each removal, incident links were eliminated and scale and efficiency metrics were updated. The process continued until complete network disarticulation. This design contrasted non-selective perturbations with the progressive removal of topologically relevant nodes.

Dynamic attack mode

The dynamic attack mode employed a load–capacity framework to simulate how functional pressure may propagate through the ESP after the failure of a source node [52]. In this model, functional load represents the relative ecosystem-function contribution of each source node, operationalized through the synthetic functional-load index. Load transfer is interpreted as a modeled redistribution of compensatory functional pressure within the ESP: after a source node fails, directly connected neighboring sources become more important for maintaining potential ecological connectivity and ecosystem-function support within the network. Redistribution is assigned to connected neighbors using an inverse-distance rule, which represents a spatial-decay assumption within the corridor network: closer connected sources receive a larger share of transferable functional load because shorter links indicate greater spatial proximity and more immediate potential continuity. If this additional pressure exceeds the receiving node’s additional absorption capacity, the node enters a failure state, triggering subsequent redistribution rounds until no further modeled failures occur.

Definition of initial load, capacity, and redistribution rules

After ecological sources had been selected, the initial functional load of each node was defined using the nodal functional-importance index calculated for the ecological sources. This index integrates four normalized components: cooling or thermal-regulation capacity (CC_i^*), land-use suitability (LUS_i^*), habitat quality (HQ_i^*), and carbon storage (CAR_i^*). The resulting value, T_i , represents the relative functional contribution of each source node within the cascade model:

$$T_i = (\lambda_1 \times CC_i^*) + (\lambda_2 \times LUS_i^*) + (\lambda_3 \times HQ_i^*) + (\lambda_4 \times CAR_i^*) \quad (4)$$

where T_i is the initial functional load of node i ; CC_i^* , LUS_i^* , HQ_i^* and CAR_i^* are the normalized values of cooling or thermal-regulation capacity, land-use suitability, habitat quality, and carbon storage, respectively; and λ_1 , λ_2 , λ_3 , and λ_4 are the weights assigned to each component, satisfying $\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1$. In this study, the weights were calculated using an entropy-weighting procedure: $\lambda_1 = 0.110$, $\lambda_2 = 0.488$, $\lambda_3 = 0.195$, and $\lambda_4 = 0.207$ (Table S9). Entropy-derived weights express the discriminatory power of each component among the analyzed nodes.

The additional absorption capacity of node i (C_i) was defined as a fraction of its initial functional load:

$$C_i = \beta T_i \quad (5)$$

where β is an exploratory tolerance parameter controlling the additional absorption margin of each node relative to its initial functional load. It should be noted that C_i represents only the additional tolerance to load received during cascading failures, not the total load that the node can support.

$$r = \alpha/\beta \quad (6)$$

where α is the load redistribution coefficient and β is the tolerance coefficient. This ratio does not constitute an independent model parameter but rather a derived index used to interpret the balance between the intensity of load transfer from failed nodes and the additional absorption capacity of receiving nodes. Higher values of r indicate greater potential propagation pressure, whereas lower values reflect smaller redistribution relative to nodal tolerance. Consequently, sensitivity analysis was conducted on explicit combinations of α and β , and the ratio r was used as a synthetic descriptor to compare the resulting dynamic regimes.

The redistribution of load from a failed node to its neighbors was weighted according to spatial proximity within the corridor network. For each node i , a normalized weight was calculated for each directly connected neighbor j using the inverse of the spatial distance of the link connecting them, operationalized as the Euclidean link distance. This rule assigns a larger share of transferable functional load to closer connected neighbors and represents a spatially explicit redistribution criterion within the cascade model:

$$\omega_{ij} = \frac{1/d_{ij}}{\sum_{k \in N(i)} (1/d_{ik})} \quad (7)$$

where d_{ij} is the Euclidean link distance between directly connected nodes i and j , and $N(i)$ is the set of nodes directly connected to node i .

The base flow potentially transferable from node i to a neighbor j was defined as the fraction of the initial functional load of node i determined by this spatial weight:

$$W_{ij} = T_i \omega_{ij} \quad (8)$$

When a node i fails in round $r - 1$, it is assumed to transfer to each of its neighbors a fraction α of this base flow. The incremental load transferred from the failed node i to the receiving node j in round r is expressed as

$$\delta W_{ij^{(r)}} = \alpha W_{ij} \quad (9)$$

where $\alpha \in [0,1]$ is an exploratory parameter controlling the fraction of transferable functional load redistributed after the initial failure.

The total load received by a node j in round r corresponds to the sum of the contributions from all failed nodes connected to it in the immediately preceding round:

$$\Delta W_j^{(r)} = \sum_{i \in F^{(r-1)} \cap N(j)} \delta W_{ij}^{(r)} \quad (10)$$

where $F(r-1)$ is the set of nodes that entered the failure state in round $r-1$. The cumulative additional load received by node j up to round r is then updated as

$$L(r) = L_{j^{(r-1)}} + \Delta W_{j^{(r)}}, \text{ with } L_{j^{(0)}} = 0 \quad (11)$$

Finally, a node j transitions to the anomalous (failure) state in round r if the cumulative additional load received exceeds its additional absorption capacity:

$$L_{j^{(r)}} > C_j \quad (12)$$

The cascade was simulated over successive rounds starting from an initial random or targeted perturbation. In each round, load redistribution, cumulative load at receiving nodes, and the failure condition were updated until a state with no new failures was reached or complete network disarticulation occurred [21,53]. As a preliminary spatial-consistency check, the simulation outputs were compared with observed tree-cover loss from Hansen Global Forest Change v1.12 at 30 m spatial resolution for 2019–2024. The analysis was restricted to areas with more than 30% baseline tree cover. Tree-cover loss was quantified by spatially overlaying the 30 m Hansen tree-cover-loss raster with the 58 ESP source-node polygons and aggregating the loss pixels falling within each polygon. The resulting values were aggregated by the four operational cascade-risk categories. Statistical significance was evaluated using a one-sided node-level permutation test, complemented by density-based robustness checks normalized by baseline forest area and total node area (Table S10).

3. Results

3.1. Identification of the ESP

3.1.1. Distribution of Ecosystem Services

The evaluated ecosystem services exhibited marked spatial heterogeneity (Figure 3). In terms of habitat quality, the high and relatively high categories covered 140.06 km² (22.29%) and were primarily concentrated in mountainous sectors, whereas the low and relatively low categories encompassed 488.37 km² (77.71%) and were widely distributed across the western and central sectors (Figure 3a).

Carbon storage and sequestration exhibited a similar pattern. The high and relatively high categories reached 174.87 km² (24.63%), whereas the low and relatively low categories covered 473.56 km² (75.35%). The highest values were located in areas with greater vegetation cover, whereas the lowest values were associated with urbanized and infrastructural areas (Figure 3b).

The water yield index showed a contrasting distribution. Areas with high and relatively high values totaled 276.40 km² (44.59%) and were predominantly located in the eastern and northeastern sectors of the territory, characterized by higher elevations and greater vegetation cover. Areas with low and relatively low values covered 343.43 km² (55.41%), mainly concentrated in the western and southwestern sectors (Figure 3c).

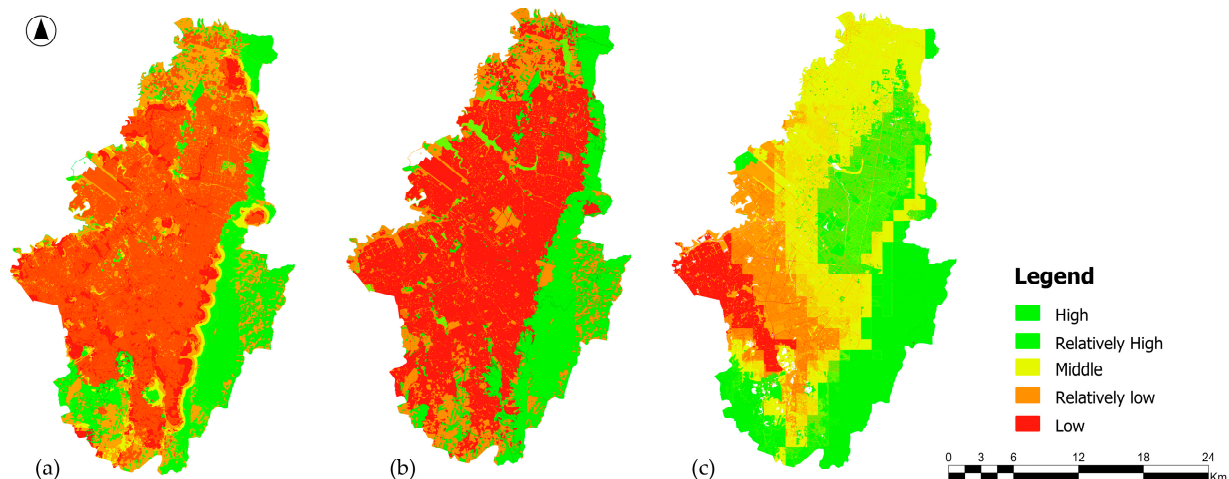


Figure 3. Spatial distribution of ecosystem service indicators: (a) habitat quality; (b) carbon storage and sequestration; (c) water yield.

3.1.2. Landscape Pattern Analysis Based on MSPA

The MSPA identified seven morphological classes that describe the spatial structure of the urban ecological landscape (Figure 4a–c; Table 3). Core areas represented the dominant fraction (234.40 km², 90.10% of the foreground) and were predominantly concentrated in the eastern sectors of the study area.

