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# Proposed spatial decision support system for delineating ecological corridors in green infrastructure planning constrained by lack of data: a case study in Galicia, Spain

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## Abstract
In response to the constant loss of biodiversity in European ecosystems, which is partly due to the impacts of climate change, the European Commission urges member states to include Green Infrastructure (GI) in their land-use plans. However, although the European Commission establishes the fundamental principles to be applied, the ambiguity of some terms generates a certain degree of complexity regarding the delineation of GI elements, especially Ecological Corridors (ECs). Thus, a straightforward methodology for delineating GI elements is required. Here, we propose a Spatial Decision Support System (SDSS) that could help non-expert planners identify areas with a high potential to function as ECs and that could thus facilitate the inclusion of these areas in regional GI plans. Probability distribution maps were constructed by fitting a maximum entropy model (MaxEnt) to publicly available data on selected focal species. The maps were combined with other variables that negatively affect species mobility and later inserted in a graph theory tool to determine the least-cost path that would serve as the basis for delineating ECs. The method was applied to the design of an EC network in Galicia (NW Spain), and use of the system as a tool to help spatial decision-making was evaluated. Despite some limitations, the method yielded promising results that could help non-expert planners to establish the basis for delineating EC networks and other GI elements.

**Keywords** Spatial planning · Landscape connectivity · MaxEnt · Climate change adaptation

## Introduction

Green Infrastructure (GI) is defined by the European Commission as "a strategically planned network of natural and semi-natural areas with other environmental features designed and managed to deliver a wide range of ecosystem services" (European Commission 2013a). More recently, the European Union Biodiversity strategy for 2030 (European Commission 2020) has identified the impact of climate change as one of the main factors causing biodiversity loss in Europe, with GI being one of the ways proposed to tackle the impact. As the aforementioned European GI strategy commits member states to include GI in their land-use plans (European Commission 2013a), there is concurrence across different contexts regarding the need to integrate GI in planning and design (Bolliger and Silbernagel 2020).

The European Commission establishes three main principles for GI: multifunctionality (granting the provision of multiple ecosystem services), conservation (e.g., by preserving key habitats for biodiversity), and connectivity (ensuring the long-term persistence of species by fostering ecological connectivity) (European Commission 2013b). However, the specific criteria for GI planning and design are far from being well defined. Some authors (e.g., Monteiro et al. 2020) point out that certain principles are too theoretical to be fully applicable in GI-integrated spatial planning. Moreover, stronger emphasis is placed on the GI role of promoting multifunctionality and provision of ecosystem services

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relative to previous conceptualizations, which have focused on greenways and ecological networks (Grêt-Regamey et al. 2021). Currently, the aim is not only to enhance ecological connectivity to protect biodiversity but also to ensure the provision of multiple ecosystem services that depend on biodiversity, such as pollination and pest control (Mitchell et al. 2015). This induces an overlap between concepts and principles, such as those related to "ecological connectivity" and others such as "accessibility". The ambiguity of the terms complicates the GI delineation process, especially the delineation of Ecological Corridors (ECs), which are GI elements that enable or enhance ecological connectivity through the establishment of links between core areas (European Commission 2013b; Valladares et al. 2017). As a result, a variety of approaches, methodologies, and tools are used to delineate ECs (e.g., Cushman et al. 2009; Frei et al. 2016; Koen et al. 2014; Landguth et al. 2012; Pascual-Hortal and Saura 2006), but a few studies focus on establishing specific ECs for GI (e.g., Cannas et al. 2018; de la Fuente et al. 2018; Zhang et al. 2019). Thus, methods must be developed to delineate GI elements and to facilitate the inclusion of these elements in land planning at various scales (Aguilera Benavente et al. 2018; Cannas et al. 2018; García et al. 2020; Liquete et al. 2015).

Within this framework, the aim of this study was to develop a Spatial Decision Support System (SDSS) that could help non-expert planners to propose areas with a high potential to function as ECs and to facilitate the inclusion of these areas in land plans. The proposed methodology represents the first step in the overall design of an EC network that will be part of a regional GI strategy in the Autonomous Community of Galicia (NW Spain). In response to the lack of a definition of some terms and to increase the methodological certainty, we assumed the following in regard to the design of ECs to be included in spatial planning processes:

1. EC design is constrained by time and resources.
2. EC design is based on ecological connectivity between core areas.
3. Ecological connectivity will be defined functionally for specific types of animal movements.
4. Spatial planning constrains the choice of specific ECs designs towards those involving specific implementation measures.

The first assumption was made bearing in mind the absence of data specifically obtained for EC delineation in the planning processes and considering only publicly available data regarding species distribution and land cover in the study area.

The second assumption is based on one of the conditions defined in the European GI Strategy (European Commission 2013a), as a characteristic of GI is the connective capacity between the core areas defined by the European Nature 2000 network.

The third assumption is necessary due to the different conceptualizations of connectivity that may affect the definition of an ecological corridor network. Considering the nature of the publicly available data for the study area (Galicia, NW Spain), we propose delineating functional ECs that do not focus on the speed of dispersion or migratory movements, but that focus on identifying areas (routes) that allow some animal species to modify their distribution area in response to the effects of climate change or other impacts by moving to new areas where environmental conditions are suitable (Gurrutxaga et al. 2009). Species Distribution Models (SDM) estimate the most suitable areas and infer the probability of presence of a species (Elith and Burgman 2002), which can be used to estimate the resistance of the landscape to species mobility (Fattebert et al. 2015). Thus, the proposed SDSS will produce probability distribution maps using a maximum entropy model (MaxEnt) (Phillips et al. 2006). By determining the probability distribution of maximum entropy, this model estimates a target probability distribution, which is subject to a set of restrictions that represent incomplete information about the target distribution (Phillips et al. 2006). The model uses appropriate environmental data for the entire study area as pseudo-absence data, making it quite versatile for different types of data on a wide range of species (Melo-Merino et al. 2020), since absence data for the species are not required. Furthermore, MaxEnt can provide accurate species distribution maps at many scales (Hoffman et al. 2010; Wisz et al. 2008), particularly with presence-only data derived from non-systematic surveys (Elith et al. 2006), as in the present study.

Consequently, the MaxEnt model was used to obtain animal species distribution probability maps in combination with variables that prevent or hinder species mobility (Singleton et al. 2002), which were fed into a connectivity modelling tool based on graph theory (Urban and Keitt 2001) to determine the regional least-cost paths that serve as the basis for delineating a network of GI ecological corridors. The graph theory model simplifies the landscape by considering spots that host species populations as nodes and the potential movements of species between these spots as links, so that each link connects two nodes (Pascual-Hortal and Saura 2006; Urban and Keitt 2001), under the assumption that movement through a landscape occurs randomly (Liu et al. 2018). The model is based on the idea that resistance to movement of species can be mapped by designating each cell a "cost" of moving through it. This may also be compatible with low-resolution data (e.g., national-level species inventories or presence-absence maps), which in the context and time scale of planning and management processes are considered the best available data (in the absence of optimal data).

