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Combined use of urban Atlas and Corine land cover datasets for the implementation of an ecological network using graph theory within a multi-species approach

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ABSTRACT

Ecological sustainability has recently risen to prominence in scientific research and management applications. Approaches to measuring ecological connectivity and their application to optimize ecological network (EN) design are powerful tools against landscape fragmentation and biodiversity loss.

We focused on building an EN by identifying the most sensitive areas for ecological connectivity within the Reggio Calabria (Italy) metropolitan area. We also proposed a defragmentation scenario to improve the obtained EN.

The CORINE Land Cover and the Urban Atlas 2018 were used to obtain a fine-scale representation of the study area. Ten terrestrial mammal species were used to model connectivity following a multi-species approach. Dispersal distance, patch size, and resistance to species movement were used to identify patches and corridors. Vegetational fractional coverage based on three years time series of Sentinel-2 red-edge normalized difference vegetation index was used to discriminate areas with higher naturalness. We used graph theory and connectivity metrics to test the EN's robustness and identify locations for restoration in a defragmentation scenario.

The obtained EN, formed by three separate components, was composed of 724 arcs and 300 nodes with an average patch area of 27.04 ha. After the defragmentation hypothesis, the EN, formed by only one component, was composed of 771 arcs and 328 nodes with an average patch area of 26.82 ha.

It was possible to analyze an EN's connectivity and evaluate the impact of a scenario intended to enhance multi-species connectivity. By comparing several connectivity metrics, we highlighted the potential of land interventions as a planning tool to enhance future ecological sustainability and biodiversity conservation.

1. Introduction

Over the last century, rapidly growing human populations, economic development, and associated land use changes have led to a progressive loss of habitat and fragmentation of the landscape (Cushman, 2006; Sauter et al., 2019). Over most of the Earth's biomes, contiguous natural landscapes have been fragmented into a mosaic of residual patches divided by barriers dispersing animal species across the landscape (Diniz et al., 2020; Hudson, 1991). Species have evolved, and populations were previously sustained in often dramatically different environments than the one in which human-driven perturbations have produced; moreover, the reduction of areas of residual natural ecosystems inevitably has effects on the life cycles of the species themselves (Hanski, 1999).

Meanwhile, in the countries of the European continent, recognition of the negative consequences of these processes has forced a radical change in the way of thinking about landscape management and planning in recent decades (Jongman et al., 2004). Starting with the "Environmental Ecological Network" (EECONET) project in the Netherlands (1991), followed by the Institute for European Environmental Policy (IEEP) the "European Landscape Convention" (CoE,

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2000), the “EU Biodiversity Strategy for 2030”, the ‘Natura 2000’ project (EU), and in Italy, the ‘Carta della Natura’ project of the Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA), the continent’s scientific community and governments have become increasingly aware of the importance of managing natural spaces in a sustainable and resilient manner.

An early example of the Ecological Network (EN) concept originates from the EECONET project (Bennet,1991). EECONET was intended as a set of interconnected habitats that protect animal and plant biodiversity. The EN envisaged by EECONET comprises patches and ecological corridors. In EECONET, a patch is defined as a cover type providing habitat value that differs from its surroundings, for which it is possible to delineate a perimeter. An ecological corridor is defined as a portion of land that connects two patches, habitats, or ecosystems and allows the movement of a species between EN elements (Clark, 2010). To include the analysis of the ecological connectivity among the elements of an ecological network in landscape planning/management is widely recommended (Cushman et al., 2013, 2016, 2018; Kaszta et al., 2020; Rudnick et al., 2012; Tarabon et al., 2021). In this scenario, for sustainable spatial planning, ecological networks are themselves the object of spatial planning (Balbi et al., 2019; Mateo-Sánchez et al., 2015; Tarabon et al., 2020; Tiang et al., 2021) and their implementation can counteract landscape fragmentation (Liccari et al., 2022), create and strengthen relationships, and promote exchanges between otherwise isolated elements (De Montis et al., 2016; Fichera et al., 2015). Moreover, landscape improvement policies and actions are widely recommended as tools for combating climate change (Heller & Zavaleta, 2009).

Given urban sprawl affecting many regions worldwide and the conflict between urbanization and ecological planning, assessing landscape connectivity in *peri*-urban areas is of crucial importance (Dong et al., 2020). Rural fringe areas are characterized by specific dynamics and patterns of contiguity, inclusion with the urban environment and its sprawling, and the natural contexts and their connectivity elements. Such dynamics often underline alterations affecting the ecosystem functionality, reducing the provision of ecosystem services, and jeopardizing the quality of life of many animal and vegetal species and human settlements. Rivers and riparian zones are the most threatened ecosystems and should be protected adequately (Samways and Pryke, 2016). Moreover, it was recently recognized as riparian zones can play an essential role in improving landscape ecological connectivity (Ribeiro et al., 2022).

For modeling ENs there are three dominant approaches (Cushman et al., 2013), based, respectively, on (1) single-species, (2) multi-species, and (3) coarse-filters or ecological systems. In single-species modeling, the analysis considers the needs of only one species of interest (Bourdouxhe et al., 2020; Cushman et al., 2009; Cushman et al., 2016; Hardion et al., 2019). In contrast, multi-species modeling considers the needs of a set of species, called focal species, considered representative of all species present in the examined context (Cushman et al., 2012; Cushman & Landguth, 2012; Guimarães, 2020; Lechner & Lefroy, 2014; Savary et al., 2021; Zhang et al., 2021). Finally, the coarse-filter approach assesses the connectivity of intact or natural ecosystems irrespective of any focal species (Cushman & Landguth, 2012; Diniz et al., 2020). For this work, we chose a multi-species approach based on the needs of 10 focal species, identified exclusively among medium and small mammals. A widespread practice for modeling an EN is to anchor the ecological network in nodes defined by protected areas (Bonnin, 2008; Kheirkhah Ghehi et al., 2020). This allows the identification of network building blocks such as patches and ecological corridors, but the exclusive use of these areas for habitat conservation has been widely criticized by numerous researchers (Beier et al., 2011; Chapron et al., 2014; Cushman, 2006; Cushman et al., 2013; Cushman & Landguth, 2012; Forrest et al., 2011; Modica et al., 2021).

The approach adopted in this paper is novel in employing two different land use maps for the network modeling: Urban Atlas (UA2018) and Corine Land Cover (CLC2018). These datasets, provided by the European Union Copernicus programme, were created to meet different needs. CLC provides a representation of the land uses of 39 countries and contains information that can support the European Union’s Environmental Action Programmes. UA was created to provide a very detailed representation of urbanized areas, covering 788 FUAs (Functional Urban Areas) of 39 European countries in the 2018 release. A Digital Terrain Model (DTM) and multispectral satellite images were used to support the UA and CLC, which together allowed a high degree of detail set for the representation of natural and artificial elements of the study area. Our model proposes an accurate choice of faunal species, considering the adopted large spatial scale (1:10,000) and the heterogenous landscapes with the significant and increasing occupation of urbanized areas. Moreover, we optimized our model of EN using a high-resolution DTM and a multi-temporal Vegetation Fractional Coverage (VFC) capable of better discriminating areas with higher naturalness and based on a three-year (2016–2019) time series of Sentinel-2 red-edge Normalized Difference Vegetation Index ($NDVI_{4re}$). Finally, the proposed EN and the current landscape configuration were assessed and compared with a defragmentation scenario proposed, reconnecting isolated patches and improving riparian zones in specific areas. A set of landscape indicators was defined to this end. Reconnecting isolated patches, especially in rural–urban fringe areas, is crucial in promoting climate-resilient defragmentation measures in heterogeneous landscapes. The entire proposed method has been developed using free open-source software (FOSS).

The main objectives of the work presented here are: (i) to identify the most important areas for wildlife connectivity based on a multi-species approach; (ii) to develop a defragmentation scenario within a heavily anthropized area to improve network connectivity; (iii) to compare the pre- and post-defragmentation networks to assess their effectiveness.

2. Materials and methods

The method (Fig. 1) is structured in 4 phases: (i) collection and organization of the database to accurately describe the geomorphological characteristics of the area, as well as the ecological characteristics of the area and the autecological characteristics of the considered species (habitat, home range, dispersal distance, level of affinity to various land uses); (ii) data processing using FOSS and remote sensing techniques, to create the structure of the EN of the entire examined area; (iii) analysis of the implemented EN through connectivity metrics and indices; (iv) defragmentation intervention scenario development to improve the current network and comparison of pre- and post-intervention network connectivity metrics and indices.

2.1. Study area

The analysis was applied in the metropolitan area of Reggio Calabria, which has an extension of 47,822.63 ha and is located in the southernmost part of the Calabria Region (Italy) (Fig. 2). According to the Urban Atlas 2018 data, the urbanized areas and the road system cover an area of 6773.25 ha (14.16% of the investigated area).

The region is characterized by a typical Mediterranean climate (Pellicone et al., 2018), with a rainy winter and dry summers. The study area includes twelve municipalities between Villa San Giovanni and Montebello Ionico, with a 68.9 km coastal strip facing the sea at the Stretto di Messina. The investigated territory extends to the highest peaks of Aspromonte, including part of the Aspromonte National Park.