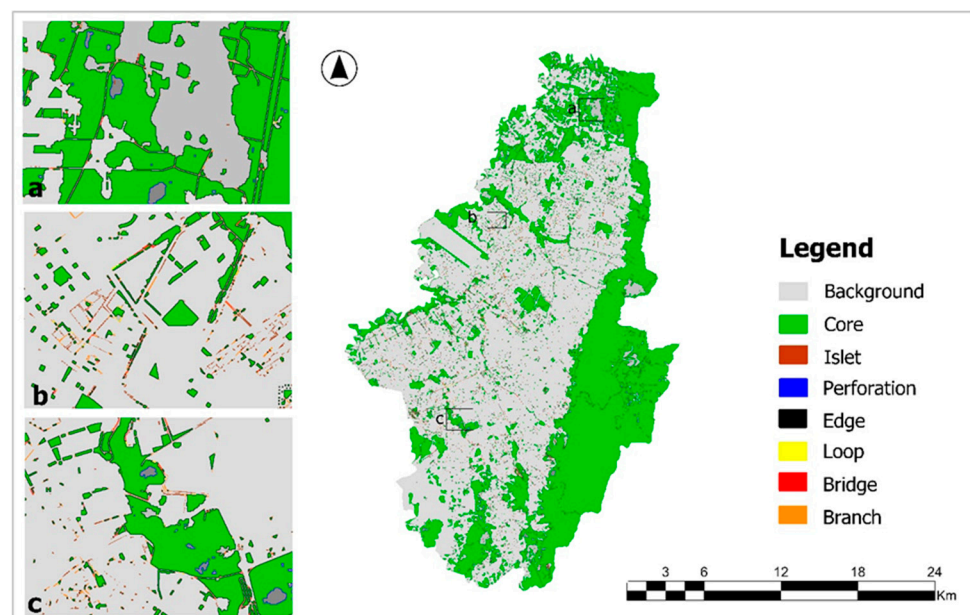


Figure 4. Morphological Spatial Pattern Analysis. Forests, wetlands, grasslands, and water bodies (foreground) are classified into seven structural categories, revealing the spatial configuration of internal habitat cores and narrow linear connectors within the urban matrix. (a) Detail view of the northern zone; (b) detail view of the central zone; (c) detail view of the southern zone—illustrating the seven MSPA structural categories at a finer spatial resolution.

The size distribution of core areas revealed a hierarchical structure. Large cores (>11.5 ha) accounted for 76.7% of the total core area, whereas small cores (<1 ha) constituted the numerical majority (10,589 patches). Non-core morphological classes exhibited a contrasting spatial configuration. Edge elements were distributed around core areas, whereas linear elements associated with structural connectivity, such as bridges and loops, showed

limited spatial presence. In contrast, classes corresponding to islets, branches, and perforations exhibited a higher frequency within the urban matrix. The area, percentage, and number of patches for each class are presented in Table 3.

Table 3. Ecological landscape characterization based on MSPA.

Landscape Element	Area (km ²)	Percentage of Ecological Foreground (%)	Number of Patches
Core (total)	234.40	90.10	11,489
Core (small) (<1 ha)	11.20	4.31	10,589
Core (medium) (1–11.5 ha)	23.70	9.10	723
Core (large) (>11.5 ha)	199.50	76.69	177
Edge	20.50	7.86	8171
Islet	1.40	0.52	6737
Branch	2.30	0.90	27,994
Bridge	0.68	0.26	4248
Perforation	0.78	0.30	712
Loop	0.15	0.06	924
Total ecological foreground	260.21	100.00	-

3.1.3. Ecological Sources and Resistance Surface

Based on the core areas identified through MSPA, 58 ecological sources were delineated, with a combined area of 123.02 km², equivalent to 19.58% of the total study area (Figure 5a). These sources were predominantly concentrated within the forest blocks of the eastern sector.

The final set was retained using an AMI threshold > 0.14, corresponding to the Jenks natural break at 0.1391. This value identifies a discontinuity in the multicriteria performance distribution of candidate patches and was treated as an operational source-selection criterion. To evaluate selection stability, two sensitivity checks were conducted. First, index-component weights were varied by $\pm 10\%$ and renormalized while keeping the reference threshold fixed. Under these scenarios, the number of selected sources ranged from 56 to 61, the selected area ranged from 122.67 to 123.12 km², and 96.6–100.0% of the reference source set was retained. Second, fixed-weight thresholds of 0.12, 0.14, and 0.16 were evaluated using the same candidate-patch set and index formulation. These values selected 73, 58, and 47 sources, respectively, with total areas of 124.90, 123.02, and 120.89 km². The lower threshold added 15 small marginal patches (1.88 km²), whereas the higher threshold removed 11 marginal patches (2.14 km²). The 47 sources retained under the stricter threshold represented 98.26% of the reference source area. Overall, threshold changes mainly affected small marginal patches, while the dominant source-area structure remained stable and concentrated in the eastern forest blocks. Patch-level values and sensitivity summaries are reported in Tables S11 and S12.

The ecological resistance surface exhibited a differentiated spatial pattern, with values ranging from 20.5 to 1000 (Figure 5b). The lowest values were concentrated along a band on the eastern edge, associated with forest cover and other areas with lower anthropogenic transformation. This pattern coincided with the main ecological block of the Eastern Hills. In contrast, the central and western urbanized plain exhibited moderate to high values, corresponding to built-up areas, road infrastructure, and higher population density. This polarization between a low-resistance eastern edge and a higher-friction central–western matrix defined the baseline conditions for corridor delineation.

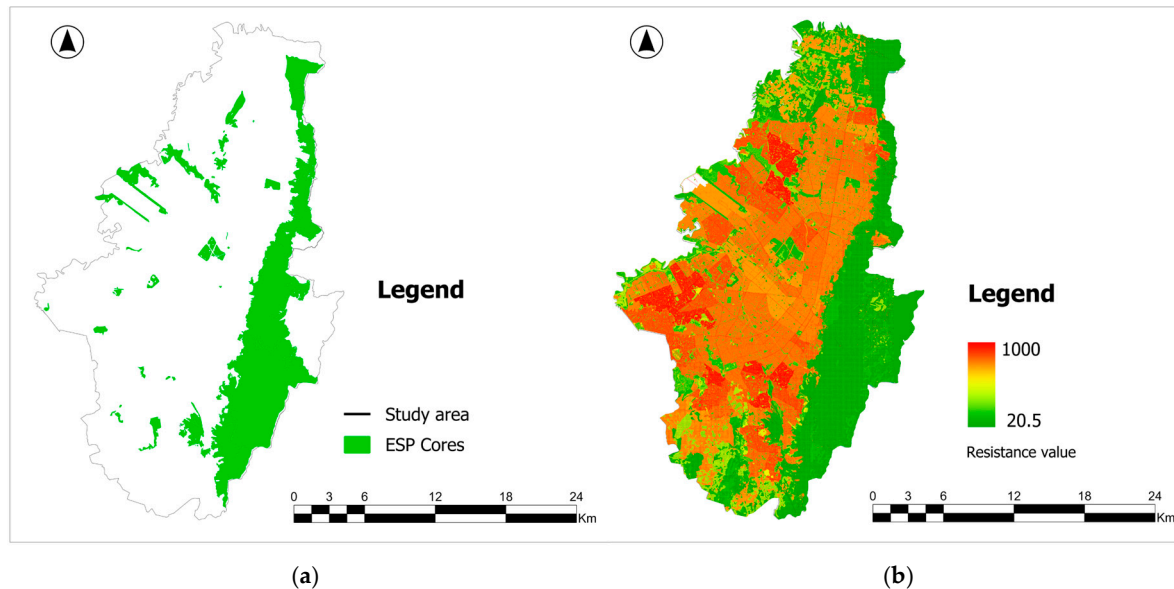


Figure 5. (a) Selection of core areas of the ESP. (b) Ecological resistance surface of the Bogotá study area.

3.1.4. Ecological Corridors, Pinch Points, and Connectivity Barriers

The potential ecological connectivity network of the study area was composed of 107 active corridors and 59 inactive corridors, derived from the 58 ecological sources previously identified. Active corridors represented direct connections between ecological sources, whereas inactive corridors corresponded to potential connections whose least-cost paths were articulated through intermediate cores and therefore did not constitute direct links within the final network (Figure 6a).

Active corridors exhibited a total length of 333.56 km, with a mean length of 3.12 km, a maximum length of 14.35 km, and a minimum of 0.017 km (≈ 0.02 km) (Table 4). In contrast, inactive corridors reached a total length of 360.50 km, with a mean length of 6.11 km, a maximum length of 26.15 km, and a minimum of 0.35 km. These values showed that direct connections within the final network tended to be more compact, whereas connections not retained as direct links exhibited longer paths.

Spatially, active corridors were mainly concentrated in sectors with more direct connections between sources, whereas inactive corridors were frequently located in the central and northwestern sectors, with partial overlap in some segments. This configuration showed that the potential connectivity of the study area was not organized as a network of equivalent pathways, but rather as a system composed of direct connections and an additional set of potential connections with greater spatial complexity.

Table 4. Characteristics of active ecological corridors.

Category	Value
Number of active corridors	107
Total length (sum)	333.56 km
Mean length	3.12 km
Maximum length	14.35 km
Minimum length	0.017 km (≈ 0.02 km)

Ecological pinch points exhibited current density values ranging from 0 to 0.238. The total area delineated as pinch points was 1.70 km², representing 0.27% of the total study area. Spatially, pinch points were distributed across the central and western sectors of the

urban landscape and were absent from the continuous habitat block in the eastern sector. Their location coincided with remnant vegetation strips and linear landscape elements, such as riparian corridors, small urban parks, and interstitial green spaces, within areas of high ecological resistance.