Finally, the fourth assumption was made as the outcome should address a specific design for the implementation of different measures or policies. Thus, the foremost aim of the EC design is not to characterize species connectivity in the territory, but to support further planning steps for implementing GI in Galicia.

Taking all of the above into account, the model was tested using it to design an EC network for a Galician GI, and its value as a tool to help spatial decision-making for non-expert planners was assessed.

## Materials and methods

### Study area

The autonomous region of Galicia (NW Spain) (located between latitude 43°48′ N and 41°49′ N and longitude 6°44′ W and 9°18′ W) (Fig. 1) occupies an area of 29,577 km$^2$ and has 2,695,645 inhabitants (INE 2022).

Most of Galicia is included in the Atlantic biogeographical region, while the south-eastern area is included within the Mediterranean region. There are therefore two types of macroclimate in the region: the temperate Atlantic climate, characterized by the absence or low incidence of summer drought, and the Mediterranean macroclimate, in which there is a period of more than 2 months of drought during the summer season (Rodríguez Guitián and Ramil-Rego 2018).

The region, which is predominantly rural, is mainly occupied by broadleaved forest (23.62%), complex crop patterns (21.27%), moor and heathland (19.78%), and coniferous forest (9.99%), according to CORINE land-cover data for 2012 (CLC2012).

Regarding protected areas, despite the great diversity of flora and fauna in the region, only 11.74% of the area is classified as Sites of Community Importance (SCIs). These sites will be used as the basis for establishing the core areas of the GI (Valladares et al. 2017) to comply with article 10 of the Habitat Directive, which urges the Member States to improve the ecological coherence of the Natura

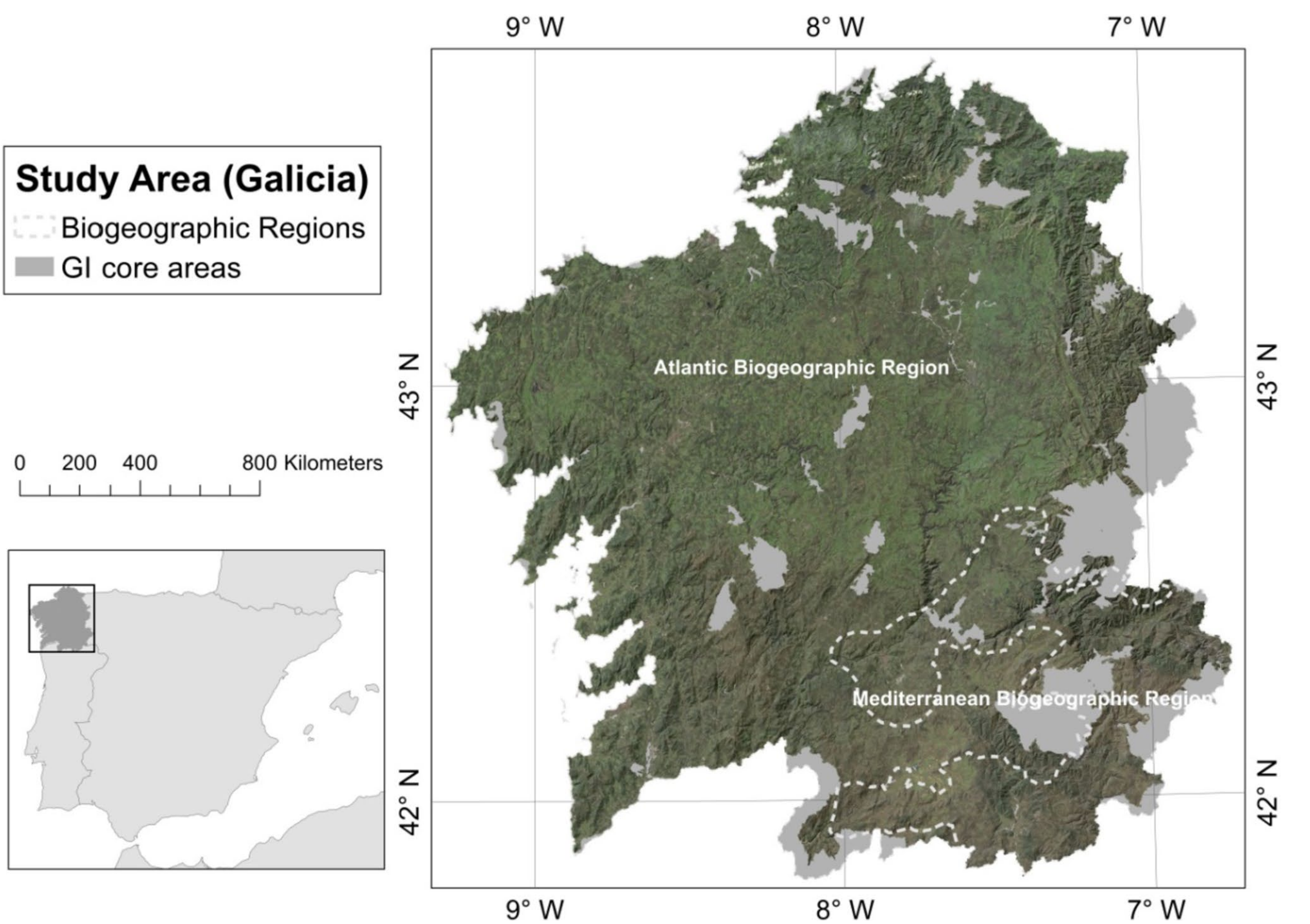


**Fig. 1** Maps of the study area

2000 network, i.e., the nodes between which the ECs will be established to increase the ecological connectivity of the study area.

Finally, the establishment of ECs in Galicia is complicated by the highly fragmented landscape due to population dispersion (Otero-Enriquez and Gómez Rodriguez 2007) and to other factors such as small land ownership, varied orography, and the dynamics of agricultural land abandonment and afforestation (Corbelle-Rico and Sánchez 2017).

## Methodology

The proposed SDSS uses a Species Distribution Model (SDM) to construct animal probability distribution maps from publicly available data and a series of biogeographical and bioclimatic variables. These maps are combined with data on obstacles to mobility and are included in a tool based on graph theory to identify the least-cost paths that will be used as a basis for delineating ECs. The main steps are as follows (Fig. 2). (1) Construction of probability distribution maps from the SDM using the maximum entropy model (MaxEnt) (section "Probability distribution maps"). This is applied to a few focal species selected considering the Spanish GI strategy (Valladares et al. 2017) (see section "Focal species") to delineate useful ECs for a greater number of animal species. (2) Running the graph theory tool with the nodes or core areas and the resistance maps obtained for each focal species selected (section "Graph theory model").

### Probability distribution maps

The MaxEnt model was used to relate the considered species presence data in the $10 \times 10$ km grid from the Spanish Terrestrial Species Inventory grid (MITECO 2012) with the values of a set of the most common variables potentially affecting species distribution (bioclimatic and topographic variables, remotely sensed land-cover classification, distance from transportation networks, population density, and hydrological variables, among others; Mateo et al. 2011). More detailed information related to the variables is provided in Table 1.