2.2. Base data collection and organization

All data used for building the EN are synthesized in Table 1. Two vector data layers provided by the European Union Copernicus programme were used (https://land.copernicus.eu/ - last access 30/06/2022). The CLC data was characterized by a minimum mapping unit

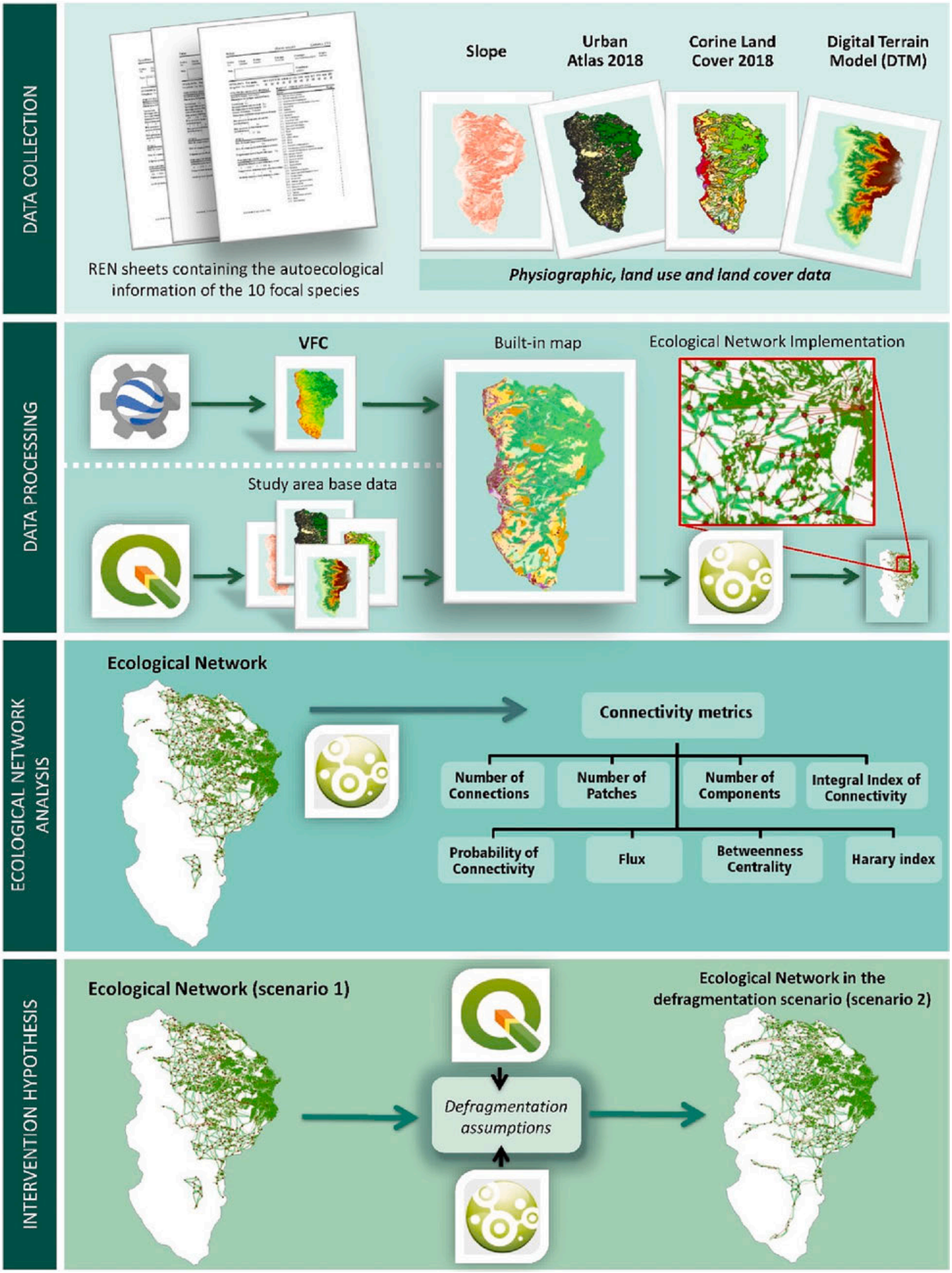


Fig. 1. Workflow of the proposed method, entirely developed in free open-source software (FOSS) environments (QGIS, Google Earth Engine, and Graphab).

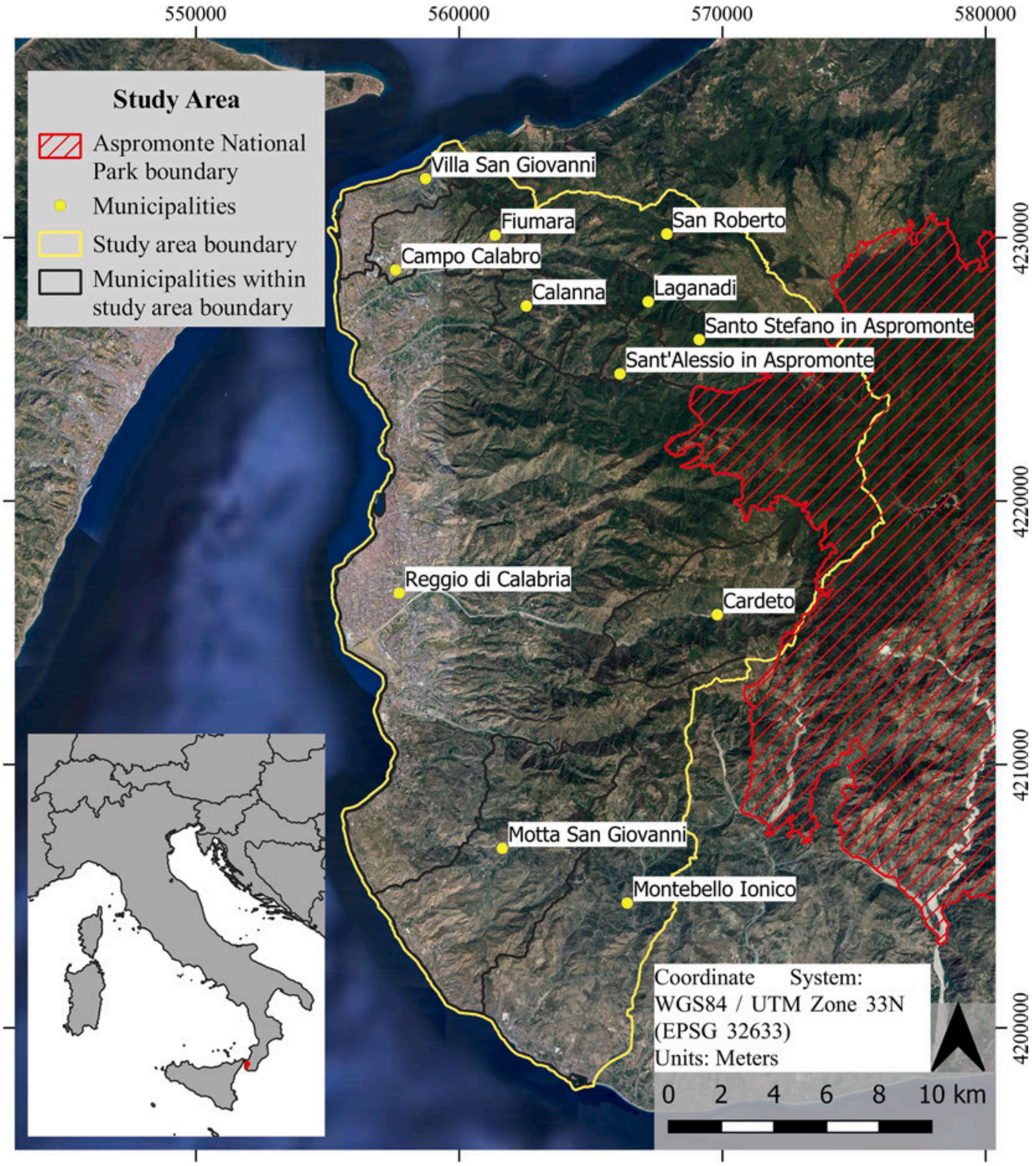


Fig. 2. Study area. In yellow is the perimeter of the Urban Atlas Reggio Calabria data for 2018, including 12 municipalities (black line) in the province of Reggio Calabria. In red is the boundary of the Aspromonte National Park, which partially crosses the study area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(MMU) of 25 ha and 25 different land use classes grouped into 5 categories. The UA dataset has very high geometric and thematic detail of man-made elements (buildings, infrastructure, etc.), including 27 different land use classes with an MMU of 0.25 ha for category 1 and 1 ha for categories 2 to 5. The legend used by UA and CLC has a hierarchical structure on several levels. The first level is the most general and consists of 5 categories: 1, highly artificial areas; 2, agricultural areas; 3, natural areas; 4, wetlands; 5, water elements. In the present study, the 2018 UA and CLC datasets were integrated using the UA for land use classes of the first category, which goes up to the fourth hierarchical level by highlighting important infrastructural elements such as secondary roads (Bourgeois & Sahraoui, 2020), which are missing in CLC. For the remaining categories, we used the CLC dataset. Although it has a lower spatial resolution, it shows greater thematic detail in the differentiation of agricultural and forest land, going up to the third hierarchical level, unlike the UA datum, which remains at the second level. Through the code editor of the Google Earth Engine (GEE) cloud platform (Gorelick et al., 2017), multispectral images of Sentinel-2 in a time series from 2016 to 2019 were processed. A cloud masking operation was performed, removing images with cloud coverage of 70 % or more in the first instance. This was done to exclude cloud-covered pixels from the analysis and, secondly, in images with high cloud cover, even pixels not covered by clouds may have noise, cirrus, or georeferencing problems (Xu et al., 2019). At this point, further filtering was performed, masking all pixels with a probability of being covered by clouds greater than 20% (this value is referred to as the band named “probability” in the S2_Cloud_Probability dataset). Finally, Sentinel-2 multispectral images were used to obtain vegetation vigor and naturalness information through specific spectral indices (§ 2.4).