Ecological barriers covered 10.05 km², equivalent to approximately 1.6% of the total study area (Figure 6b). They were concentrated along corridors connecting ecological sources in the central and western sectors with the continuous ecological core in the eastern sector, coinciding with areas of high road infrastructure density and intensive land use.

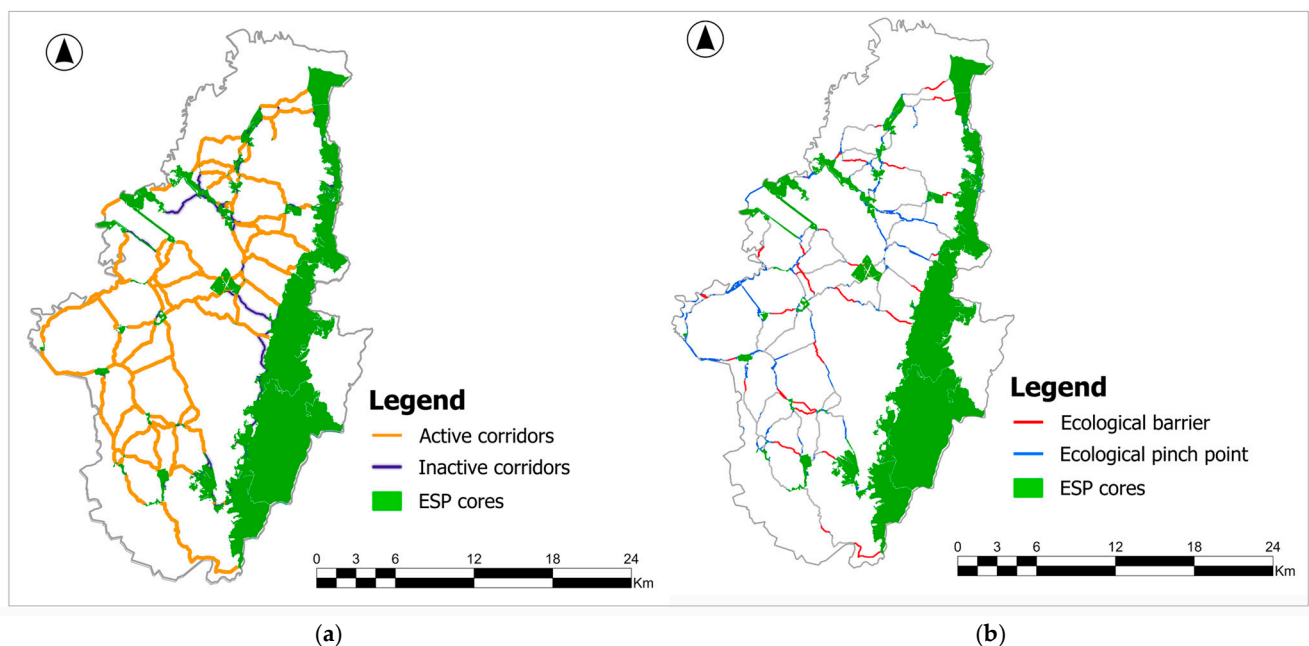


Figure 6. Spatial configuration of ecological corridors, pinch points, and connectivity barriers within Bogotá's urban Ecological Security Pattern (ESP), Colombia (WGS 84/UTM Zone 18N; EPSG:32618). (a) Active direct corridors (orange) and inactive indirect connections (purple) between ecological sources (green), representing least-cost pathways over the resistance surface; active corridors connect sources directly, while inactive connections cross intermediate ecological cores. (b) Ecological pinch points (blue) and ecological barriers (red) identified along the connectivity network, representing, respectively, areas of concentrated connectivity flow and locations restricting potential connectivity across the ESP cores (green). The scale bar indicates distances in kilometers (km).

3.2. Topological Structure and Evaluation of Node Functional Importance

3.2.1. Analysis of the Network Topological Structure

The ecological network of Bogotá exhibited a heterogeneous topological structure, characterized by relatively low average connectivity and by the concentration of spatial articulation within a limited subset of nodes. The global network summary showed 58 nodes and 107 links, with a mean degree of 3.69, an average clustering coefficient of 0.292, and 48 nodes with degree values below 6, equivalent to 82.76% of the total. These values described a sparse network, in which low-connectivity peripheral nodes predominated and connectivity was concentrated in a reduced subset of articulating elements.

Centrality rankings confirmed this hierarchical structure. Node 540 ranked first in both degree centrality and PageRank, with 10 connections, a betweenness value of 0.3076, and a PageRank of 0.0387. Nodes 433 and 847 appeared among the highest-ranked elements in the system: both exhibited a degree of 7, while node 433 recorded the highest betweenness in the entire network (0.3095), and node 847 combined high betweenness

(0.2331) with the second-highest PageRank value (0.0340). This core was complemented by nodes such as 427, 935, 459, 701, and 715, which also occupied high positions across multiple topological indicators, forming the most prominent structural cores of the network by simultaneously concentrating direct connectivity, intermediary capacity, and relational importance.

The comparison among metrics showed that structural importance did not depend on a single topological attribute: node 540 stood out for direct connectivity and relational importance, node 433 for its intermediary role, and node 847 for its simultaneous performance in degree, betweenness, and PageRank. This convergence positioned nodes 540, 433, and 847 as the most structurally prominent subset of the network. In contrast, the large number of nodes with degrees between 1 and 5 indicated that system cohesion depended on a limited number of articulation pathways, which increased its sensitivity to targeted perturbations affecting bridge nodes (Figure 7).

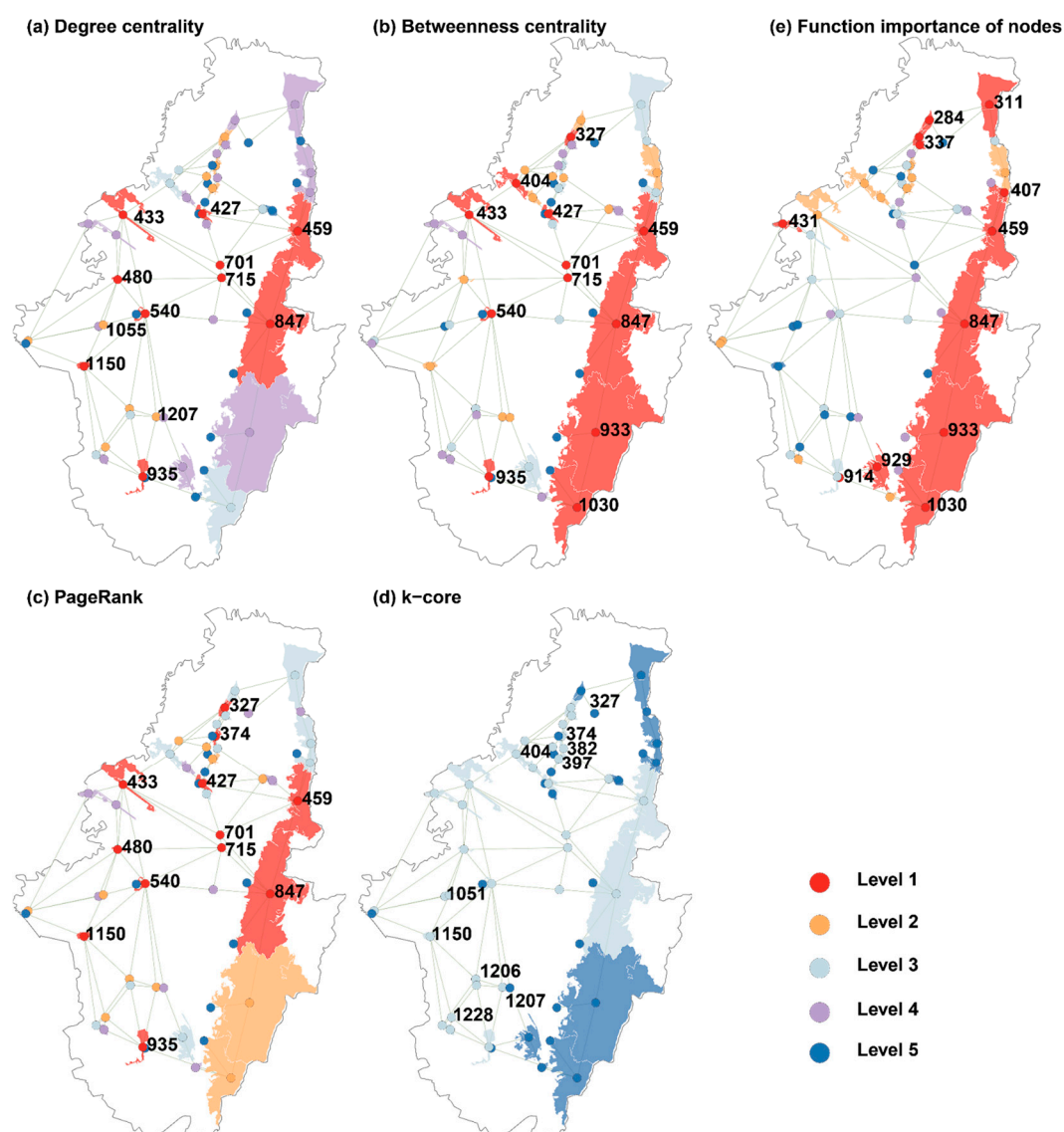


Figure 7. Topological attributes and functional importance of nodes: (a–d) show the spatial distribution of four topological indicators, and (e) represents the spatial distribution of functional importance, with levels 1 to 5 indicating scores from highest to lowest.