The presence data for each species were generated by assigning a value of 1 to the Spanish Terrestrial Species Inventory grid (MITECO 2012) where the species are present. The species were selected by considering the criteria proposed in the Methodological Guide for the Identification of the Spanish GI (MITECO 2020). According to this guide, endangered species included in EU, and national and regional red lists were initially selected. Those species only present in the regional red lists and that occur in other parts of the EU were disregarded. From the initial list of species, only those present in Galicia and that were included in the inventory were chosen. As the method focused on establishing terrestrial ECs, marine species were not considered.

A bilinear method was used to resample the variables, at a resolution of $100 \times 100$ m, which is the minimum cell size of CORINE land-cover data. Land cover is the main proxy used to relate landscape resistance. The variables were obtained

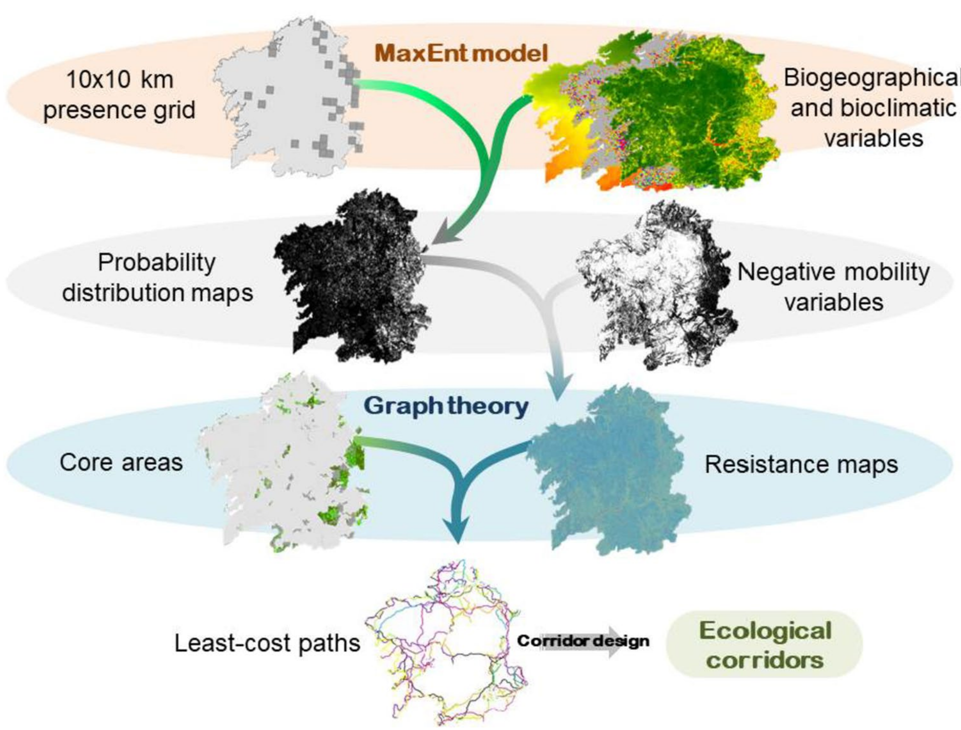


**Fig. 2** Flowchart of the approach used

**Table 1** Source and data information used in the MaxEnt model

| Layer name | Source and data information | Initial cell size | Final variable |
|---|---|---|---|
| Spanish Terrestrial Species Inventory | Spanish Terrestrial Species Inventory (MITECO 2012)<br>Downloaded from: https://www.miteco.gob.es/es/biodiversidad/temas/inventarios-nacionales/inventario-especies-terrestres/inventario-nacional-de-biodiversidad/bdn-ieet-default.aspx<br>10 × 10 km grid Database | 10 × 10 km | Species presence data |
| Digital Terrain Model | The Spanish National Geographic Institute<br>Downloaded from: http://www.ign.es/web/ign/portal<br>25 × 25 m raster resolution layer | 25 × 25 m | Mean slope and mean elevation |
| Transportation network | The Spanish National Geographic Institute<br>Downloaded from: http://www.ign.es/web/ign/portal<br>Linear shapefile layer format | | Mean distance from main roads and railway lines |
| Hydrographic network | The Spanish National Geographic Institute<br>Downloaded from: http://www.ign.es/web/ign/portal<br>Linear shapefile layer format | | Mean distance from rivers |
| Population settlement | The Spanish National Geographic Institute<br>Downloaded from: http://www.ign.es/web/ign/portal<br>Point shapefile layer format | | Mean population density |
| Bioclimatic variables | The Worldclim database (Fick and Hijmans 2017)<br>Downloaded from: https://www.worldclim.org/data/worldclim21.html<br>1 × 1 km raster resolution layer | 1 × 1 km | Mean value of each bioclimatic variable |
| CORINE Land Cover 2012 | The Spanish National Geographic institute<br>Downloaded from: http://www.ign.es/web/ign/portal<br>Polygon shapefile layer format | | Percentage of each reclassified CORINE land-cover type (PLAND) |

in the following steps. Slope and elevation maps were calculated from the Digital Terrain Model. Raster maps showing the distance of the areas from hydrographic networks and transportation networks were generated. A population density map was obtained by rasterizing the population values of the settlement points, at a resolution of 100 × 100 m, and the population density (per km$^2$) was then calculated with a focal of 11 × 11 cells, which is equivalent to a square of approximately 1 km$^2$.

The mean values or variances of the variables within each 10 × 10 km cell of the national inventory of terrestrial species were calculated with a spatial statistics GIS tool and used as the MaxEnt model input data.

The CORINE land-cover categories were reclassified to better represent the main habitats in the study area (see supplementary material Table 1). The year 2012 was chosen because it is closest to the when the Spanish Terrestrial Species Inventory was conducted.

Finally, the percentage of each land-cover type (PLAND) was calculated using Fragstats v. 4.2. (McGarigal and Ene 2015) for each cell of the Spanish Terrestrial Species Inventory grid.

Before running the model, the correlations between all the variables were determined using Spearman's correlation coefficients (Spearman 1904). Bioclimatic variables related to temperature were closely correlated with mean annual temperature (values of the index higher than 0.7). Mean annual temperature and mean annual solar radiation were also closely correlated. The same applied to variables related to precipitation and mean annual precipitation. We therefore decided to retain only annual mean temperature (B1), temperature seasonality (B4), annual precipitation (B12), and precipitation seasonality (B15) as bioclimatic variables in the model.

Once the model was calibrated for each species, it was run with the values of the variables for a 1 × 1 km grid to produce species probability distribution maps at this resolution (Albuquerque and Beier 2016; Daliakopoulos et al. 2017; Keil et al. 2013; Olivero et al. 2016).