A 5 × 5 m resolution raster DTM and the derived slope raster were used to characterize the topographic conditions of the study area, highlighting those areas not suitable because of their slope or elevation.

Table 1
Spatial dataset used in this research work.

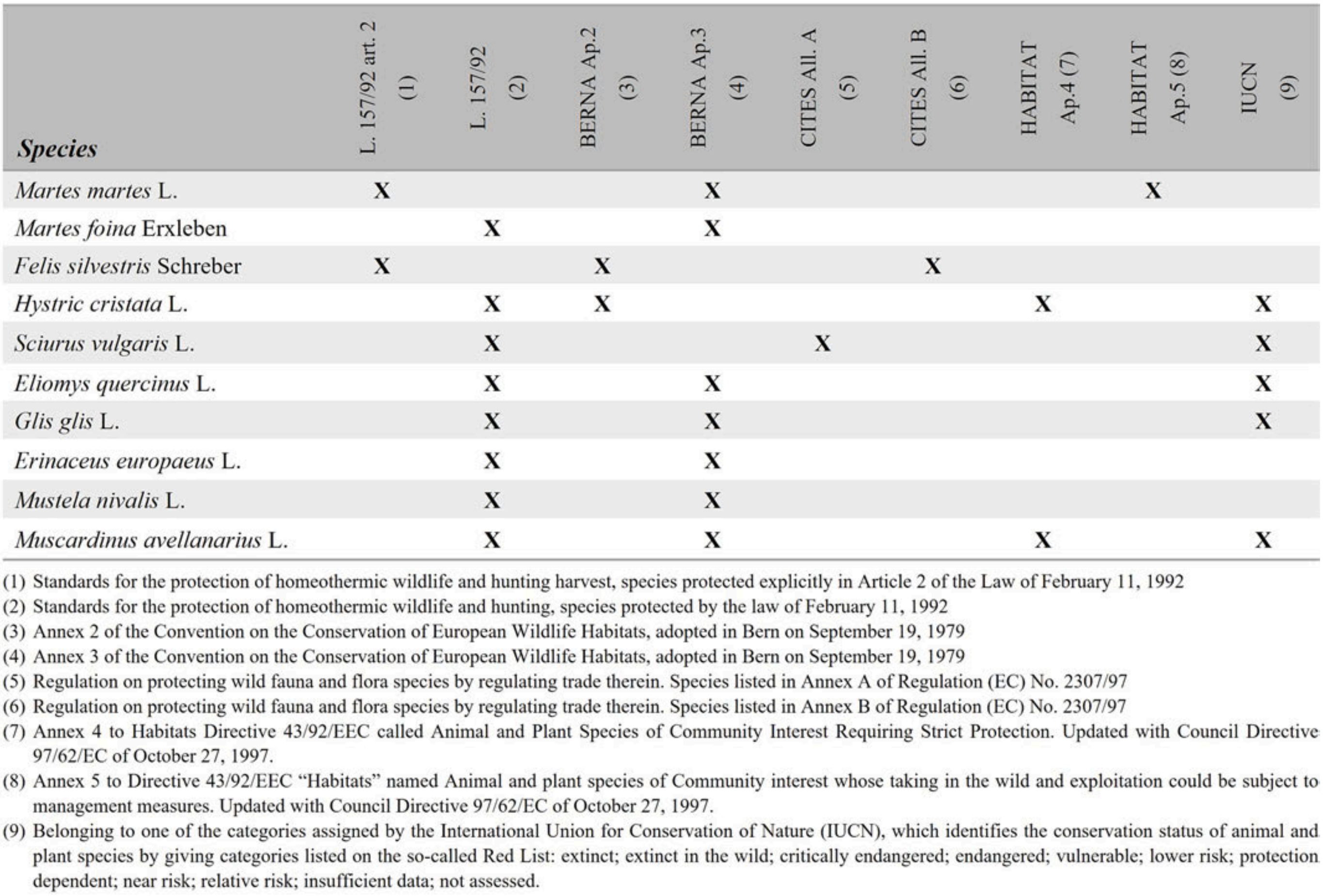
Data description	Reference year	Data source
Land use - CORINE Land Cover (CLC) at the third level of representation	2018	Copernicus, Land Monitoring Service (https://land.copernicus.eu/ -last access 17/02/2023)
Land use - Urban Atlas (UA) at the fourth level of representation	2018	
Digital Terrain Model (DTM) 5 × 5 m geometric resolution	2008	Calabria Region Cartographic Centre (CCR) (https://geoportale.regione.calabria.it/opendata - last accessed 06/06/2022)
Multispectral imaging - Sentinel-2 MultiSpectral Instrument (MSI), Level-1C	From 2016 to 2019	European Space Agency (ESA) (https://sentinel.esa.int/web/sentinel/user-guides/sentinel-2-msi/product-types/level-1c - last accessed 17/02/2023)
Cloudiness - Sentinel-2 Cloud Probability		

2.3. Animal species identification

For the construction of the EN, ten medium and small mammal species, summarized in Fig. 3, were identified and selected as focal species, which we considered representative, in terms of ecological requirements, of other mammal species with which they share the ecosystem. They act as umbrella species, i.e., at the top of the trophic chain and of particular conservation interest, and their protection implies the conservation of the underlying trophic levels. The method is based on actual data collected by Boitani (Boitani et al., 2002) on the behavioral and auto-ecological properties of the selected species. This information gives values that refer to optimal minimum/maximum thresholds, such as the distance an animal can travel in a hostile environment to reach resources, the size of the surface area it needs to carry out its life cycle, and the affinity of the species to a given environment.

Different types of territory present a diverse permeability depending on the various species' mobility passing through it (Battisti, 2004), so the ten focal species were selected, taking this factor into account as well. For instance, some reptiles' perception of a vertical wall - in terms of a barrier or impediment to free mobility - is different from that of some mammals and even birds. The decision to not consider large species such as the wolf is linked to the objective of planning at a detailed urban scale. Small and medium-sized species searching for resources have considerably less mobility (10 km on average) than the wolf's 90 km travel capacity. Considering the size of the study area (35 km at the two furthest extremes), it would be more appropriate to conduct evaluations over larger areas for a species with high space requirements, such as the wolf. The assumption is that when studying the landscape and designing planning interventions within it, it is necessary to consider the scale of analysis and thus check whether the needs of the reference species are compatible with that level of detail (Beier et al., 2011; Compton et al., 2007). To capture the details and needs of certain species, it is, therefore, sometimes necessary to reduce the observation scale of the landscape (or vice versa to increase it) (Nie et al., 2021).

The species selection was based on existing literature for the same study area (Modica et al., 2021), prioritizing species protected by national and international legislation (https://www.mite.gov.it/pagina/repertorio-della-fauna-italiana-protetta - last accessed 16/02/2022).



Species	L. 157/92 art. 2 (1)	L. 157/92 (2)	BERNA Ap.2 (3)	BERNA Ap.3 (4)	CITES All. A (5)	CITES All. B (6)	HABITAT Ap.4 (7)	HABITAT Ap.5 (8)	IUCN (9)
Martes martes L.	X			X				X	
Martes foina Erxleben		X		X					
Felis silvestris Schreber	X		X			X			
Hystric cristata L.		X	X				X		X
Sciurus vulgaris L.		X			X				X
Eliomys quercinus L.		X		X					X
Glis glis L.		X		X					X
Erinaceus europaeus L.		X		X					
Mustela nivalis L.		X		X					
Muscardinus avellanarius L.		X		X			X		X

(1) Standards for the protection of homeothermic wildlife and hunting harvest, species protected explicitly in Article 2 of the Law of February 11, 1992
(2) Standards for the protection of homeothermic wildlife and hunting, species protected by the law of February 11, 1992
(3) Annex 2 of the Convention on the Conservation of European Wildlife Habitats, adopted in Bern on September 19, 1979
(4) Annex 3 of the Convention on the Conservation of European Wildlife Habitats, adopted in Bern on September 19, 1979
(5) Regulation on protecting wild fauna and flora species by regulating trade therein. Species listed in Annex A of Regulation (EC) No. 2307/97
(6) Regulation on protecting wild fauna and flora species by regulating trade therein. Species listed in Annex B of Regulation (EC) No. 2307/97
(7) Annex 4 to Habitats Directive 43/92/EEC called Animal and Plant Species of Community Interest Requiring Strict Protection. Updated with Council Directive 97/62/EC of October 27, 1997.
(8) Annex 5 to Directive 43/92/EEC "Habitats" named Animal and plant species of Community interest whose taking in the wild and exploitation could be subject to management measures. Updated with Council Directive 97/62/EC of October 27, 1997.
(9) Belonging to one of the categories assigned by the International Union for Conservation of Nature (IUCN), which identifies the conservation status of animal and plant species by giving categories listed on the so-called Red List: extinct; extinct in the wild; critically endangered; endangered; vulnerable; lower risk; protection dependent; near risk; relative risk; insufficient data; not assessed.