3.2.2. Analysis of Node Functional Importance

The functional importance of nodes exhibited a hierarchy distinct from that observed in the network topological structure. Nodes 933, 337, 847, 311, 1030, 914, 284, 459, 407, and 431 recorded the highest functional importance values, with node 933 ranked first, followed by nodes 337 and 847. Individual component values for each node can be consulted in Figure S1; the carbon component exhibited the greatest discriminative capacity among nodes within the top functional decile.

In contrast to structural connectivity, functional importance exhibited a more selective distribution and was less associated with hub condition. The clearest contrast was observed in node 933, which ranked first in functional importance without appearing among the main structural nodes, whereas node 540, the node with the highest topological hierarchy, did not appear among the top ten in functional terms. Only nodes 847 and 459 occupied prominent positions in both rankings, evidencing a partial convergence between structural centrality and ecological capacity.

3.3. Changes in Network Resilience Under Static Attack Mode

3.3.1. Network Scale

The patterns of network scale degradation differed according to the attack strategy (Figure 8a). Under random attack, the network exhibited the highest robustness, with a slow rate of decline. The relative size of the largest connected component decreased to 0.88 with 10% removal, 0.74 with 20%, and 0.58 with 30%. Even with 50% of nodes removed, the network retained a largest component equivalent to 0.27 of its original value. In the final stages, the reduction continued steadily, reaching residual values of 0.10, 0.06, and 0.03 at 70%, 80%, and 90% removal, respectively.

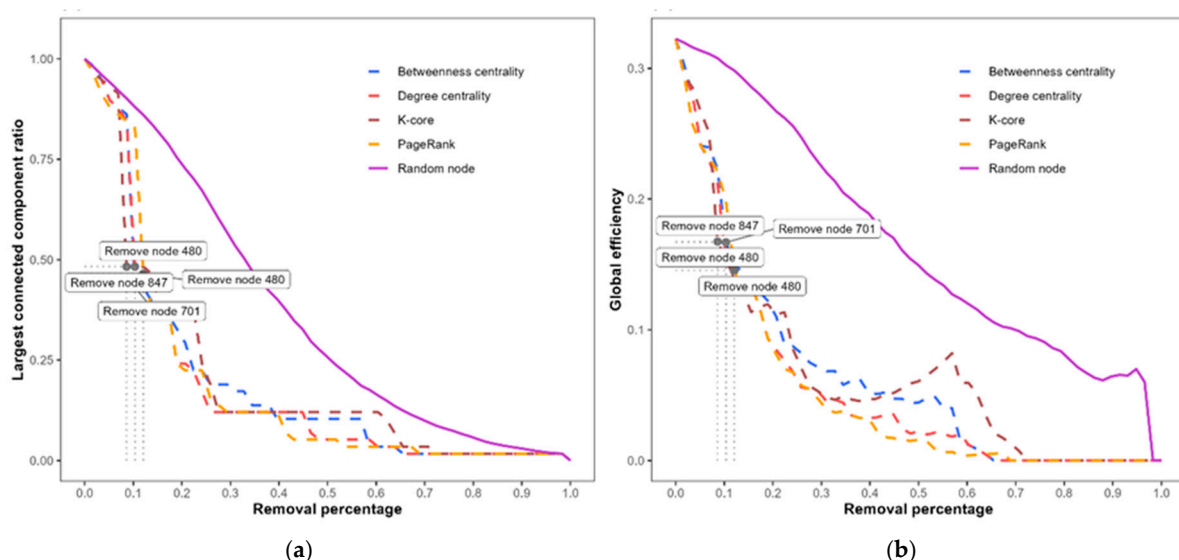


Figure 8. Network scale and network efficiency under static attack mode: (a) changes in the size of the largest connected subgraph under static attack; (b) changes in global efficiency under the corresponding attack mode.

In contrast, targeted attacks caused more abrupt fragmentation. The initial inflection points of the targeted curves were concentrated in the early removal stage, coinciding with the elimination of nodes 847, 480, and 701 highlighted in Figure 8a. At 10% removal, the size of the largest component had already decreased to 0.43 under betweenness-based attack, 0.48 under degree-based attack, and 0.48 under k-core-based attack, whereas PageRank maintained a higher value at this stage, followed by an abrupt contraction to 0.22

at 20% removal. At the same level, the network decreased to 0.29 under betweenness, 0.24 under degree, and 0.38 under k-core. At 30% removal, the largest component declined to 0.19 under betweenness and to 0.12 under degree, k-core, and PageRank. From 70% removal onward, targeted strategies drove the network to a residual state close to collapse. Degree- and betweenness-based attacks produced the greatest loss of scale, whereas k-core exhibited a more gradual disruption pattern.

3.3.2. Network Efficiency

Global efficiency exhibited greater sensitivity to node removal than structural scale (Figure 8b). Under random attack, efficiency decreased from 0.323 in the initial state to 0.300 at 10% removal, 0.271 at 20%, 0.238 at 30%, and 0.193 at 40%. In subsequent stages, the curve continued to decline to 0.158, 0.121, 0.102, 0.089, and 0.071 at 50%, 60%, 70%, 80%, and 90% removal, respectively.

The rate of efficiency loss varied according to attack strategy. Degree- and PageRank-based attacks produced the fastest decline, followed by betweenness. At 20% removal, efficiency had already declined to 0.085 under degree, 0.081 under PageRank, and 0.110 under betweenness. From 30% removal onward, all three curves remained at low values and reached zero from 70% onward. The k-core-based attack exhibited a slower decline. Although efficiency decreased to 0.154 at 10% removal and to 0.112 at 20%, the curve maintained slightly higher residual values during the intermediate phase, with 0.046, 0.061, and 0.059 between 40% and 60% removal, before approaching zero in the final stage. The faster decline of efficiency relative to scale reflected that the loss of short paths between patches occurred before fragmentation of the largest connected component.

The input data used to calculate the complementary resilience metrics are summarized in Table S13. The complementary assessment showed that the severity of degradation varied according to the metric considered. The values selected by removal level are reported in Table S14, while the AUC summaries and algebraic-connectivity disconnection thresholds are presented in Table S15. The normalized effective-mesh-size AUC showed the strongest area-weighted fragmentation under betweenness-based attacks (AUC = 0.080), followed by PageRank (0.124), degree (0.145), k-core (0.213), and random removal (0.291). This pattern indicates that betweenness-based removal generated particularly severe area-weighted fragmentation of the remaining ecological sources. Algebraic connectivity reached zero after one removed node under degree, PageRank, and k-core, after two removed nodes under betweenness, and after six removed nodes under random removal, indicating an early loss of global spectral cohesion under directed attacks. Together, these indicators support the general pattern of greater simulated vulnerability under directed attacks, while showing that the exact hierarchy of severity depends on whether degradation is evaluated through connected scale, path efficiency, area-weighted fragmentation, or spectral cohesion.

3.4. Changes in Network Resilience Under Dynamic Attack Mode

3.4.1. Sensitivity of the Cascade Model to α and β Parameters

Dynamic results varied as a function of the ratio r , showing a clear gradient between regimes of weak propagation, high sensitivity, and near-saturated response (Figure 9a,b). At higher values of r , approximately between 9 and 12, the system produced larger-scale avalanches with lower size diversity, consistent with a regime close to saturation. In contrast, within the interval of highest sensitivity, greater heterogeneity in avalanche size distribution was observed. Within this range, the parameter set $\alpha = 0.70$ and $\beta = 0.09$ ($r \approx 7.78$) was located within the high-sensitivity region, exhibiting a more heterogeneous distribution of avalanche sizes without reaching the near-saturated behavior observed at higher r values.

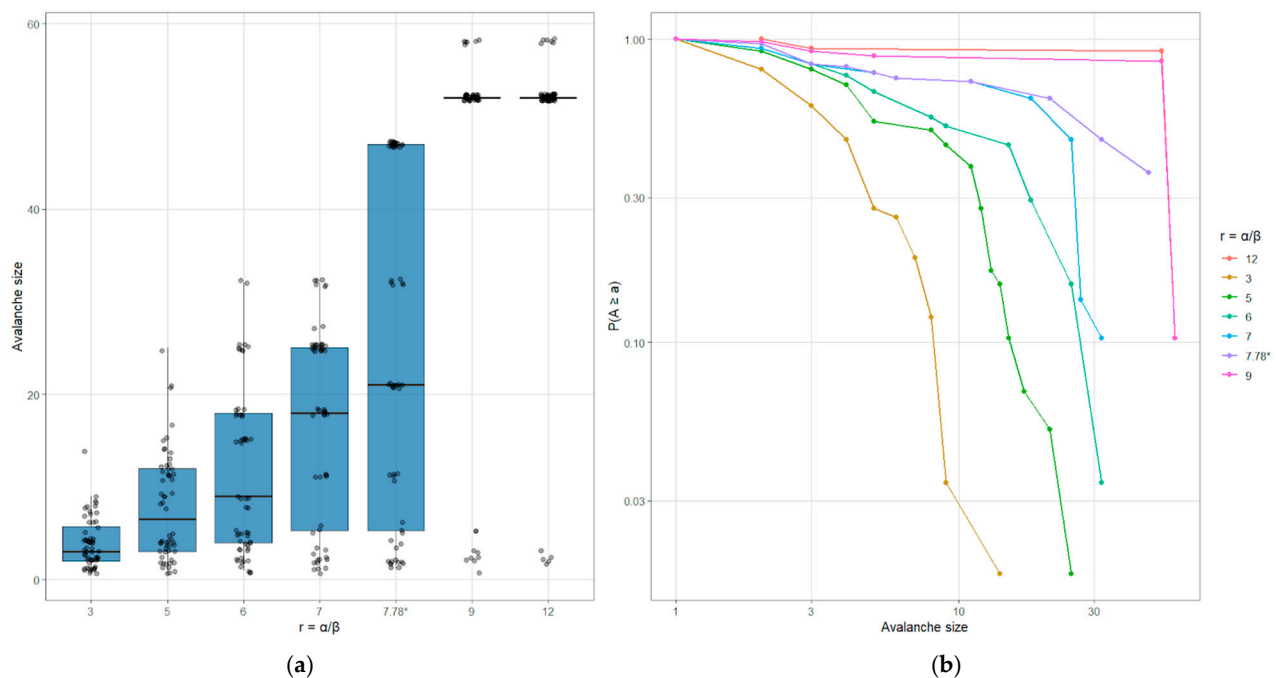


Figure 9. Avalanche size distributions under alternative load capacity cascade regimes. Avalanche size (A) denotes the total number of ecological source nodes collapsed after an initial perturbation. The ratio $r = \alpha/\beta$ represents propagation pressure, where α is the load redistribution coefficient and β is the nodal tolerance coefficient. Panel (a) shows the cumulative distribution of avalanche sizes across tested r values. Panel (b) shows the complementary cumulative probability $P(A \geq a)$, indicating the probability that a cascade reaches or exceeds avalanche size a . The asterisk (*) denotes the reference cascade parameterization used in the subsequent analyses.