To validate the models, default values were considered: some data (66%) for each species were randomly sampled for calibration, and the rest of the data were used to test the calibrated models. The Receiver-Operating-Characteristic (ROC) was calculated for each calibrated model. The accuracy of the models was assessed using the Area Under the Curve (AUC) of the receiver operating curve. AUC values can range from 0 to 1, where a value of 0 indicates that the model has no predictive power and a value of 1 indicates a model with maximum prediction capacity. For an adequate interpretation, it is considered that AUC values greater than 0.9 indicate very precise models, values between 0.7 and 0.9 indicate useful models, and values less than 0.7 indicate poor models (Guisan et al. 2007).

### Graph theory model

The tool used, ArcGIS 10.7 "Cost Connectivity", is based on graph theory. This tool produces the least-cost paths between two or more nodes from resistance surfaces. Therefore, the nodes correspond to the specific core areas of each species and the links correspond to the paths that will be used as the basis for delineating future ECs. The resistance maps constructed to determine the least-cost paths and the nodes (core areas) to be connected are defined as explained below.

**Focal species resistance maps** As previously mentioned, to obtain the resistance maps, the animal species distribution probability maps will be combined with variables that prevent or facilitate mobility of the species. The resistance values were assigned by establishing a range between 0 and 1000, where 1000 indicates the highest resistance and 0 indicates the lowest resistance, with values varying depending on the species or taxon considered. Three types of resistance maps were constructed, because the resistance to landscape movement differs according to taxa or species. In addition, the variables were combined as follows.

- R1 (Includes mammals *Felis silvestris* and *Galemys pyrenaicus*). Slope, population density and probability distribution values were summed and divided by 3. The cells of the resulting map that correspond to the transportation network were assigned values of the cells of the transportation network resistance map.
- R2 (Includes all reptiles and amphibians selected). Probability distribution maps, slope, and transportation network were considered. The probability distribution values and slope were summed and divided by two. The resulting map was combined with the transportation network map as in the previous case.
- R3 (Includes the species of bat *Rhinolophus ferrumequinum*). Population density and distribution probability values were summed and divided by two. The resulting map was combined with the transportation network map.

The variables taken into account and the values assigned to each of them based on the "cost" or resistance to movement are described in Table 2.

The values in the probability distribution maps for each species were inverted, by subtracting the probabilities in each map (ranging from 0 to 1). The cells with the highest probability of presence would thus correspond to the lowest

**Table 2** Values assigned in each type of resistance map

| Variable | R1 | R2 | R3 |
|---|---|---|---|
| Probability distribution | 0—most likely presence<br>1—least likely presence | 0—most likely presence<br>1—least likely presence | 0—most likely presence<br>1—least likely presence |
| Slope | 0 less than 20%<br>1 more than 20% | 0 less than 20%<br>1 more than 20% | – |
| Population density | $0 \leq 50$<br>$1 \geq 50$ | – | $0 \leq 50$<br>$1 \geq 50$ |
| Transportation network | 1000—fenced roads<br>50—unfenced roads and railways<br>25—secondary roads | 50—fenced roads<br>50—unfenced roads and railways<br>25—secondary roads | 50—fenced roads<br>50—unfenced roads and railways<br>25—secondary roads |

resistance to species movement (0) and the cells with the lowest probability would correspond to the highest resistance (1).

Slopes less than 20% were assigned a value of 0 and values greater than 20% were normalized between 0 and 1 (Eq. 1), where 0 indicates a slope of 20% and 1 indicates higher values.

Population density values were normalized between 0 and 1 (Eq. 1), with 1 being the value of the highest population density (population densities equal to or greater than 50) and therefore the most resistant to species movement. This threshold was considered, because it is used in the European Union regulation to define sparsely populated areas (Regulation (EU) No 1303/2013)

$$Normalized\ value = \frac{Value - minValue}{maxValue - minValue}. \tag{1}$$

Transportation network values were then obtained by assigning values of 1000 to fenced roads (e.g., highways and motorways), 50 to primary unfenced roads and railways, and 25 to secondary roads. The values were assigned to the cells of each transportation infrastructure according to the assumed negative influence on the mobility of the species throughout the territory. For amphibians and reptiles, a value of 50 was assigned to fenced roads in the resistance maps as, although these small animals can pass through or cross over fences, they may be run over on adjoining roads. The same value was assigned to the selected bat species (*R. ferrumequinum*), which although able to fly, may be killed by collision with vehicles, and their roosts and foraging areas may be damaged or degraded and critical flight routes used for commuting and migration may be disrupted by transportation networks (Berthinussen and Altringham 2012). In all cases, areas corresponding to bridges and tunnels were assigned a resistance value of 0.

All of the variables were resampled using a bilinear interpolation method at a resolution of 50 × 50 m, which is the highest resolution that least affects the calculation speed of the model.

**Core areas for focal species** According to the technical specifications for developing the Spanish Green Infrastructure Strategy proposed by Valladares et al. (2017), which is based on European GI Strategy (European Commission 2013a), the ECs delineated should connect the core areas of the GI. These mainly correspond to areas of the Natura 2000 network of sites of high natural value, which was created to preserve these values. Thus, the areas representing nodes of the ECs were thus determined by considering the presence areas generated by MaxEnt for each species occurring within a Natura 2000 site that overlaps a 10 × 10 km cell of the Spanish Terrestrial Species Inventory grid where the species have been surveyed. The presence areas obtained from MaxEnt results comprised those with a species presence probability higher than the threshold at which the sum of true positives of the calibrated MaxEnt model and the true-negative rate is highest. Finally, to reduce the number of nodes for each species, the areas including the five largest types of land cover were selected from the previous presence areas (Table 4 in the section "Analysis of MaxEnt results".).

## Results

### Probability distribution maps

From the initial list of 2081 species, only 28 met the criteria described in the section "Probability distribution maps". Species that were widely distributed throughout the study area or were located in only a few cells were not considered. This led to the exclusion of all bird species, as the only bird species in the list (*Alauda arvensis*) is widely distributed (Example a in Fig. 3). As a result, 26 species are finally considered.

#### Focal species

The focal species approach, which chooses a limited number of species to serve as surrogates for a large group (Lambeck 1997)—under the assumption that the ECs delineated may also be suitable for a wide range of species—was applied.

Thus, once the probability distribution maps were obtained for these 26 species, the species distribution inventory grids were examined to select the focal species, as some species belong to the same order and even the same family or had very similar habitat requirements and the AUC values are in most cases greater than 0.7 (Table 3). For example, *Rhinolophus ferrumequinum* was selected rather than other species of bats, because, despite having a lower AUC, it is more widely distributed, and the aim is to connect different areas within the core areas of the GI. The same applies to *Felis silvestris*, which was chosen in preference to other species, such as *Martes martes*, linked to wooded areas.

A total of 8 focal species were selected, including 3 mammals, 2 reptiles, and 3 amphibians: *Rhinolophus ferrumequinum* (the greater horseshoe Bat), *Felis silvestris* (the European wildcat), *Galemys pyrenaicus* (the Pyrenean desman), *Iberolacerta monticola* (the Iberian mountain lizard), *Coronella austriaca* (the smooth snake), *Pelobates cultripes* (the Iberian spadefoot toad), *Chioglossa lusitanica* (the golden-striped salamander), and *Hyla arborea* (the European tree frog) respectively.