Fig. 3. National and international legislation protecting identified focal species.

2.4. Data processing

UA and CLC data layers were integrated into QGIS 3.22 (http://www.qgis.org - Last accessed 05/06/2022). All class 1 geometries of the Urban Atlas were saved separately and overlaid with the CLC vector, obtaining the comprehensive vector data of the study area. A topological check of the data obtained was then carried out and the errors detected (points, broken lines, redundant features, etc.) were corrected using the GRASS toolset 'v.clean'. In addition, all polygons with a surface area smaller than the MMU were merged with those neighboring them. The MMU for UA was retained as it was lower than that of CLC. The vector data was then converted to a raster to allow subsequent processing. Considering that the UA datum was produced by interpretation from satellite images with a resolution of 2 or 4 m (e.g., Pléiades, KOMPSAT, Planet, SPOT6, SuperView, etc.), the rasterization process was fixed at 2.5x2.5 m of spatial resolution.

Using the FOSS Graphab 2.6 (Foltête et al., 2012a, Foltête et al., 2012b, Foltête et al., 2021), for each raster pixel, we assigned a value expressing the resistance that a given land use opposes to the movement of species in an interval ranging from 1 (lowest resistance) to 100 (highest resistance). Pixels with increasing values refer to increasingly artificial areas, while pixels with low values refer to highly natural areas. These values express the difficulty a species has in crossing the different landscape elements according to the autecological needs of the focal species, identified by Boitani et al. (2003). Slope, derived from the 5 m DTM, was considered in identifying patches and corridors. In Graphab 2.6 environment, the importance of slope (p) was weighed through a coefficient (c) as in the following equation (Eq.1) (Tarabon et al., 2022):

$$r_{final} = r^*(1 + c \cdot p) \tag{1}$$

where r is the pixel resistance and r_{final} is the pixel resistance weighted by the slope (p). When $c = 1$, the resistance value is doubled for a slope of 10%, while if $c = 10$, the resistance is doubled for a slope of 100% ($p = 1$). Since in this work, we considered the value of the coefficient c to be 1, as the slope increases, the permeability decreases.

Through the Code Editor of GEE, we implemented a function to calculate the area's average Vegetation Fractional Coverage (VFC) index over 3 years, from 2016 to 2019, using Sentinel-2 L1C satellite images. This indicator is widely used in remote sensing to monitor the condition of plant communities (Shobairi et al., 2018), making it possible to discriminate areas of higher naturalness falling within the study area (Shobairi et al., 2018; Yu et al., 2021). Before calculating the VFC index, we processed the time series masking all pixels with a probability of being covered by clouds. The latter operation was developed in the GEE environment by exploiting the S2 Cloud:probability dataset produced by the European Commission in collaboration with the European Spatial Agency (ESA) and the SentinelHub service. For the production of the S2 Cloud:probability dataset, in particular, ESA used the Sentinel2-cloud-detector (whose library is available in the s2cloudless python package), an algorithm based on machine learning for the automatic detection of clouds in Sentinel-2 images. Once processed the images of the time series, we calculated the average 4-band red-edge Normalized Difference Vegetation Index ($NDVI_{4re}$) (Eq. (2) using the formula proposed by Liu et al. (2022). It has been shown that the red edge indices can correct the underestimation of vegetation vigor when vegetation cover is high and mitigate its overestimation when levels of vegetation cover are low (Liu et al., 2022):

$$NDVI_{4RE} = \frac{(\alpha^* R_{RE3} + (1-\alpha)^* R_{RE2}) - (\beta^* R_{red} + (1-\beta)^* R_{RE1}}{(\alpha^* R_{RE3} + (1-\alpha)^* R_{RE2}) + (\beta^* R_{red} + (1-\beta)^* R_{RE1}} \tag{2}$$

where R_{RE1}, R_{RE2}, R_{RE3}, and R_{red} are the Red-Edge and Red bands of Sentinel-2 imagery; α and β are weighting coefficients representing the proportion of RE3 and Red reflectance, respectively (Liu et al., 2022). In our proposed method, the value of both coefficients was fixed at 0.7.

The average VFC value was then calculated (Eq. (3):

$$VFC = \frac{NDVI_{4RE} - NDVI_{4REmin}}{NDVI_{4REmax} - NDVI_{4REmin}} \tag{3}$$

VFC value ranges between 0 and 1. For our purposes, we considered suitable areas only those with a VFC value greater than 0.6.

2.5. Construction of the multi-species ecological network (EN)

Graphab 2.6 was used to construct the multi-species ecological network of the entire study area, using the principles of graph theory (Ersoy et al., 2019; Foltête, 2019; Foltête et al., 2012a, Foltête et al., 2012b; Godet & Clauzel, 2021). Graphab is compatible with GIS software, which makes it versatile and capable of providing significant support to those working in the field of cartography and planning (Clauzel & Godet, 2020). It can also include the construction and graphs visualization, connectivity analysis, and links to external data (https://sourcesup.renater.fr/www/graphab/en/home.html - last accessed 05/07/2022).

The maximum affinity of a species to a particular land use has been considered as possible habitat. The home range, defined here as the extent of land large enough to contain the resources necessary for the completion of the individual's life cycle (Boitani et al., 2003), was used to set a lower area threshold for habitat patches. Only habitats with a surface of at least 2 ha were considered possible patches. This choice is consistent with Boitani's finding that 2 ha are the minimum home range size for each focal species we selected. Considering the above variables (slope less than 100%, home range $\geq$ 2 ha, VFC $\geq$ 0.6, and excellent affinity to land use), we finally identified the EN patches.

For the identification of ecological corridors, a crossing threshold was established to be valid for all focal species, understood as the maximum distance an animal can travel in a hostile environment to reach resources. The threshold was set at 2 km because literature and empirical evidence obtained through interviews with local experts indicate it as the maximum distance that focal species can travel with less mobility. This value will therefore be more than sufficient for species capable of spanning greater distances.

2.5.1. Building network components: Patches and ecological corridors

The modelling process in Graphab 2.6 returns a series of nodes and arcs as graphic representation of patches and ecological corridors, respectively. The arcs were identified by considering two topological and weighting parameters of the arcs themselves. The Graphab 2.6 software allows for two different alternatives, 'planar topology', in which only the links forming a 'planar graph' are considered (i.e., in the construction of the graph, only the arcs that connect the nodes in the planar representation of the graph itself, and never intersect, would be considered), and 'complete topology' in which all the arcs between patches are potentially taken into account. In our case, the latter method was used, as it does not exclude any possible pathways and provides an initial linear representation of displacements, allowing for a realistic representation of ecological corridors (Godet & Clauzel, 2021). Taking into account the patches, the maximum crossing threshold, and the strength value assigned to each pixel of the raster relating to the land uses of the study area, it was possible to identify ecological corridors and Least Cost Paths (LCPs). LCP is defined as the pathway that offers the least resistance to an animal moving from one patch to another (Cushman et al., 2013) and is represented as the linear element (least-cost pathway) that connects two patches. Ecological corridors represent potential pathways for species movement within patches best suited to connectivity due to their ecological characteristics. They are in a raster dataset in which each pixel has a value indicating the resistance to animal movement. These values tend to increase as one approaches the edges of the ecological corridor. Conversely, they decrease as one approaches the center of the ecological corridor, in the area that coincides with the identified LCP. The areas where the ecological corridor shows the least resistance to animal movement correspond to those of maximum connectivity in the vicinity of LCPs (Theobald, 2006; Zeller et al., 2012). For this reason, to have an adequate representation of the most suitable ecological corridors, we defined a 100 m buffer around the LCPs and retained only those ecological corridors branching off within the limits of this buffer. Patches, surfaces elements identified by nodes, and ecological corridors, surface elements identified by arcs, represent the component of the obtained EN.

2.5.2. *Network connectivity metrics and indices analysis*

To analyze the obtained EN, several connectivity parameters and indices were calculated. The selection of these indices is related to their ability to characterize the network, quantify its connectivity, and identify its elements of centrality. This was possible by calculating the following metrics (Table 2): Integral Index of Connectivity (IIC), Number of Components (NC), Harary Index (H), Betweenness Centrality (BC), Flux (F), and Probability of Connectivity (PC) (Saura & Pascual-Hortal, 2007). The indices described in the table were calculated on the entire network.

2.6. *Hypothesis of ecological defragmentation scenario*

The last phase involved a defragmentation scenario proposed to improve the connectivity of the areas identified at the end of the previous phase. The defragmentation scenario was developed considering a peculiar element of the Calabrian region, the so-called ‘fiumare’. These torrential watercourses were identified as crucial elements connecting the urban fabric’s green spaces with the rest of the network. In fact, these rivers cross the entire Calabrian territory from upstream to downstream, also passing through the core of the urban center of Reggio Calabria. The Calabrian rivers are considered fragile and delicate elements, and hydrogeological constraints are imposed on them.