To further examine this response, 72 refined parameter combinations were evaluated within the high-sensitivity region, and four indicators were calculated: mean cascade size, mean cascade duration, probability of large cascades, and standard deviation of cascade size. The heatmaps (Figures S2–S5) showed abrupt transitions in the region of relatively high α and relatively low β , where all four indicators increased simultaneously. Single-parameter sensitivity analysis confirmed the same pattern (Figures S6 and S7). Holding $\beta = 0.085$ constant, the mean avalanche size increased from 13.1 at $\alpha = 0.55$ to 39.8 at $\alpha = 0.70$, and then stabilized at high values of 45.0–47.4 for $\alpha \geq 0.75$. Conversely, holding $\alpha = 0.75$ constant, the mean avalanche size decreased from 56.1 at $\beta = 0.05$ to 41.6 at $\beta = 0.09$, and then dropped sharply to 18.0 at $\beta = 0.10$, followed by 15.6 and 11.3 at $\beta = 0.11$ and $\beta = 0.12$, respectively. In parallel, the probability of large cascades decreased from 0.966 to 0.0345 as β increased. The model response exhibited a high-sensitivity regime under relatively high α and low β values. The pair $\alpha = 0.70$ and $\beta = 0.09$ was retained as an illustrative reference parameterization within this region, with a heterogeneous distribution of cascade sizes and without reaching an extreme saturation state. Across the 72 evaluated regimes, the mean cascade size ranged from 6.50 to 56.07 nodes, and the number of nodes classified as High-Risk varied between 0 and 33 per scenario, indicating that the model response was sensitive to the adopted α – β regime.

3.4.2. Network Scale and Efficiency Under Dynamic Attack Mode

Under dynamic attack mode, network scale exhibited differentiated degradation trajectories depending on the attack strategy (Figure 10a). Betweenness- and degree-based attacks produced the most abrupt initial decline: in both cases, the first cascade removed 21 nodes, equivalent to 36.2% of the network, and reduced the size of the largest connected component to 0.448. Random attack also generated an early decline, with the removal of

23.6 nodes (40.7%) and a reduction of the largest component to 0.561. In contrast, the k-core-based attack exhibited greater initial robustness: the first cascade affected only two nodes (3.45%) and maintained the network scale at 0.966. The main scale breakpoints were located at 0.362 for betweenness- and degree-based attacks, at 0.407 for random attack, and at 0.759 for k-core-based attack. In all four cases, complete structural collapse of the largest component occurred only when cumulative removal reached the total network size. In this mode, the fraction reported on the x-axis corresponded to the cumulative number of removed nodes, including the triggering node and nodes that collapsed through cascading in each round; therefore, it was not directly comparable to the percentage of deliberate removal in static mode.

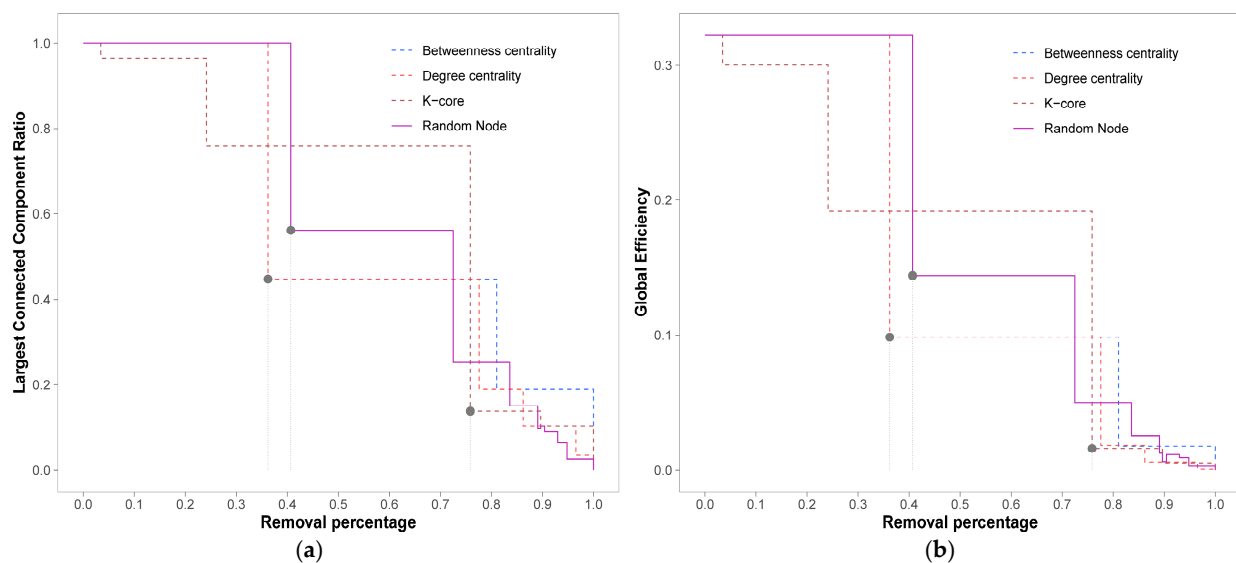


Figure 10. Network scale and global efficiency under the reference dynamic cascading attack scenario. The dynamic attack represents a load–capacity cascade simulation with $\alpha = 0.70$, $\beta = 0.09$, and $r = \alpha/\beta \approx 7.78$, where α denotes load redistribution, β represents nodal tolerance, and r is the propagation pressure ratio. The x-axis indicates the cumulative fraction of removed source nodes, including the initial trigger node and nodes that subsequently fail through cascading processes. Panel (a) shows the normalized Largest Connected Component (LCC), and panel (b) shows global efficiency. Curves represent random, degree-based, betweenness-based, and k-core-based attack strategies.

Global efficiency exhibited a similarly differentiated pattern of functional degradation, but with more pronounced early losses under some attack modes (Figure 10b). After the first dynamic cascade, efficiency decreased to 0.0985 under betweenness- and degree-based attacks, to 0.144 under random attack, and to 0.300 under k-core-based attack. The first major efficiency breakpoints coincided with those observed for scale: 0.362 for betweenness and degree, 0.407 for random attack, and 0.759 for k-core. However, functional loss preceded complete structural collapse in several cases. Efficiency reached a practical collapse at 0.862 under degree-based attack and at 0.897 under k-core and random attacks, whereas under betweenness this threshold was reached only at the final removal stage. Under dynamic mode, betweenness- and degree-based attacks concentrated the earliest and most severe losses, whereas the k-core-based strategy delayed the initial degradation of the network.

3.5. Cascading Failure Process

The cascading failure process exhibited a non-linear relationship between the number of propagation rounds and the total magnitude of damage. Among the 58 source nodes evaluated, the maximum avalanche size reached 47 collapsed nodes, and a total of 21 nodes were capable of triggering this maximum level of damage. In terms of duration, the longest cascade process extended over 20 propagation rounds and was recorded in two source nodes. In contrast, two nodes with no effective propagation were also identified, corresponding to nodes 1207 and 549, whose initial failure affected only one node and did not generate additional rounds of collapse.

To evaluate node-specific risk, the number of collapsed nodes and the inverse of the propagation rounds were represented on the x-axis and y-axis, respectively (Figure 11). Classification thresholds were set at 21 collapsed nodes and 0.125 for the inverse of propagation rounds, defined as operational cutoffs based on the observed distribution in this illustrative reference parameterization. These cutoffs established analytical categories to organize the variability of the results, without constituting predefined ecological thresholds. Under this criterion, the network included 11 high-risk nodes, 26 medium-high-risk nodes, 19 medium-low-risk nodes, and 2 low-risk nodes. High-risk nodes combined relatively high damage magnitudes with comparatively rapid propagation; for example, node 933 produced the collapse of 32 nodes in eight rounds and was located in the upper-right quadrant. In contrast, medium-high-risk nodes maintained larger total impacts but through longer propagation trajectories; node 425 exemplified this pattern, triggering an avalanche of 47 nodes over 20 rounds and was thus located in the lower-right quadrant. Medium-low-risk nodes exhibited relatively rapid propagation but with smaller total extent, such as node 914, which produced 11 failures in six rounds and was located in the upper-left quadrant. Finally, low-risk nodes combined low impact with the absence of effective propagation, such as node 1207, whose failure affected only one node and did not generate additional cascade rounds, placing it in the lower-left quadrant. Figure 12 shows that nodal risk in Bogotá depended simultaneously on propagation speed and the total magnitude of accumulated damage.