**Fig. 3** An example of 10×10 km presence grid of Spanish Terrestrial Species Inventory (MITECO 2012) (in dark gray) for **a** *Alauda arvensis* (bird), **b** *Felis silvestris* (mammal), and **c** *Iberolacerta galani* (reptile). Examples **a** and **c** were excluded from the model because of their wide (**a**) and sparse (**c**) distribution in the study area (light gray)

**Table 3** AUC values for different species

| Taxa | Species name | AUC | Reasons for disregarding | |
|---|---|---|---|---|
| | | | < 0.7 AUC | Grid distribution of the Spanish Inventory of terrestrial species |
| Mammal | *Barbastella barbastellus* | 0.946 | | X |
| | *Rhinolophus euryale* | 0.939 | | X |
| | *Martes martes* | 0.896 | | X |
| | *Ursus arctos* | 0.885 | | X |
| | *Myotis myotis* | 0.847 | | X |
| | ***Rhinolophus ferrumequinum*** | **0.842** | | |
| | *Rhinolophus hipposideros* | 0.838 | | X |
| | *Myotis emarginatus* | 0.819 | | X |
| | ***Felis silvestris*** | **0.812** | | |
| | *Mustela putorius* | 0.802 | | X |
| | ***Galemys pyrenaicus*** | **0.783** | | |
| | *Genetta genetta* | 0.761 | | X |
| | *Lutra lutra* | 0.528 | X | |
| Reptile | *Chalcides bedriagai* | 0.954 | | X |
| | ***Iberolacerta monticola*** | **0.884** | | |
| | *Podarcis muralis* | 0.871 | | X |
| | ***Coronella austriaca*** | **0.795** | | |
| | *Lacerta schreiberi* | 0.692 | X | |
| Amphibian | ***Pelobates cultripes*** | **0.921** | | |
| | ***Chioglossa lusitanica*** | **0.866** | | |
| | *Rana temporaria* | 0.834 | | X |
| | ***Hyla arborea*** | **0.773** | | |
| | *Bufo calamita* | 0.745 | | X |
| | *Triturus marmoratus* | 0.730 | | X |
| | *Alytes obstetricans* | 0.721 | | X |
| | *Rana perezi* | 0.654 | X | |

The species highlighted in bold were chosen as focal species

**Table 4** The five main types of land cover representing the largest surface area in each species presence area determined by MaxEnt

| Species | CLC | Area (%) | Species | CLC | Area (%) |
|---|---|---|---|---|---|
| *Rhinolophus ferrumequinum* | Moor and heathland | 25.29 | *Coronella austriaca* | Broadleaved forest | 42.12 |
| | Broadleaved forest | 20.73 | | Moor and heathland | 21.49 |
| | Coniferous forest | 15.22 | | Complex cultivation patterns | 11.17 |
| | Complex cultivation patterns | 13.77 | | Transitional woodland-shrub | 6.28 |
| | Land principally occupied by agriculture with large areas of natural vegetation | 8.42 | | Coniferous forest | 4.36 |
| *Felis silvestris* | Broadleaved forest | 37.10 | *Pelobates cultripes* | Moor and heathland | 29.21 |
| | Moor and heathland | 28.92 | | Complex cultivation patterns | 16.26 |
| | Complex cultivation patterns | 6.87 | | Land principally occupied by agriculture with large areas of natural vegetation | 10.27 |
| | Coniferous forest | 6.31 | | Broadleaved forest | 11.04 |
| | Land principally occupied by agriculture with large areas of natural vegetation | 5.70 | | Discontinuous urban fabric | 7.12 |
| *Galemys pyrenaicus* | Broadleaved forest | 38.04 | *Chioglossa lusitanica* | Broadleaved forest | 42.39 |
| | Complex cultivation patterns | 18.25 | | Complex cultivation patterns | 19.68 |
| | Moor and heathland | 13.87 | | Moor and heathland | 13.56 |
| | Coniferous forest | 11.07 | | Coniferous forest | 6.96 |
| | Land principally occupied by agriculture with large areas of natural vegetation | 5.24 | | Land principally occupied by agriculture with large areas of natural vegetation | 3.62 |
| *Iberolacerta monticola* | Broadleaved forest | 38.06 | *Hyla arborea* | Broadleaved forest | 33.12 |
| | Moor and heathland | 27.38 | | Complex cultivation patterns | 20.74 |
| | Complex cultivation patterns | 10.27 | | Discontinuous urban fabric | 7.63 |
| | Transitional woodland-shrub | 7.60 | | Coniferous forest | 7.47 |
| | Mixed forest | 3.18 | | Moor and heathland | 6.64 |

### Analysis of MaxEnt results

The most important variables in the models and the type of land cover occupying the largest proportion of the species presence areas, predicted by MaxEnt, were compared with the information in the MITECO technical sheets for each selected species (MITECO 2007) to determine whether the probability distribution maps obtained with MaxEnt correspond to the real requirements of the focal species.

The types of land covering the largest surface in the MaxEnt presence areas were determined using zonal statistics. The results are shown in Table 4, along with the five types of land cover representing the largest surface area for each focal species.

**Table 5** Jackknife contribution variables for each focal species

| Species | Jackknife variables | |
|---|---|---|
| | Highest gain when used in isolation (provides most useful information by itself) | Greatest decrease in gain when omitted (most information not provided by others) |
| *R. ferrumequinum* | Mean.B12 (annual precipitation) | PLAND_4 (% of Low intensity agriculture) |
| *F. silvestris* | Mean.B1 (annual mean temperature) | PLAND_2 (% of Wasteland) |
| *G. pyrenaicus* | Mean.B1 (annual mean temperature) | PLAND_9 (% of Scrub) |
| *I. monticola* | Mean.slope | PLAND_4 (% of Low intensity agriculture) |
| *C. austriaca* | PLAND_5 (% of Agricultural) | PLAND_9 (% of Scrub) |
| *P. cultripes* | Mean.slope | Mean.B4 (temperature seasonality) |
| *C. lusitanica* | Mean.B4 (temperature seasonality) | PLAND_2 (% of Wasteland) |
| *H. arborea* | Mean.slope | |

Examination of the probability distribution maps revealed the variables contributing most to the model results. The most important variables for each focal species are shown in Table 5. The contributions of the variables to the probability of presence for the focal species are shown in more detail in the supplementary material.