On the one hand, the rivers are considered efficient natural ecological corridors (Bishop-Taylor et al., 2015; Guo & Liu, 2017; May, 2006). These characteristics are the ideal place to focus an urban defragmentation scenario (Wang et al., 2022; Wang et al., 2021). On the other hand, it is difficult and expensive to expropriate urbanized public or private property areas to build and enhance EN. For this reason, the characteristic of the rivers as environments protected by regional legislation, and their natural tendency to connect the elements of the landscape, offers the opportunity to efficiently design conservation designed around the river network (Tarabon et al., 2021).

This phase of analysis aimed to connect isolated environments within the urban context through the re-naturalization of the torrents, which inappropriate agricultural uses have often degraded. Significant portions of these riparian areas, especially in the mid-valley and valley sections, are characterized by no or little vegetation cover. Therefore, we proposed restoration by planting suitable shrubs and tree species typical of Calabrian woods with a prevalence of hygrophilous species.

Starting from the vectorial data of the study area obtained from the previous operations, resistance values were reassigned in a buffer strip of 100 m around the river rod in the stretches that fall within land-use classes of category 2. Areas belonging to classes of category 1 were excluded from the reassignment for the reasons specified in section 1. The resistance values of these areas were assigned, assuming the natural vegetation of poplars, willows, and alders, which are commonly found in rivers affected by human activity. Once the new resistance values had been assigned to the areas affected by the defragmentation intervention, a new EN was constructed to consider the assumed improvements. Finally, the connectivity indices were recalculated, highlighting their quantitative and qualitative variation.

3. Results

3.1. *Vegetation Fractional Coverage (VFC)*

The VFC index can take values from 0 to 1, extremes included and reflects the size of the plants’ photosynthetic area and the vegetation’s growth density. Much closer it gets to zero, the more the stand is devoid of vegetative activity (Zhang et al., 2019). Four different vegetation categories were identified based on the VFC values: (i) high naturalness VFC greater than 0.7; (ii) medium naturalness VFC between 0.4 and 0.7; (iii) low naturalness, VFC between 0.1 and 0.4; (iv) zero naturalness

Table 2
Ecological network connectivity metrics calculated in this work.

Connectivity metrics	Ecological meaning	Definition	Formula	References
Integral Index of Connectivity (IIC)	The probability that individuals randomly located in the landscape within a patch can access each other. A higher value indicates greater connectivity.	For the entire graph: product of the capacities of the patches divided by the number of links between them, the sum is divided by the square of the area of the study area.	$\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{a_i{}^*a_j}{1+nl_{ij}}}{A_L^2}$	(Freeman, 1977)
Number of Components (NC)	Measure describing the number of isolated areas in the landscape. A high number of components in relation to the total number of patches indicates that the landscape is highly fragmented.	Helpful in describing the level of isolation between groups of landscape patches.	//	(Urban & Keitt, 2001)
Harary Index(H)	The number of patches that help connect other patches across the landscape. A high value indicates a highly connected landscape.	Sum of the inverse of the number of connections between all patch pairs.	$H = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{1}{nl_{ij}}\mathrm{j} \neq i$	(Ricotta, 2000)
Betweennes Centrality (BC)	The sum of the shortest paths through the focal patch i, each path being weighted by the product of the capacities of the connected patches and their probability of interaction. P_jk represents all patches traversed by the shortest path between patches j and k.	//	$BC_i = \sum_i\sum_k a_j^\beta a_k^\beta e^{-ad_{jk}}j,$ $k \in \{1..n\}, k < j, i \in P_{jk}$	(Bodin & Saura, 2010)
Flux (F)	For the entire graph: sum of the potential dispersions of all patches.	//	$F = \sum_{i=1}^{n}\sum_{j=1}^{n} a_j^\beta e^{-ad_{ij}}\mathrm{j} \neq$ i	(Foltête et al., 2012a, Foltête et al., 2012b)
Probability of Connectivity (PC)	The probability that two random points in the landscape fall within interconnected habitat areas (i. e., reachableto each other) . Values are between 0 and 1.	Sum of the products of the capacities of all pairs of patches weighted by their interaction probability, divided by the square of the area of the study zone. This ratio is the equivalent of the probability that two points randomly placed in the study area are connected.	$PC = \frac{\sum_{j=1}^{n} a_i a_j p_{ij}^*}{A_L^2}$	(Saura & Pascual-Hortal, 2007)

VFC less than 0.1 (Fig. 4). The threshold of VFC values ≥ 0.6 was used to improve the process of identifying possible patches, as this threshold only includes areas of medium and high naturalness. Overall, VFC values greater than 0.6 were found in hilly and mountainous areas, while progressively lower values are found as one approaches sea level, falling below 0.1 along the entire coastal strip (Fig. 4).

3.2. *Ecological network (EN) spatial configuration*

We present the design of the ecological network in the study area and describe its connectivity indices that characterize its quality and robustness in two different situations: the one using the UA and CLC datasets and the other based on the defragmentation scenario. In Fig. 5, the two ENs are shown according to their canonical components (patches, nodes, arcs, and ecological corridors) in the two scenarios analyzed, pre- (scenario 1, Sc1) and post- (scenario 2, Sc2) improvement proposal.

For the first scenario (Sc1), 724 arcs and 300 nodes were identified. The 300 patches range in size from 2 ha to 856 ha, with an average area of 27.04 ha. The total area occupied by the network (patches, ecological corridors) is 10776.93 ha (22.28 % of the surveyed area), of which 8114.93 ha are occupied by the patches and 2662 ha by the ecological corridors. A total of 58.71% of the ecological corridors fall within the areas occupied by wooded areas and natural environments (class 3), 36.86% within agricultural areas (class 2), 2.67% within the class of water bodies (class 5) and finally only 1.77% fall within artificial areas (class 1, mainly distributed on secondary roads and railways). Concerning the patches, on the other hand, 93.11% are occupied by wooded areas and natural environments (class 3), and 5.6% by agricultural areas (class 2). Fig. 6 shows the network distribution data concerning land uses summarized at the first level for class 1, and the third level for classes 2, 3 and 5.

For the second scenario (Sc2), 771 arcs and 328 nodes were identified. The patches range in size from 2 ha to 936 ha, with an average area of 26.82 ha. The total area occupied by the network (patches, ecological corridors) is 11237.2 ha (23.49 % of the surveyed area), of which 8549.91 ha are occupied by patches and 2687.28 ha by ecological corridors (Fig. 7). The majority of the corridors is concentrated in natural land cover types, with 65.44 % in the areas occupied by woodlands and natural environments (class 3), 30.37 % in the areas occupied by

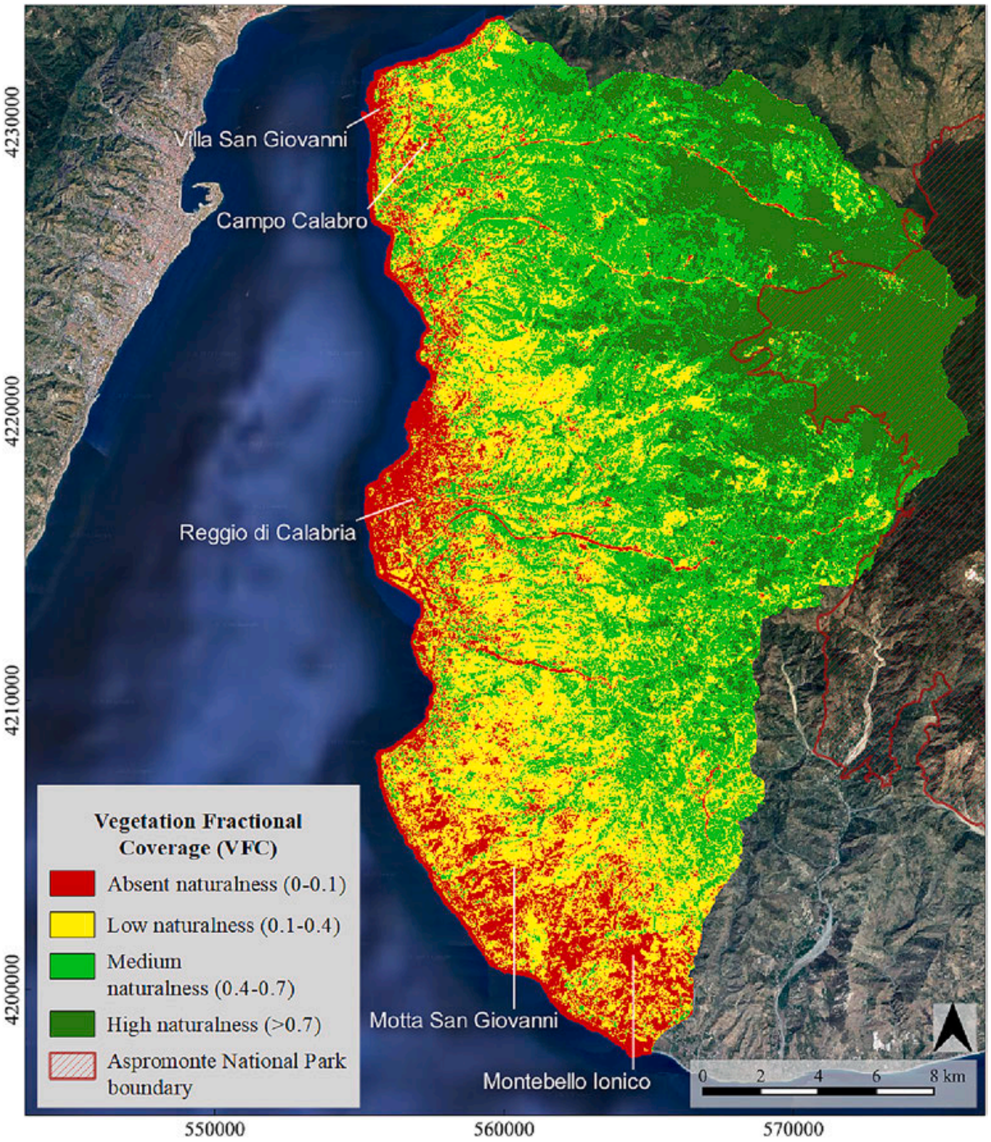


Fig. 4. Vegetation Fractional Coverage (VFC) of the study area for the period 2016–2019, reclassified according to four classes: high naturalness, medium naturalness, low naturalness, and absent naturalness.