To assess the stability of this classification, the 58 nodes were reclassified under the 72 (α)-(β) regimes using the same operational criterion. The number of High-Risk nodes varied between 0 and 33 per scenario. No node remained High-Risk across all regimes; the highest recurrence corresponded to node 933, which was classified as High-Risk in 43 of 72 regimes (59.7%), followed by nodes 311 and 459, with 34 of 72 regimes (47.2%), and nodes 322 and 847, with 32 of 72 regimes (44.4%) (Table S16).

The propagation pathways of cascading failures exhibited a pronounced, indirect, and multistage character. As shown in Figure S8, representative origins of severe propagation corresponded to nodes 425, 430, 427, and 385, all of which triggered avalanches of 47 collapsed nodes, with propagation durations of 20, 20, 19, and 18 rounds, respectively.

In all four cases, first-round failures were concentrated in direct neighbors of the source node. In contrast, subsequent rounds were dominated by indirect propagation through intermediate nodes. This multistage propagation structure reflected the iterative logic of the load-capacity model and allowed the identification of which corridors and nodes act as secondary transmission pathways within the Bogotá network, regardless of their topological distance from the source node.

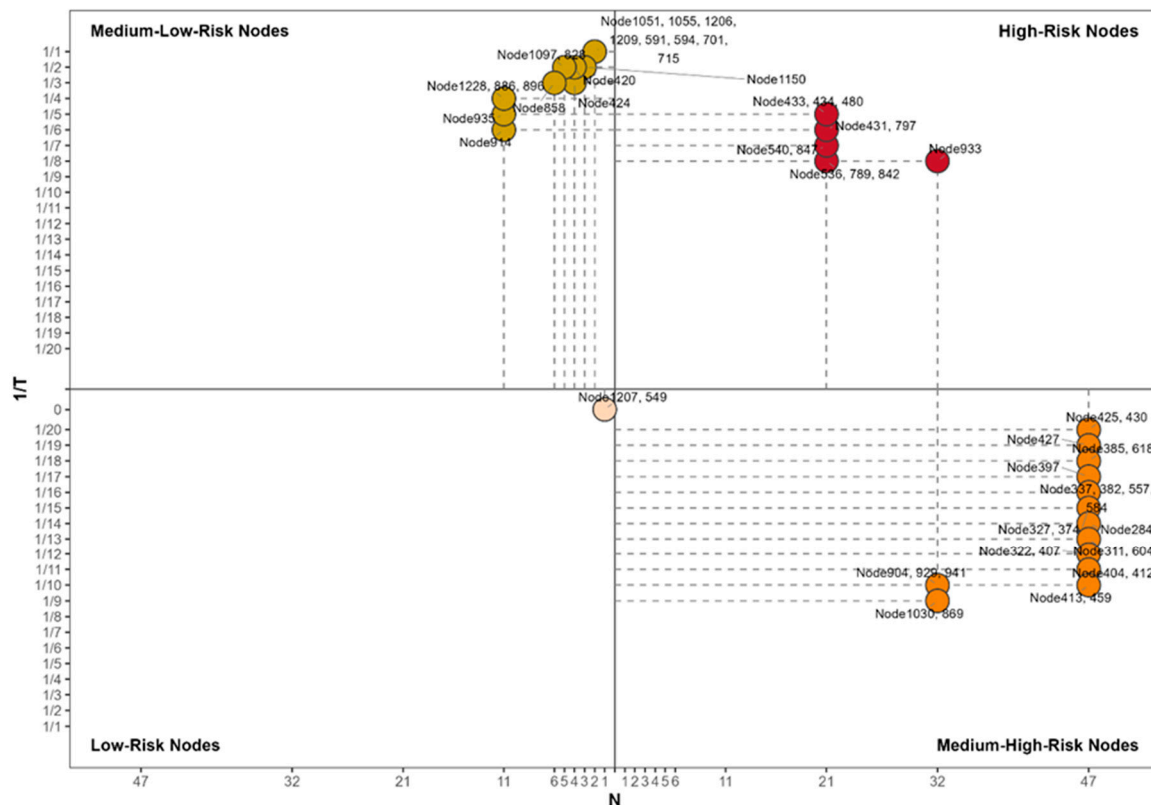


Figure 11. Node risk classification under the reference dynamic cascade scenario. Reference cascade parameters are $\alpha = 0.70$, $\beta = 0.09$, and $r = \alpha/\beta \approx 7.78$, where α is the load redistribution coefficient, β is the nodal tolerance coefficient, and r is the propagation pressure ratio. Each point represents an ecological source node. The x-axis shows avalanche size, defined as the number of collapsed source nodes; the y-axis shows the inverse of propagation rounds, defined as successive load redistribution iterations until no further failures occur. Quadrants indicate operational categories only: high risk, medium-high risk, medium-low risk, and low risk. These categories are derived from the reference scenario and are not ecological thresholds.

The temporal profiles of the cascades allowed the identification of three operational propagation patterns. Nodes 847 and 433 exhibited an early-stage rapid collapse pattern, with 5 and 4 nodes affected in the first round, respectively, peaks of impact in rounds 1–2, and a subsequent progressive decline, reaching final scales of 20 affected nodes. In contrast, nodes 425 and 430 exhibited a delayed outbreak pattern, in which only 2–3 nodes were affected in the first round, but the highest propagation intensity occurred at round 17, with total durations of 20 rounds and final scales of 46 affected nodes. Between these extremes, an intermediate or mixed pattern was observed; for example, nodes 618 and 337 also reached 46 affected nodes, but with early peaks at round 2 and durations of 18 and 16 rounds, respectively (Figure S9). These results showed that markedly different temporal trajectories could lead to contrasting or comparable final scales of impact, confirming the path-dependent nature of network vulnerability in Bogotá.

This path-dependent interpretation was supported by the comparison with observed tree-cover loss for 2019–2024. The analysis identified 11.94 ha of tree-cover loss within ESP source nodes. All detected loss occurred in High-Risk or Medium-High-Risk nodes: 8.47 ha in High-Risk nodes and 3.47 ha in Medium-High-Risk nodes. Medium-Low-Risk nodes retained 125.12 ha of baseline forest and showed no detected loss, providing the most informative lower-risk comparison. The two Low-Risk nodes had 0.00 ha of baseline forest and therefore contributed no tree-cover-loss signal. A one-sided node-level permutation test indicated that the concentration of loss-bearing nodes in the High-Risk + Me-

dium–High-Risk group was statistically significant under random reassignment of risk labels among the 58 nodes (11 of 11 loss-bearing nodes; 999 permutations; $p = 0.004$). Density-based robustness checks normalized by baseline forest area and total node area returned $p = 0.167$ and $p = 0.143$, respectively. These results support a preliminary spatial-consistency interpretation between simulated risk classification and observed tree-cover loss (Table S10).

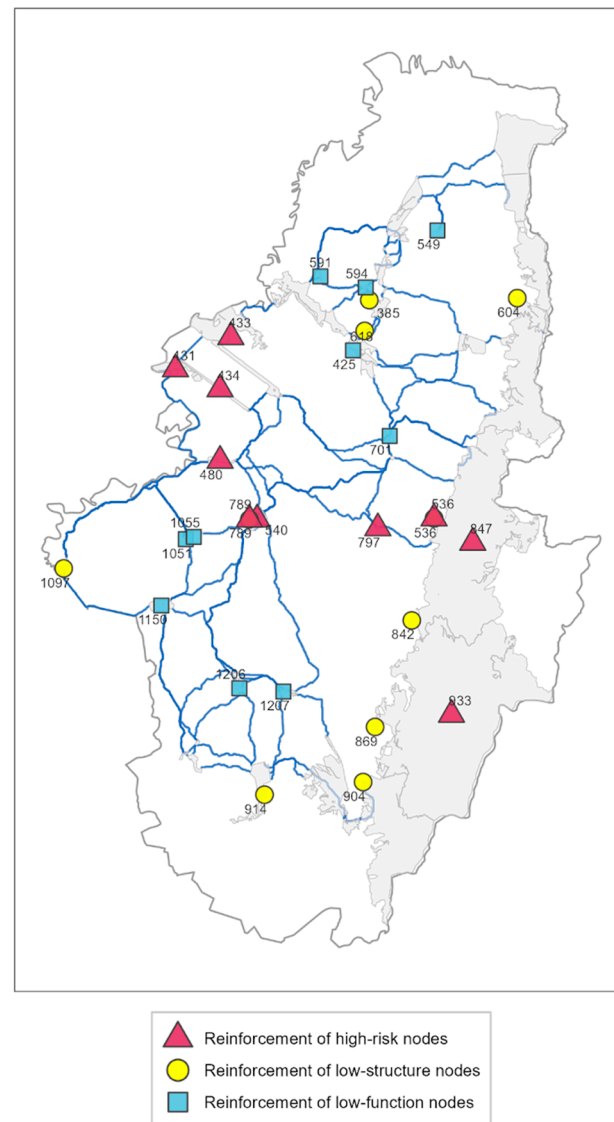


Figure 12. Candidate reinforcement nodes in Bogotá's ESP, derived from the convergence of high cascade risk, low structural performance, and low functional performance under the reference model configuration ($\alpha = 0.70$, $\beta = 0.09$; Table 5). Red triangles: high-risk nodes; yellow circles: low-structure nodes; blue squares: low-function nodes; labels correspond to source-node IDs used throughout the manuscript. Grey shading: continuous eastern ecological block; blue lines: hydrographic network. Coordinates in WGS 84/UTM Zone 18N (EPSG:32618); units in km.