## Graph theory model

The maps of resistance to mobility, the nodes to connect (core areas), and the least-cost paths for each focal species considered are shown in Fig. 4. Orange areas indicate high resistance and blue areas indicate lower resistance. Thus, for most focal species, the central and eastern zones of the study area showed high resistance to the passage of species. In this respect, as most nodes (core areas)

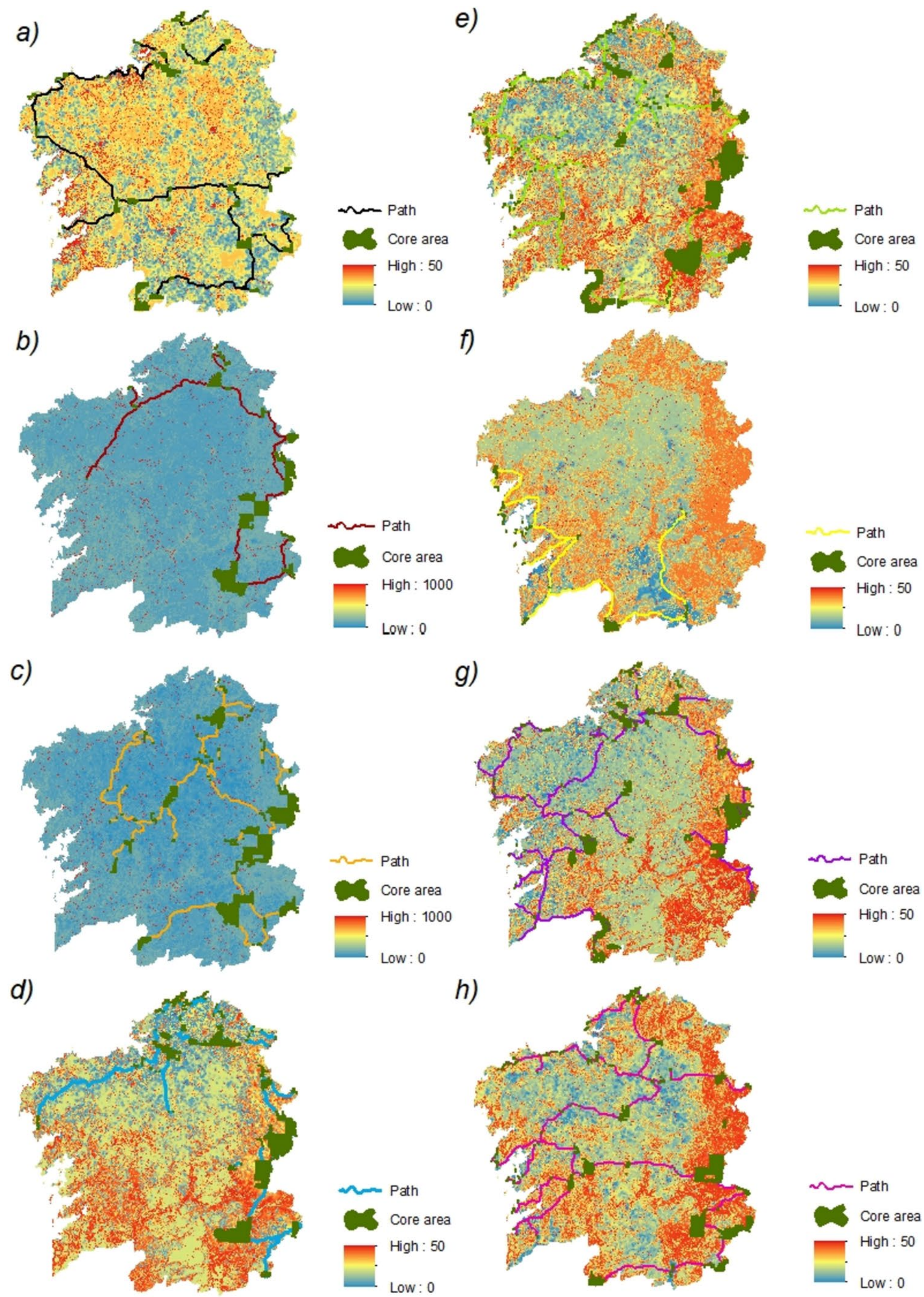


**Fig. 4** Resistance maps, core areas, and least-cost paths for **a** *R. ferrumequinum*, **b** *F. silvestris*, **c** *G. pyrenaicus*, **d** *I. monticola*, **e** *C. austriaca*, **f** *P. cultripes*, **g** *C. lusitanica*, and **h** *H. arborea*

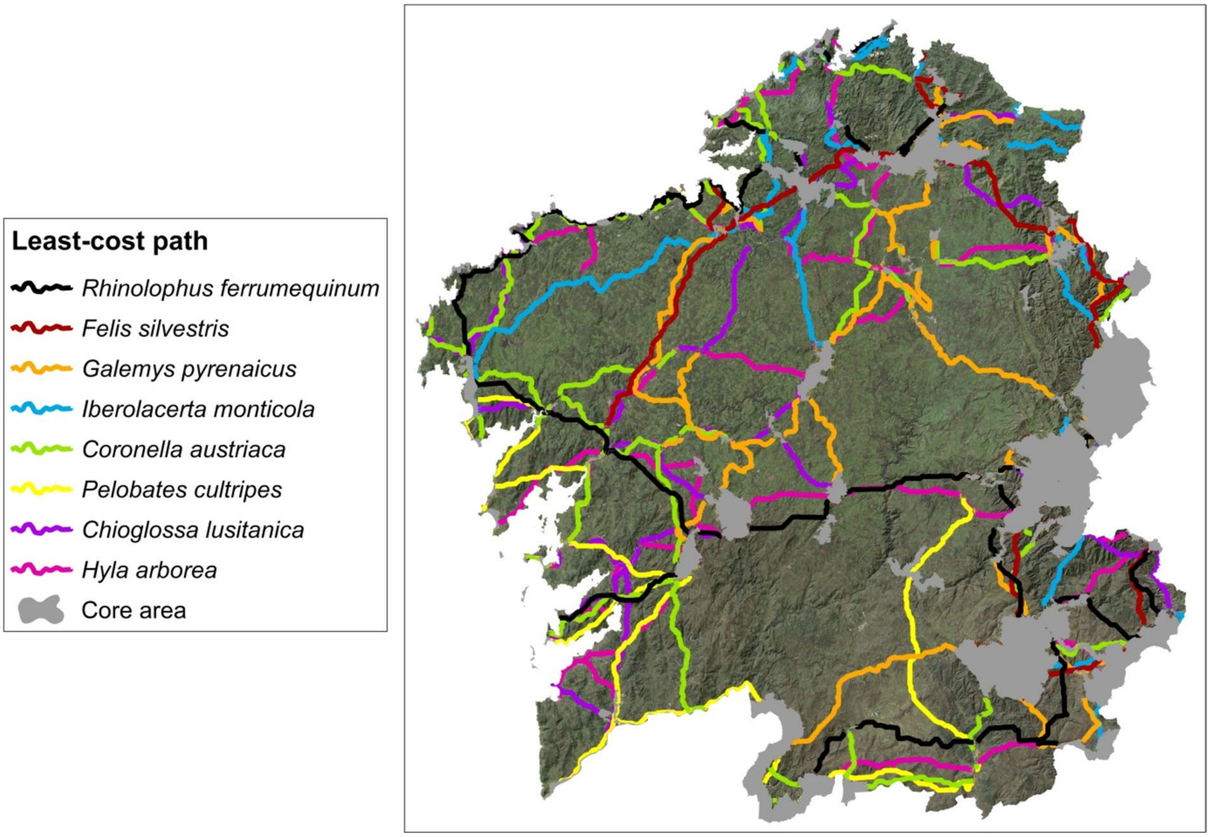


**Fig. 5** Least-cost paths identified by the proposed method

are distributed at the eastern edge of the region and on the coast, the least-cost paths are more abundant in these areas.