agricultural land (class 2), 1.29 % in the areas occupied by artificial surfaces (class 1, of which 0.51% on sports green areas, and the remaining 0.78% on secondary roads and railways) and 2.67 % in the class referring to water bodies (class 5). 97.89% of the patches are identified in class 3, 2.05% in class 2 and the remaining 0.06% in class 1. The increase in the area of the patches of + 434.98 ha is due for 257.05 ha to the direct effect of the greening interventions and the remaining 177.93 ha to the incorporation of many natural areas bordering the interventions that were of less than 2 ha in the area, and therefore not considered patches previously.

Regarding the indices analyzed (Table 3), the NC went from 3 in Sc1 to 1 in Sc2. For the connectivity indices IIC, H, F, and PC, a general value increase was seen in the defragmentation scenario. The IIC and BC indices were calculated at the level of individual nodes (Figs. 8 and 9); the highest indices' values were found in mountainous areas, far from the coast, and areas with predominantly forest land use.

The average values of both indices increased in the defragmentation scenario compared to the 2018 scenario (Table 3). In correspondence with the urban center of Reggio Calabria, we identified patches disconnected from the rest of the network with values of the indices calculated at the node level (IIC and BC) lower than the average of the entire network.

4. Discussion

The analysis of the existing landscape shows that the area with the most well-connected patches, corresponding to the strongest point of the ecological network, is located between 500 m and 1300 m a.s.l., in the municipalities of Sant'Alessio in Aspromonte, Laganadi, and Santo Stefano in Aspromonte, within and close to the Aspromonte National Park boundaries, in the central-eastern and north-eastern part of the study area. The analysis of VFC values confirms this. In these locations, areas of solid naturalness stretch broadly around built-up areas, and even near them, mean VFC values were high (VFC greater than 0.6), with values consistent with strictly forest stands (Shobairi et al., 2018). On the other hand, the most significant fragmentation problems were seen in the coastal municipalities, especially in correspondence with the most human-modified centers, such as the municipalities of Reggio Calabria, Motta San Giovanni and Montebello Ionico. The territory is mainly occupied by cultivated fields, buildings, and human infrastructure in these places. The VFC values are consistent with this trend, averaging less than 0.4. Analyzing the results referring to both Sc1 and Sc2 scenarios, it emerges that the suggested defragmentation interventions showed the best results in the most altered locations.

The proposed interventions led to an increase of the indices' values in the area occupied by patches; an increase in NP from Sc1 (300) to Sc2 (328) was observed, which is consistent with the increase in NL from 724 (Sc1) to 771 (Sc2). The increase in NP and NL generated a partial change in the spatial configuration of the post-intervention network. Here, additional connections branch off into the degraded areas to the south and west of the study area. In particular, the increase in ecological corridors made it possible to connect a group of 18 patches that were isolated in Sc1 to the rest of the network, thus having in Sc2 only one component after the intervention proposal, as opposed to the 3 identified for Sc1. Recent studies have shown that increased node connectivity leads to higher species richness at the local scale (α-diversity) (Liccari et al., 2022). The increase in the number of patches (+28) is related to the re-greening interventions. These have made it possible to increase

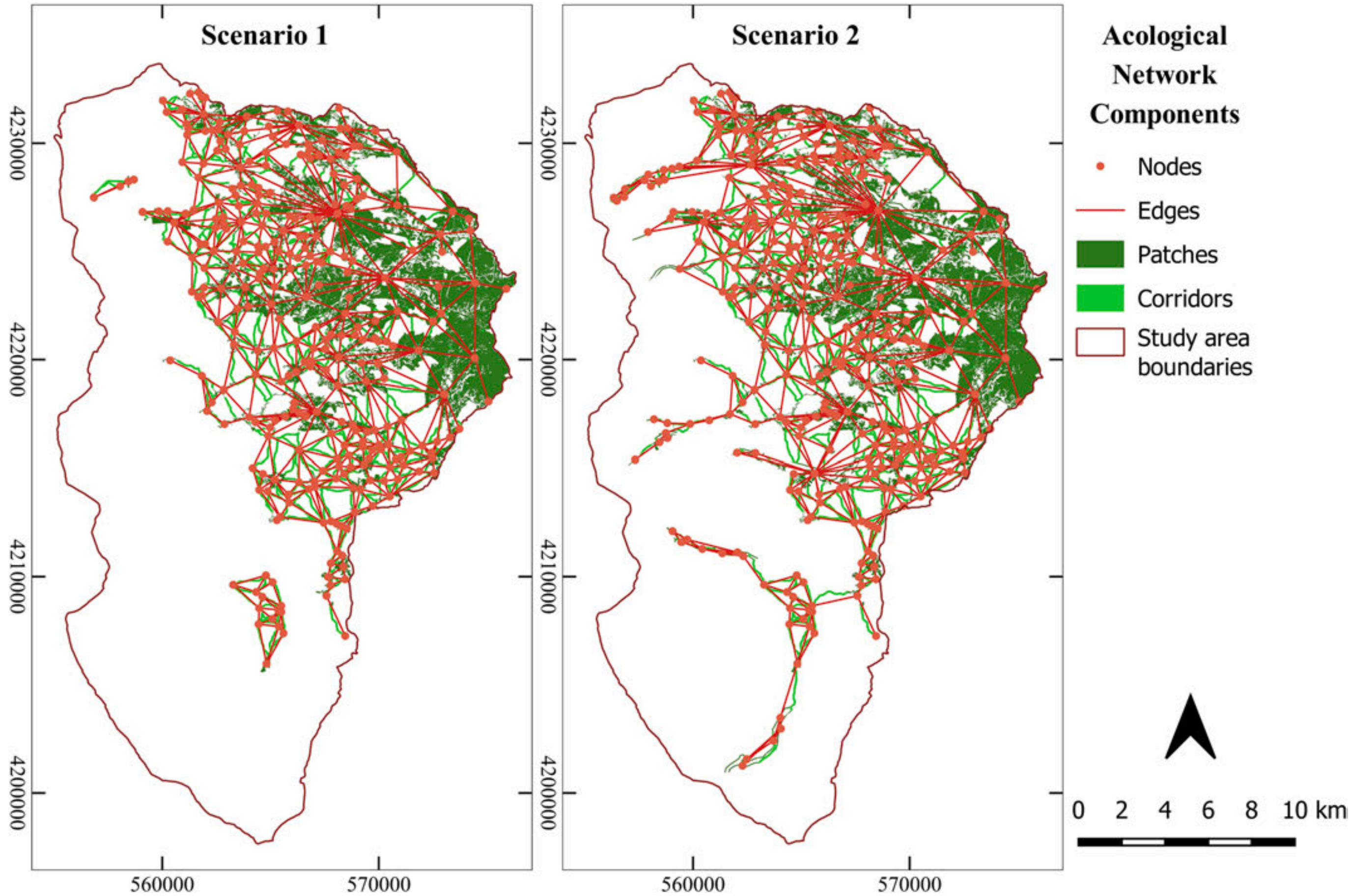


Fig. 5. Spatial configuration of the Ecological Networks, represented according to the canonical components: nodes, arcs (edges), ecological corridors and patches based on 2018 data (Scenario 1) and the defragmentation scenario (Scenario 2).