4. Discussion

4.1. Organization of Bogotá's ESP

The results show that the connectivity of Bogotá's ESP depends on a limited set of strategic components whose degradation accelerates the loss of network scale and efficiency under targeted perturbations. This pattern supports the expectation of greater vulnerability to centrality-based removals, while also qualifying the expectation that critical-

ity would be dominated by structural position. Structurally central nodes contributed to network degradation; however, simulated criticality also reflected functional importance, as shown by node 933, which ranked first and showed the highest recurrence as a High-Risk node across the evaluated α – β regimes. At the spatial scale, cascade behaviour was uneven and consistent with Bogotá's topographic polarization, especially the constrained permeability of the mountain–city transition. Nevertheless, these trajectories remain conditional on the adopted resistance surface and the α – β parameterization of the cascade model. These results are therefore interpreted as model-derived evidence, with different degrees of support for the study's expectations, rather than as empirically validated ecological responses.

This relational interpretation is consistent with landscape graph approaches, which represent ecological patches as nodes and spatial or modelled functional relationships as links within a network [33,49]. However, the urban ecological-connectivity literature has noted that many studies treat structural connectivity and potential or modelled functional-connectivity dimensions separately, limiting the identification of components that simultaneously sustain the spatial configuration and the modelled ecological performance of the network [50]. In this context, Bogotá's ESP presents a hierarchical organization in which component relevance emerges from the convergence between ecosystem-service value, structural position, and contribution to the global connectivity of the system.

This also extends the conventional “sources–resistance–corridors” framework by showing that it provides only a partial interpretation of the ESP if it does not incorporate how each component is positioned within the network. In contrast to approaches that prioritize ecological sources primarily based on isolated spatial, biophysical, or functional attributes, the results indicate that some components acquire relevance due to their articulating role, even when they do not concentrate the highest ecosystem values. This finding is consistent with recent studies that propose integrating structural and functional connectivity to develop urban green networks more aligned with ecological system stability [54]. Consequently, the hierarchy of the ESP does not represent a linear gradient of ecological importance, but rather a relational organization in which some components concentrate ecosystem value while others gain relevance through their linking function.

4.2. Evaluation of Network Resilience Considering Cascading Failure Effects

The model-based evaluation of Bogotá's ESP vulnerability shows, first, that network degradation does not depend solely on the magnitude of the perturbation, but on the structural role of the affected components within a hierarchical ecological architecture. This result is consistent with studies on complex networks, which have shown that systems with heterogeneous connectivity tend to be more robust to random failures but more vulnerable to targeted attacks on central nodes [32,55]. In Bogotá, the contrast between strategies is consistent with this logic: the earliest breakpoints are concentrated under targeted attacks and appear earlier in global efficiency than in network scale. This indicates that the loss of effective connectivity may intensify before structural fragmentation becomes fully evident. This asymmetry is further accentuated in the dynamic mode: a single trigger based on betweenness or degree removes 21 nodes, equivalent to 36.2% of the network, and reduces efficiency to 0.099, whereas k-core affects only two nodes, equivalent to 3.4%. Therefore, the modelled vulnerability of the ESP is not uniformly distributed, but depends on a subset of nodes with critical relational positions.

The joint interpretation of LCC, global efficiency, area-weighted effective mesh size, and algebraic connectivity indicates that the main patterns of simulated vulnerability do not depend on a single resilience metric. Directed attacks continued to show greater degradation than random removal; however, effective mesh size revealed that betweenness-based attacks generated more severe area-weighted spatial fragmentation, whereas alge-

braic connectivity showed a very early loss of global spectral cohesion. This result does not contradict the previous analyses, but qualifies them by showing that different metrics capture different dimensions of network degradation.

The incorporation of cascading failures deepens this interpretation by showing, second, that the severity of damage depends on the load redistribution regime and the temporal dynamics of propagation. This pattern is consistent with cascading failure models in complex networks, where collapse does not result solely from the initial loss of a component, but from the imbalance between transferred load and the residual capacity of receiving nodes [56,57]. In the univariate analysis, the mean cascade size increases from 1.31 ($\alpha = 0.1$) to 44.98 ($\alpha = 0.9$) nodes, and the frequency of large cascades increases from 0 to 0.845. As β increases from 0.05 to 0.30, the mean size decreases from 44.98 to 2.00 nodes. In Bogotá, the reference parameter set $\alpha = 0.70$ and $\beta = 0.09$ lies within a high-sensitivity regime, in which the distribution of avalanche sizes is more heterogeneous without reaching a saturated state. The 72 evaluated α – β regimes show that this α – β dependence is substantial: mean cascade size ranged from 6.50 to 56.07 nodes, and the number of nodes classified as High-Risk varied from 0 to 33 per scenario. Thus, α and β define alternative exploratory cascade regimes, and the resulting cascade severity, risk profile, and propagation patterns depend strongly on the adopted α – β parameterization. Furthermore, avalanches of similar magnitude develop with different durations, showing that collapse scale and propagation speed are not equivalent and require joint interpretation. This result extends resilience assessment beyond immediate structural loss and allows the distinction between nodes that trigger extensive damage and nodes whose criticality lies in the speed at which they transmit perturbations.

The patterns observed in Bogotá are partially consistent with those documented in other metropolitan areas, although with specific features derived from its Andean configuration. The concentration of connectivity in an eastern core and the high vulnerability of bridge nodes under targeted attacks are consistent with the findings reported by Gao et al. [58] for Shijiazhuang, where the coexistence of mountainous terrain and dense plains turns hub nodes into rapid collapse points under severe perturbations. However, in contrast to lowland cities with dense river networks, where betweenness centrality is positively correlated with regional resilience [59], in Bogotá the consolidated urban matrix of the central sector acts as a structural barrier that disconnects the eastern edge from the rest of the system, reducing the capacity of corridors to disperse risk. This difference suggests that spatial implications for strengthening the ESP must be interpreted in relation to urban morphology: in cities with pronounced topographic gradients such as Bogotá, the central issue is the permeability of the mountain–city transition.

4.3. Integration of Urban ESP Resilience into Urban Planning and Management

The spatial interpretation of Bogotá's ESP highlights three complementary diagnostic dimensions: structural performance, functional performance, and cascading-failure risk (Table 5). Read together, these dimensions help distinguish different diagnostic rationales within the network. Low structural performance identifies nodes associated with weaker relational continuity and potential needs for further assessment of network redundancy. Low functional performance identifies nodes with comparatively lower ecosystem-service capacity. High cascade risk highlights nodes with greater simulated propagation potential under the reference load–capacity scenario. Cross-dimensional convergence provides the screening logic for reinforcement candidates: nodes appearing in more than one dimension carry stronger diagnostic indications for subsequent spatial assessment. This reading is consistent with ecological network resilience approaches that identify strategic areas based on their contribution to system performance [60–62]. When spatially integrated

(Figure 12), these dimensions offer an exploratory basis for differentiated planning assessments.

Table 5. Cross-dimensional diagnostic screening of reinforcement candidates by structural performance, functional performance, and cascade-risk criteria under the reference model configuration.

Functional	Node	Structural	Node	High-Risk Nodes
0.0318	1207	0.0000	789	933
0.0362	1206	0.0043	914	433
0.0547	591	0.0064	536	434
0.0591	1055	0.0064	842	480
0.0680	701	0.0121	904	431
0.0978	549	0.0138	604	797
0.1163	594	0.0141	869	540
0.1379	425	0.1818	1097	847
0.1536	1051	0.1871	618	536
0.1858	1150	0.1876	385	789

The articulation with the propagation analysis illustrates this cross-dimensional interpretation. Node 933 appears as a high-risk reference under the adopted cascade scenario; node 425 combines severe delayed propagation with low functional performance; node 914 combines medium–low cascade risk with low structural performance; and node 1207, although it does not show effective propagation, ranks among the functionally weakest nodes. Similarly, nodes 433 and 847 are associated with rapid-collapse patterns, whereas nodes 385 and 618 reflect structural weakness. These cases illustrate different diagnostic rationales for spatial assessment based on the convergence of structural, functional, and cascade-risk criteria. The cascade-risk dimension is interpreted together with the α – β sensitivity analysis: under the 72 evaluated regimes, the number of High-Risk nodes varied between 0 and 33 per scenario, and node 933 showed the highest recurrence, appearing as High-Risk in 43 of 72 regimes (Table S16). In this sense, Table 5 provides a reference-configuration diagnostic screening of reinforcement candidates, interpreted in relation to the adopted resistance surface, functional-load definition, and cascade parameterization.

From the perspective of a preliminary spatial diagnosis, the results may help identify candidate areas for attention within Bogotá’s ESP by considering simulated functional vulnerability, structural weakness, and potential propagation risk. This interpretation provides an exploratory input for discussions on multifunctional green infrastructure that integrate ecological connectivity, ecosystem services, and spatial planning [63,64]. In contexts of urban renewal, infrastructure expansion, or the design of new developments, these results inform preliminary assessments regarding the preservation of corridors with higher connectivity and the prevention of new discontinuities in strategic segments of the network. In addition, the modelled results indicate locations where green connections between parks, ecological edges, and consolidated urban areas could be evaluated as potential opportunities to enhance spatial redundancy. These implications should be interpreted as preliminary diagnostic guidelines; the intervention benefits associated with specific measures were neither evaluated nor validated in this study.

4.4. Limitations and Future Work

This study presents several limitations. First, the spatial-consistency check with observed tree-cover loss provides a preliminary external contrast, while the cascading-failure model still requires calibration against historical disturbance records in Bogotá. This condition delimits the interpretive scope of the study: the results allow us to formulate an

exploratory, model-based diagnosis of simulated functional vulnerability of the ESP under the adopted load–capacity framework. Accordingly, the risk levels, critical nodes, and cascade trajectories should be interpreted as model-derived indications conditioned by assumptions about load, capacity, redistribution, landscape resistance, and α – β parameterization. This limitation is common in early stages of modelling complex systems, where model validation, calibration, and evaluation require explicit model purposes, performance criteria, and comparison between simulated patterns and observed evidence from the real system [65,66]. This requirement is particularly relevant in functional-connectivity modelling, where validation remains a critical step because model performance may vary across metrics and empirical data sources [67].