### Least-cost paths

The least-cost paths identified were included together in a single layer (see Fig. 5). As mentioned in the previous section, most of the paths obtained are concentrated close to the coastline and at southern and eastern limits of the region, coinciding with areas with a greater presence of GI core areas. Nevertheless, the density of least-cost paths is lower in the central zone of the region.

The land-cover types along the least-cost paths to assess their alignment with the most suitable areas for focal species are presented in Table 6. The types of land covering the least-cost path were determined using zonal statistics.

## Discussion

### Considerations regarding use of the proposed SDSS in planning

The proposed methodology is easy to apply and replicable in other territories using publicly available data. Therefore, considering the complexity involving the delineation of ECs, the main contribution of this study is not to debate the optimal approach, methodology, or tool (for which see, e.g., Alagador et al. 2016; Cushman et al. 2013; Hilty et al. 2019; LaPoint et al. 2013; Zeller et al. 2012), but is rather the practical development of a methodology to support non-expert planners in the initial planning steps for the implementation of a Galician GI in the absence of specific data. In this sense, a desirable further stage in the process would be the application of ecology expert knowledge to (a) validate the proposed EC with the utility for specific species movement, and (b) fine-tune the coarse EC delineation that the SDSS provides.

**Table 6** The five main types of land cover representing the largest surface area in the least-cost path of the focal species

| Species | CLC | Area (%) | Species | CLC | Area (%) |
|---|---|---|---|---|---|
| *Rhinolophus ferrumequinum* | Moor and heathland | 24.31 | *Coronella austriaca* | Broadleaved forest | 30.42 |
| | Broadleaved forest | 21.03 | | Complex cultivation patterns | 20.96 |
| | Complex cultivation patterns | 14.60 | | Moor and heathland | 13.94 |
| | Coniferous forest | 12.39 | | Coniferous forest | 7.96 |
| | Land principally occupied by agriculture with large areas of natural vegetation | 7.60 | | Mixed forest | 5.78 |
| *Felis silvestris* | Complex cultivation patterns | 22.68 | *Pelobates cultripes* | Complex cultivation patterns | 21.69 |
| | Broadleaved forest | 21.51 | | Moor and heathland | 17.98 |
| | Moor and heathland | 17.84 | | Broadleaved forest | 16.82 |
| | Coniferous forest | 11.98 | | Land principally occupied by agriculture with large areas of natural vegetation | 9.66 |
| | Land principally occupied by agriculture with large areas of natural vegetation | 6.45 | | Coniferous forest | 9.05 |
| *Galemys pyrenaicus* | Broadleaved forest | 30.81 | *Chioglossa lusitanica* | Complex cultivation patterns | 30.15 |
| | Complex cultivation patterns | 19.27 | | Broadleaved forest | 25.52 |
| | Coniferous forest | 14.64 | | Moor and heathland | 11.52 |
| | Moor and heathland | 12.08 | | Coniferous forest | 9.01 |
| | Land principally occupied by agriculture with large areas of natural vegetation | 7.65 | | Mixed forest | 6.56 |
| *Iberolacerta monticola* | Broadleaved forest | 34.07 | *Hyla arborea* | Complex cultivation patterns | 25.60 |
| | Complex cultivation patterns | 17.84 | | Broadleaved forest | 21.15 |
| | Moor and heathland | 17.29 | | Moor and heathland | 12.93 |
| | Land principally occupied by agriculture with large areas of natural vegetation | 7.02 | | Coniferous forest | 9.81 |
| | Transitional woodland-shrub | 6.39 | | Land principally occupied by agriculture with large areas of natural vegetation | 8.61 |

### Influence of the input data in the SDSS results

In the first instance, our methodology responds to the requirements regarding alignment with the different Biodiversity Strategies (European Commission 2011, 2020), European Commission documents (European Commission 2013a, b) and the Spanish GI Strategy (Valladares et al. 2017) for delineating ECs to counteract the effects of climate change, among other factors. However, while delineating ECs is already challenging, it is particularly so when input data are not readily available. As is common in corridor planning and design processes at the regional level, available information on species distribution relies on scarce and/or low-resolution data, and gaps in data availability are difficult to correct or improve within the scope of the method.

Although the results obtained with the publicly available data are promising, we must consider whether the proposed methodology would benefit from the inclusion of more detailed species inventory data. For example, if the inventory data included the coordinates of the site where an individual was detected instead of a low-resolution grid. More precise land-cover data may also be required, because, as we will see below, many of the habitats required by the species are not represented in the current land-cover data. As pointed out by Gonçalves et al. (2016), it is essential to improve the quality of the input data to produce better and more accurate model projections, since the usual lack of fine-scale resolution data (e.g. land-use data) and limited occurrence data (up-to-date and fine-resolution) add further constraints and uncertainty to robust assessment of species range changes.

### Considerations regarding the results obtained and whether they capture the species mobility habit

The proposed methodology does not try to validate the MaxEnt model [the distribution probability maps obtained with

MaxEnt had an AUC greater than 0.7 (see Table 3), which suggests that they are useful for predicting the distribution at a regional scale], but rather can be used as a spatial support system for decision-making in designing GI ecological corridors, and therefore, the validation process is important. Thus, the land cover in the areas identified by MaxEnt with the highest probability of presence, the most significant variables of the MaxEnt jackknife test, and the least-cost paths obtained were analyzed to determine whether the method would be useful for non-expert planners to propose the most favourable areas to function as ECs and facilitate the inclusion of such areas in land planning.

In most cases, the areas of potential presence obtained with MaxEnt comprise land-cover types generally considered as the species preferred habitats according to the technical sheets available (MITECO 2007). For almost all species, broadleaved forest was the most common type of land cover in the presence areas (see Table 4). This may be because most of the species are distributed in mountainous areas, and this is the most abundant type of land cover in these locations as well as the entire study area. In addition, this is one of the preferred types of land cover for species such as *F. silvestris* and *C. lusitanica*. For species associated with habitats such as small water sources, streams, and ponds (e.g., *G. pyrenaicus* and *P. cultripes*), the types of land cover associated with the presence areas identified include habitats that do not correspond to preferred habitats. This is because water-related land cover is generally linear in shape. Consequently, this type of cover is not well represented due to the coarse resolution of land-cover data (Spanish CORINE is based on the SIOSE land cover which only surveys land use with a minimum mapping unit (MMU) of 2 ha in the case of natural land cover and 0.5 ha in the case of linear features such as riversides forests, cliffs, and beaches). The effects of the MMUs used in CORINE have been analyzed in the previous studies (García-Álvarez et al. 2019; Gastón et al. 2017; Saura 2002), and it was concluded that land cover that is scarce and fragmented is very poorly represented in the final map as the MMU increases, while land cover occupying larger areas becomes more dominant. Thus, for species with habitat sizes smaller than the CLC minimum mapping unit, such as ponds and streams, the CLC may not be reliable.