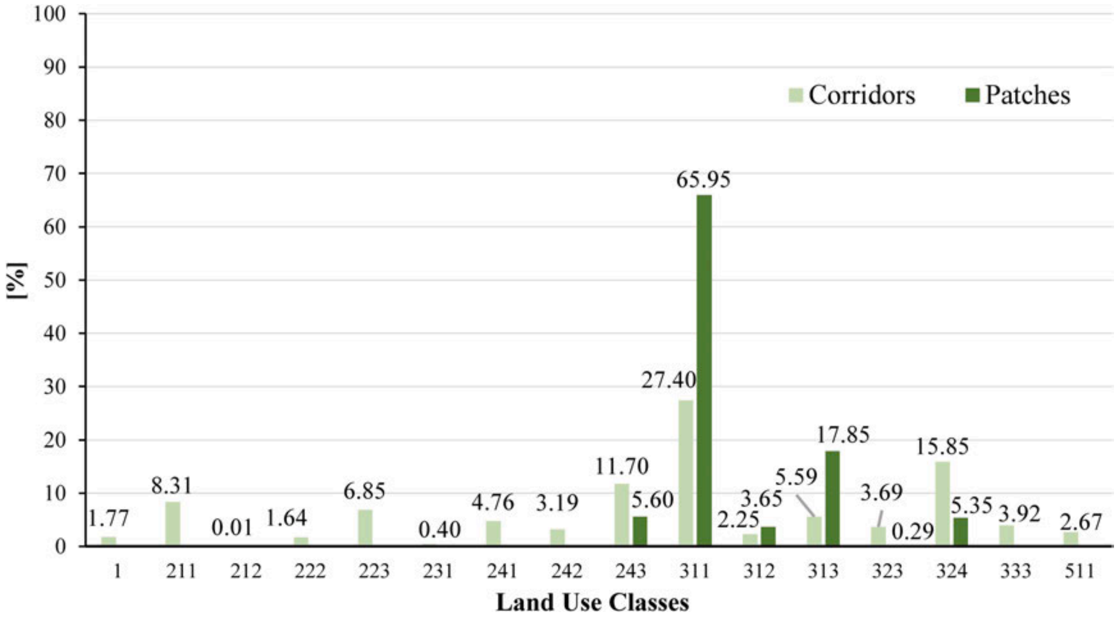


Fig. 6. Area occupied (expressed as a percentage) by land uses in the study area of Scenario 1 concerning patches (dark green) and ecological corridors (light green). Due to the low presence of corridors and patches within class 1, this was summarised at level 1, and classes 2, 3, and 5 were kept at level 3. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

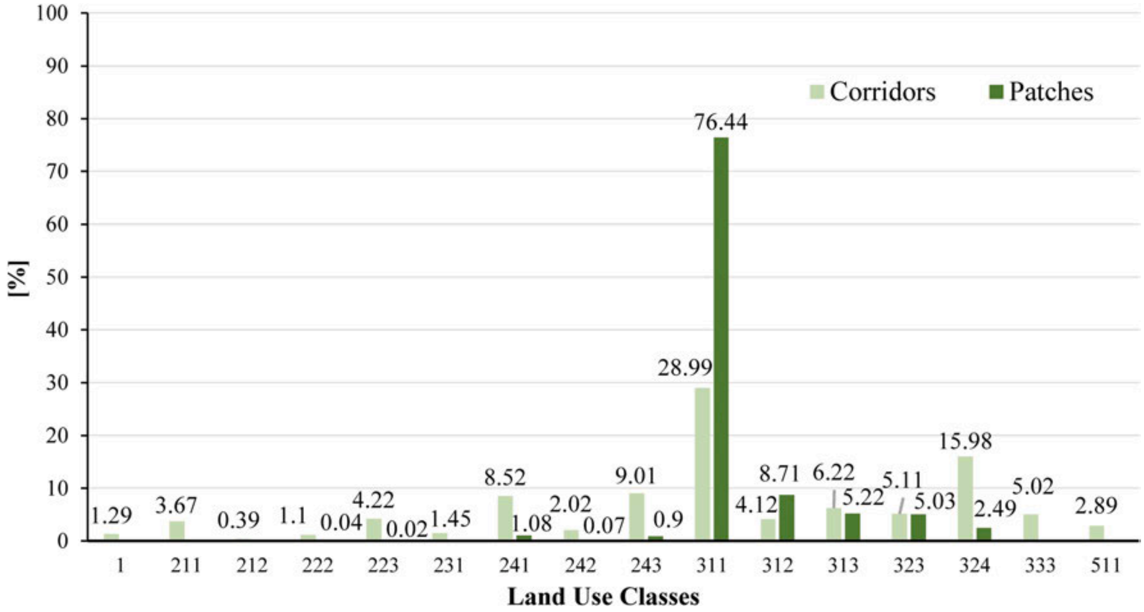


Fig. 7. Area occupied (expressed as a percentage) by land uses in the Scenario 2 study area concerning patches (dark green) and ecological corridors (light green). Due to the scarce presence of corridors and patches within class 1, this has been summarised at the first level and classes 2, 3, and 5 have been maintained at the third level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Overall connectivity indices calculated on ecological networks in the two scenarios, data as of 2018 (Scenario 1) and defragmentation (Scenario 2).

Connectivity Indices	Scenario 1	Scenario 2
Number of Patches (NP)	300	328
Number of Connections (NL)	724	771
Number of Components (NC)	3	1
Integral Index of Connectivity (IIC)	0.029	0.032
Probability of Connectivity (PC)	0.031	0.033
Flux (F)	2.23	2.95
Betweenness Centrality (BC)	0.20	0.25
Harary Index (H)	8200.50	9704.03

the eligible area of those areas bordering watercourses with fewer than 2 ha and had therefore been considered unsuitable as patches in Sc1. This reveals the capacity of the interventions to restore habitat fragments that were excluded from connectivity even outside the intervention area itself.

The analysis suggests that the proposed ecological corridors could create a bridge between the coastal and mountainous areas, leading to greater accessibility by the rest of the network to these patches, which in some cases (5 patches in the municipality of Reggio Calabria), were dead ends of the network route, connected by a single connection and therefore at greater risk of disappearance. This led to an increase in the number of connections of the isolated areas and created new

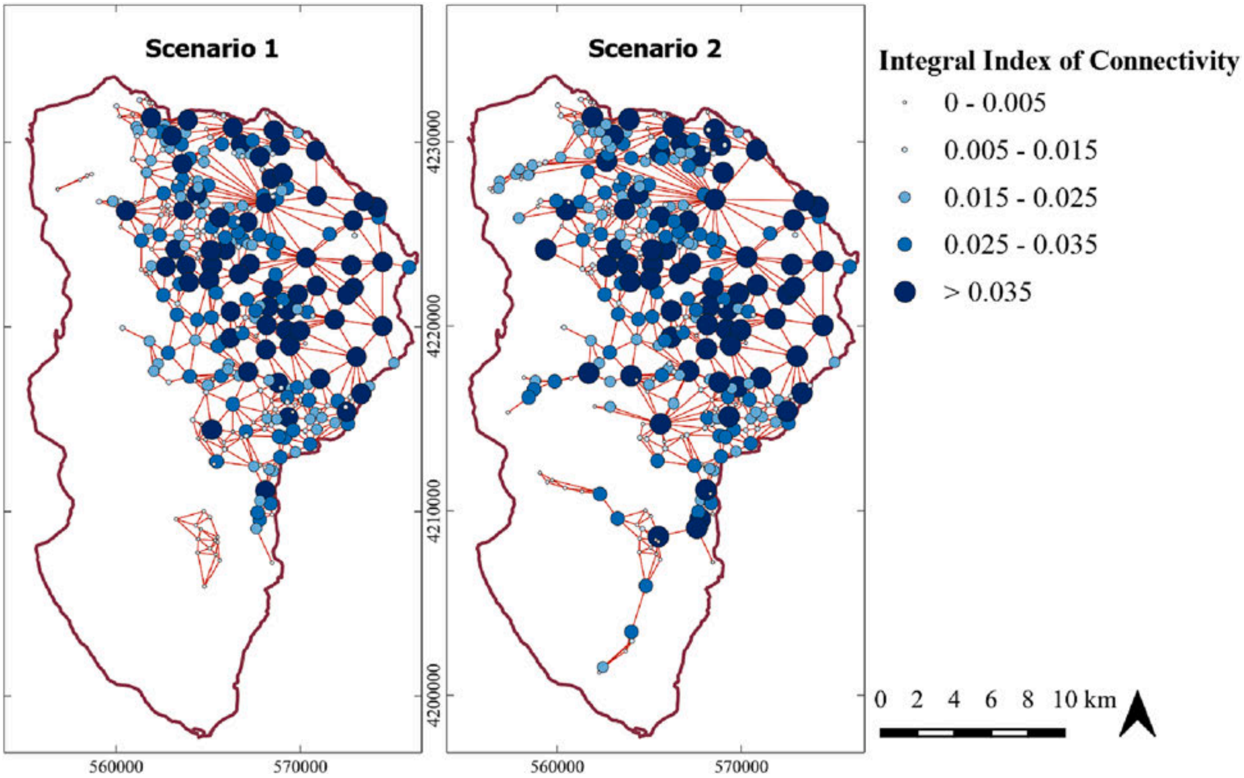


Fig. 8. Integral index of connectivity (IIC) calculated at node level for the two scenarios analysed: scenario 1 (data as of 2018) and scenario 2 (defragmentation hypothesis).