Therefore, empirical calibration using documented events, such as forest fires, infrastructure-driven fragmentation, or impacts associated with extreme hydrometeorological events, constitutes a necessary extension of the model. Second, the analysis is temporally static, as the ESP is characterized for a single landscape state and does not capture the spatiotemporal evolution of the network under continuous urbanization pressure. Under scenarios of accelerated urban expansion, the loss of peripheral sources or the disruption of bridging corridors could modify the structural hierarchy identified in the current network; under climate-induced vegetation changes, the distribution of functional load could shift in ways not captured by the current parameterization. Consequently, the simulated vulnerability patterns should be interpreted as diagnostics contingent on the analyzed landscape state, not as stable properties of the system [68]. Third, source selection, resistance-surface construction, and initial functional load all depend on composite indices and operational parameterization decisions. The $AMI > 0.14$ threshold was established from the Jenks natural break in the multicriteria index distribution and functions as an operational criterion for retaining the subset of patches with higher integrated multicriteria performance. Although the sensitivity analysis showed stability of the selected source set under $\pm 10\%$ weight variations and alternative thresholds from 0.12 to 0.16, source selection should be interpreted as a multicriteria prioritization of candidate patches, open to future comparison with specific ecological criteria, such as focal-species requirements, functional-connectivity evidence, or observed hydrological processes.

In addition, although the uniformly weighted resistance surface is a literature-supported baseline configuration [42–45], this study did not compare alternative resistance-weighting schemes. Equal-weight configurations can perform comparably to differentially weighted alternatives in circuit-theory connectivity modelling [69], and objective weighting methods such as CRITIC show that contrast intensity and inter-criteria conflict affect weight allocation [70]. In Bogotá, the low-resistance eastern edge and higher-resistance central-western matrix reported in Section 3.1.3 support interpreting this surface as a reference representation of the macro-scale resistance gradient. Nevertheless, alternative weight allocations may modify corridor geometry, network topology, node rankings, cascade behaviour, and reinforcement candidates. These outputs are therefore conditional on the adopted resistance configuration. Future applications should compare equal-weight, expert-based, analytically derived, and empirically calibrated resistance surfaces.

Similarly, the initial functional load was defined using an entropy-weighted composite functional index; this definition makes the components and weights used in the model explicit, while the interpretation of cascade results remains conditioned by the selected functional components, the adopted weights, and the exploratory α – β regime. Studies on urban green infrastructure show that such systems provide multiple ecosystem services and that their evaluation requires broader multifunctional approaches [71,72]. Accordingly, the selected sources, corridor priorities, critical nodes, risk levels, propagation trajectories, and reinforcement candidates, including the diagnostic screening summarized

in Table 5, should be interpreted as model-derived prioritization criteria for further planning assessment rather than as direct intervention prescriptions.

Based on these limitations, three priority directions for future work and framework adaptation to other cities are identified. The first is to compare cascade outputs with georeferenced records of documented disturbances in Bogotá, including fires, infrastructure expansion, and tree-cover loss, to evaluate correspondences between simulated risk and observed degradation, and to establish minimum data requirements for other cities: land-use/land-cover data, biophysical layers for ecosystem-service assessment, inputs for MSPA and structural-connectivity analysis, resistance factors, and local disturbance records. The second is to incorporate spatiotemporal urbanization and climate scenarios to evaluate the stability of sources, corridors, resistance surfaces, and critical nodes under changing conditions, and to locally calibrate key operational parameters, including AMI weights and source-selection thresholds, resistance-surface weights, and α - β regimes, through sensitivity analysis, empirical evidence, or expert consultation. The third is to evaluate the applicability of the framework in cities with fragmented urban matrices, identifiable ecological remnants, and sufficient spatial data, and to integrate post-failure recovery mechanisms to analyze trajectories of functional restoration within the network.

5. Conclusions

Addressing the question of how the simulated vulnerability of Bogotá's ESP is organized under the assumptions of the adopted model, this study examined the modelled behaviour of its ecological network as a hierarchical configuration in which the system response does not derive from a single dimension, but from the interaction among ecosystem-service value, structural connectivity, landscape resistance, and the relational position of nodes. The construction of the ESP resulted in a network of 58 nodes and 107 links, with limited overlap between the components that were best positioned structurally and those with the highest functional importance. This divergence suggests that synthetic functional connectivity within the fragmented urban matrix is approximated through the articulation between high ecosystem-service-value blocks and structural connectors.

The perturbation simulations indicated that the modelled vulnerability of the ESP is not uniformly distributed. Under static attacks, degradation was stepwise, whereas in the reference dynamic cascade scenario the earliest breakpoints appeared earlier under targeted strategies than under non-targeted scenarios; a single trigger based on betweenness or degree produced 21 modelled failures, equivalent to 36.2% of the network. The analysis showed that the simulated propagation of degradation does not follow a single temporal pattern, such that cascading failures of comparable magnitude may develop over different durations. The analyses across the 72 α - β regimes showed that criticality and node-risk classification depend on the adopted parameterization. In model terms, the model-derived functional vulnerability of Bogotá's ESP is concentrated in relationally critical components, rather than in a homogeneous loss of ecological cover.

The main contribution lies in integrating structure, function, and simulated risk propagation within an exploratory and model-based interpretation of Bogotá's urban ESP. This integration allowed the characterization of the hierarchical organization of the network, the examination of its simulated vulnerability under static and dynamic perturbations, and the recognition of critical nodes, risk levels, and modelled propagation trajectories relevant to spatial prioritization. The study extends ESP analysis toward an exploratory vulnerability and cascading framework in an Andean metropolis of the Global South, adapts the load-capacity model to an ESP through an initial functional load based on ecosystem-service indicators, and offers model-derived indications that mountain-city topographic polarization may structure the spatial distribution of risk within the network. In an Andean metropolis, the results suggest that the simulated functional vulnerability

of the network does not depend solely on the amount of natural cover, but also on how its components are connected, hierarchically organized, and exposed to perturbations under the adopted assumptions. Testing these indications against georeferenced records of documented disturbances constitutes a priority empirical extension of this work.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/ijgi15070330/s1>, Table S1: complete sources, providers, and access URLs of the datasets used in the study; Table S2: inferential sequence, methodological components, and parameter status of the ESP vulnerability assessment; Table S3: threat factors and related coefficients used in the InVEST Habitat Quality model; Table S4: sensitivity of habitat types to each threat factor in the InVEST Habitat Quality model; Table S5: carbon storage values assigned to each land-cover class for the InVEST Carbon Storage and Sequestration model; Table S6: biophysical parameters assigned to each land-cover class for the InVEST Water Yield model; Table S7: characterization of ecosystem services for the identification of ecological sources; Table S8: definitions and interpretation of complementary resilience metrics; Table S9: entropy-based weights used to calculate nodal functional importance (T_i); Table S10: preliminary spatial-consistency check between simulated cascade-risk levels and observed tree-cover loss, 2019–2024; Table S11: normalized ecosystem service indicators and final Aggregated Multicriteria Index (AMI) scores for ecological core areas; Table S12: sensitivity of ecological-source selection to AMI threshold and AMI component-weight variation; Table S13: input data used to compute complementary resilience metrics; Table S14: selected values of complementary metrics at key removal levels by attack strategy; Table S15: AUC summaries and algebraic-connectivity disconnection thresholds by attack strategy; Table S16: recurrence of nodes classified as High-Risk under 72 α – β parameter regimes; Figure S1: topological centrality attributes of nodes and their functional importance values (specific 645 values of degree centrality, betweenness centrality, PageRank, k-core, and functional importance 646 for the 58 nodes); Figure S2: combined sensitivity analysis 1: mean cascade size; Figure S3: combined sensitivity analysis 2: mean cascade duration; Figure S4: combined sensitivity analysis 3: probability of large-scale cascades; Figure S5: combined sensitivity analysis 4: standard deviation of cascade size; Figure S6: single-factor sensitivity analysis 1; Figure S7: single-factor sensitivity analysis 2; Figure S8: cascading failure diagram (propagation pathways following the initial failures of nodes 425, 430, 427, and 385 are shown; connecting lines represent the simulated diffusion of failure within the network, and colored circles indicate the nodes that failed in successive propagation rounds); Figure S9: Cascade process trajectory diagram. In each subplot, the x-axis represents the number of propagation rounds and the y-axis represents the number of nodes affected in each round; the number at the top of each subplot corresponds to the identifier of the source node. The variation among panels reflects node-specific differences in cascade intensity and duration: higher peaks indicate rounds with greater numbers of newly affected nodes, longer curves indicate more prolonged propagation, and nearly flat trajectories indicate source nodes with limited or no effective cascade propagation.

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Abbreviations

The following abbreviations are used in this manuscript:

AMI	Aggregated Multicriteria Index
DEM	Digital Elevation Model
dPC	Delta Probability of Connectivity
ESP	Ecological Security Pattern
IDECA	Spatial Data Infrastructure of the Capital District (Infraestructura de Datos Espaciales de la Capital)
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
LCC	Largest Connected Component
MCR	Minimum Cumulative Resistance
MSPA	Morphological Spatial Pattern Analysis
NDVI	Normalized Difference Vegetation Index
NPP	Net Primary Productivity
PC	Probability of Connectivity
POT	Territorial Land-Use Plan (Plan de Ordenamiento Territorial)

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