Analysis of the most important variables in the MaxEnt model estimated using the jackknife test revealed that the variables that provide the most useful information by themselves are mainly the climatic variables and the mean slope (see Table 5). The variable that provides most information that is not included in other variables is the percentage land cover. In this respect, the information obtained is useful as land-cover variables are the most important to help non-expert planners delineate ECs. Thus, knowing which types of land cover and climatic variables influence the distribution of species enables fine-tuning of EC delineation.

On the other hand, the least-cost paths of the focal species considered produced more refined results related to the functional approach of the proposed methodology. However, the land-cover types are more representative of the habitat of some species (see Table 6), because the cost-connectivity tool selects the areas with the highest probability of presence and avoids the transportation network as well as the areas with more human activity. For example, discontinuous urban fabric, which appeared in the top five land-cover types of MaxEnt presence areas for *P. cultripes* and *H. arborea*, was replaced by coniferous forest and land principally occupied by agriculture with large areas of natural vegetation, respectively, more in line with the habitat preferences of these species. *P. cultripes* are usually found in places with sandy substrate or at least little compacted that allow them to bury themselves without difficulty, although can inhabit wooded areas, including Holm oaks and pine forests, but also open areas like agricultural fields, pastures, dunes, marshes, river meadows, etc. (MITECO 2007; Recuero 2014) and *H. arborea* prefers dense vegetation located near permanent water (MITECO 2007). Additionally, broadleaved forest is not the most predominant land cover; for certain species, such as *H. arborea, P. cultripes*, and *C. lusitanica*, complex cultivation patterns appear to be more abundant. This type of land cover, which refers to a mosaic of small cultivated land parcels with diverse cultivation types, including annual crops, pasture, and/or permanent crops, aligns more closely with the habitat preferences of these species, as mentioned above.

In addition, we can observe a certain correspondence between species' habitat preferences and the least-cost paths distribution throughout the study area (see Fig. 4). For instance, *R. ferrumequinum* is mainly distributed in forest areas with open spaces (MITECO 2007), and the methodology therefore identifies the optimal path parallel to the coastal and inland areas where this type of land-cover mosaic predominates. Conversely, *C. lusitanica*, which has more specific habitat requirements, prefers mountainous habitats or rugged topography. This species depends on the presence of clean streams, although it can also be found in deciduous or eucalyptus forests, gorse, and rocky sites with almost no vegetation cover (MITECO 2007; Vences 2015). Indeed, the established paths pass through these habitats, which are also predominant in the above-mentioned types of land cover. Thus, if these least-cost paths appear to pass through areas similar to the species' preferred habitats, they could be a first step to guide non-expert planners to delineate the final corridors.

Also, the spatial distribution of the least-cost paths obtained (see Fig. 5) revealed that many were included at the periphery of the study area, especially in northern, southeastern, and central-western areas. This trend was observed in the corridors delineated by de la Fuente et al. (2018). The spatial model developed by de la Fuente et al. (2018), based on functional connectivity at a different scale, aimed to assess the connectivity in forest GI at the national level in Spain, and constitutes the basis for the proposal of WWF-Spain for a strategic network of ECs within Natura 2000 sites (WWF-Spain 2018). Specifically, the ECs established by de la Fuente et al. (2018) are defined for habitats (forests and shrublands) in the Natura 2000 sites, and the resistance maps were constructed on the basis of expert knowledge and validated with data from the landscape for *M. martes*. Despite the difference in scale, some overlap between the corridors is evident in some areas. In particular, in the east and southeast, the ECs coincide or are very close to the paths established for *F. silvestris*, which is also associated with forest land. The inclusion of species adapted to other habitats in our model may explain the higher path density identified between core areas along the coastal fringe of the region, where species such as, e.g., *R. ferrumequinum* are present.

### Future steps for the application of the proposed SDSS to GI planning

The definition of high-density least-cost paths at the periphery of the study area is clearly related to the spatial configuration of the core areas, which act as nodes in the connectivity network. In this respect, only a few paths have been identified between core areas of the central zone of the region. This may be due to a combined effect of the scarcity of core areas in the central part of the study area and the cumulative resistance to movement of the species between these. One possible solution to this problem is to increase the number of core areas that could act as nodes in the EC network, by restoring habitats in strategically located sites that could potentially host the focal species (Edelsparre et al. 2018; Keil et al. 2013; Rubio et al. 2012; van Langevelde 2000; Zetterberg et al. 2010). It would then be possible to test whether the inclusion of these (restored) areas favours the connectivity of the central area of the region and thus increases the ecological connectivity of the region. Detection of such areas allows prescription of GI elements in the design process for specific areas. For example, this would be potentially useful in the ongoing process of scaling up the Natura 2000 network. This acknowledges the recursive nature of the design process for ECs and GI elements, for which the proposed methodology appears to be useful. However, integration of the methodology in planning schemes would benefit from the adoption of adaptive landscape planning (Ahern 2011; Jennings et al. 2020), adaptive management (Garmestani and Allen 2015; Jones et al. 2013; Zurlini et al. 2013), and other perspectives for iterative planning (Nassauer and Opdam 2008), which in turn would require adequate institutional, organizational, and policy environments.

In addition, the methodology enables the identification of climatic variables that contain important information for predicting species distribution probability maps. Thus, the variables used in MaxEnt model could be updated and include climate change scenarios to simulate future least-cost paths, as the combination of the proposed methodology and models that predict land-use change scenarios would be useful for analyzing how the distribution of species would be altered by climate change (e.g., Ashrafzadeh et al. 2019; Kang et al. 2016; Lawler et al. 2013). This would also enable the delineation of ECs that would enhance the resilience of species to the impacts of climate change.

## Conclusions

The proposed SDSS provides promising results that should help non-experts planners delineate ECs. Despite some restrictions, the methodology could be helpful as a first step in designing an EC network as well as other GI elements.

Use of an SDM such as MaxEnt to construct probability distribution maps enables analysis of the drivers that influence the distribution of each species, thus providing more detailed information that enables fine-tuning of the exact positions of the ECs. This enables the identification of potentially significant ECs for particular animal species and increases the potential of GI to enhance the mobility of a wider range of taxa, thus enabling these species to move to new areas where environmental conditions are suitable and helping to increase species resilience against impacts such as climate change.

Once the models are calibrated, it will be possible to include future climate change projections and to assess how future scenarios will affect species distribution probability. This will improve the delineation of ECs with the aim of mitigating the impacts of climate change.

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## Declarations

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