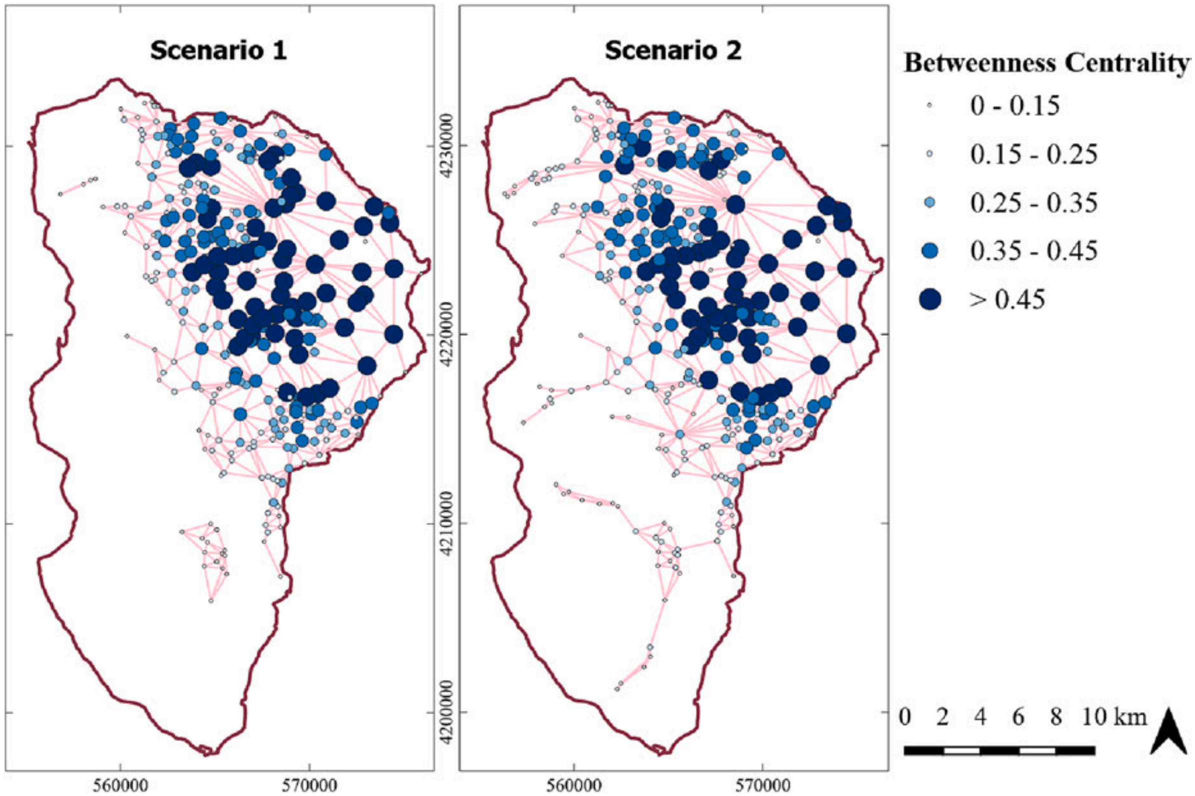


Fig. 9. Betweenness Centrality (BC) calculated at node level for the two scenarios analysed: scenario 1 (data as of 2018) and scenario 2 (defragmentation hypothesis).

connections in Sc2, which is confirmed by the rise in the Harary Index (+1503.53 in Sc2), where higher values of this index, such as those found in Sc2, indicate a more connected landscape (Harary, 1969; Pascual-Hortal & Saura, 2006; Ricotta, 2000). This evidence is confirmed by the variation in BC values at the node level in Sc2. Nodes with a higher BC value are considered stepping-stones (small areas that allow animals, which exploit their resources, to move from one patch to another) that increase the robustness of the network (Urban et al., 2009) In particular, 18 nodes that were isolated in Sc1 had their BC value increased that contributed to a rise in the mean BC value of the entire network. This is due to both the rise in the number of connections between isolated nodes and the increase in the average area of the nodes. The emergence of stepping-stones allowed the connection of previously isolated urban areas, confirming the findings of recent studies demonstrating the ability of these elements to provide favorable habitats for urban ecosystems (An et al., 2021; Luo et al., 2021).

Overall, connectivity index values are higher in upland, highly naturalized areas and lower in coastal, highly humanized areas; these results are in line with the trend found in recent pieces of research (Lechner & Lefroy, 2014; Meza-Joya et al., 2019; Mu et al., 2020; Tiang et al., 2021).

The increased potential for animals to exploit stepping-stones to move from one patch to another in Sc2 is confirmed by increases in the F-index, which expresses the probability that animals can move between patches (Saura & Pascual-Hortal, 2007). An increase in this value is highly correlated with the rise in the PC index, which expresses the probability that two individuals placed at a random point in the network can access each other by moving (Saura & Pascual-Hortal, 2007).

The changes in the IIC index further confirm the improved network quality in Sc2. The increase in IIC values measured in the entire network and the area of the 18 patches isolated in Sc1 expresses an increase in the probability of the patches accessing each other (Pascual-Hortal & Saura, 2006, 2008).

Concerning the distribution of patches and ecological corridors in the two different scenarios, it was found that the general trend remained unchanged; thus, the most occupied class, considering the adopted CLC legend, remains the third followed by the second. There was, however, a redistribution of values within the classes. In particular, in Sc2, we find an increase in the concentration of patches and ecological corridors (+5% and + 6.7%, respectively) compared to class 3 in Sc1. This has resulted in the second scenario in a network developed more on natural areas, where the fauna movements involve the crossing of smaller portions of land altered by human activity. Furthermore, the slight change in the distribution of corridors in class 1 of Sc2, compared to Sc1, shows how the interventions allowed urban green areas to enter the network while they were previously excluded. The presence of corridors crossing secondary roads gives rise to hints about the possibility of making interventions (e.g., elevated green bridges, green underpasses) that allow animals to pass through while reducing the number of road kills (Girardet et al., 2015). On the other hand, the absence of corridors on highways makes it clear how these elements are barriers to species movement, making interventions on them valuable possibilities. This type of consideration on roads is made possible by the use of Urban Atlas roads elements are absent on Corine Land Cover.

Another element of relevance is the reduction of the NC from Sc1 (3) to Sc2 (1), an indicator that the level of isolation between patch groups has been reduced. In Sc2, there are no longer any isolated patch groups and the interventions in river areas have reduced the degree of fragmentation of the network. This shows differences from other research, where no improvement interventions were planned (i.e., Modica et al., 2021; Tarabon, et al., 2021). In general, what emerges from the trend in the values of the metrics analyzed is that expanding green areas along river courses would benefit the whole EN. We have shown how these metrics offer information regarding the robustness of the network, which can be of great support for planning (Foltête et al., 2014; Rayfield et al., 2011).

5. Conclusions

With the present work, it was possible to analyze the connectivity of an ecological network built on land use data in 2018 and to evaluate the impact of a scenario intended to enhance multi-species connectivity. We demonstrated how the level of spatial detail achieved through the integrated use of highly accurate data, such as CLC and UA, in conjunction with VFC index analyses, allows for constructing a robust EN. The defragmentation scenario focused on the restoration of green vegetation in the areas surrounding the torrents and demonstrated how incorporating small fragments of land into the constructed network improved the connectivity of the entire network. The high naturalness component identified in these fragments, underlined by the VFC analyses, demonstrated their potential in ecological terms. These isolated elements are, in fact, not used for anthropogenic productive activities and are too small to be considered patches, remaining confined to disconnected islands in the landscape. Our analysis shows the high value of interventions that enhance these fragments of high naturalness in their contribution to multi-species landscape connectivity. The proposed interventions have also shown how to create new corridors and patches on the edges of urban areas.

There are limits to our analysis deriving from its development of an EN based only on land use maps. These could be overcome by having future empirically optimized habitat and resistance maps availability (Cushman et al., 2006; Cushman & Lewis, 2010; Mateo-Sánchez et al., 2014, 2015). In addition, more species could be included, adding bigger mammals, amphibious, reptiles, birds, and insects. Another limitation is the lack of specific studies of certain behavioral characteristics of species. Numerous errors are still made when evaluating an individual's behavior in the face of a land alteration, and the responses of animals to a man-made element are not always linear (Rudnick et al., 2012). Some species tend to avoid agricultural areas, others are attracted to and even benefit from them, and others may be attracted or repelled by light or noise pollution.

In terms of prospects, the use of indices calculated from multispectral satellite data shows promise for studying variations in connectivity. Variations in plant populations could be related to the phenomena that may be causing them, urban and agricultural expansion, global warming, and pollution.

The multi-species approach we used does not require long lead times for data collection and would be suitable for short- and medium-term planning (Lechner et al., 2015). Restoring connectivity requires financial actions based on concrete interventions on the ground, with the need to spatially identify patches and ecological corridors. In perspective, this type of planning approach could be considered to identify areas where attention should be focused. Targeted interventions on an urban intervention scale could be envisaged, taking into account the rivers and other sensitive elements of the territory, such as roads, gardens, and public parks. An interesting future development could be to apply this method to several metropolitan areas and then move on to assess connectivity on a regional scale. In addition, as a future perspective, it could be interesting to study the interaction and synergy between species conservation and landscape patterns in ecological network design.

CRediT authorship contribution statement

Giovanni Lumia: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Salvatore Praticò:** Conceptualization, Methodology, Formal analysis, Writing - review & editing. **Salvatore Di Fazio:** Formal analysis, Supervision, Visualization, Writing - review & editing. **Samuel Cushman:** Formal analysis, Supervision, Validation, Writing - review & editing. **Giuseppe Modica:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Visualization, Supervision, Validation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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