

1

## 2 **Species-habitat networks: Bridging applied ecology and network theory**

3

4 Lorenzo Marini<sup>1,^\*</sup>, Ignasi Bartomeus<sup>2\*</sup>, Romina Rader<sup>3</sup>, Francesco Lami<sup>1</sup>

5

6 <sup>1</sup>DAFNAE, University of Padova, Viale dell'Università 16, 35020 Legnaro, Padova, Italy

7 <sup>2</sup>Dpto. Ecología Integrativa, Estacion Biologica de Dõnana (EBD-CSIC), Avda. Americo Vespucio 26, Isla

8 de la Cartuja, 41092 Sevilla, Spain

9 <sup>3</sup>Ecosystem Management, School of Environment and Rural Sciences, University of New England,

10 Armidale, NSW 2351, Australia

11

12 ^ Corresponding author: [lorenzo.marini@unipd.it](mailto:lorenzo.marini@unipd.it), Tel.: +39 0498272807

13 \* These two authors equally contributed to the work

14

15 **Keywords:** Bipartite networks; Habitat use; Landscape heterogeneity; Land-use change; Patch-mosaic;

16 Stability

17 **Abstract**

18 Land-use change is massively reshaping terrestrial ecosystems worldwide, and is recognized as a key driver  
19 of biodiversity loss with negative consequences on ecosystem functioning. Understanding how species use  
20 resources across landscapes is essential for the design of effective management strategies. Despite recent  
21 advances in theoretical ecology, there is still a gap between theory and applied ecological science and we  
22 lack the tools to manage entire landscapes to maximize biodiversity conservation and ecosystem service  
23 delivery. Here, we propose a new approach that uses existing bipartite networks to create species-habitat  
24 networks. Networks enable powerful visualizations via a common language that defines most processes in  
25 terms of nodes and links. This approach explicitly links multiple species and habitat resources, provides tools  
26 to estimate the importance of particular species in a given landscape, and quantifies emerging properties of  
27 entire habitat networks. Most existing metrics used to study properties of bipartite ecological networks can  
28 easily be adapted to investigate species-habitat relationships. One key advantage of this approach is that the  
29 scale of the derived ecological information will match the scale of management interventions. The flexibility  
30 of the proposed approach is that it can be easily applied across a range of ecological fields such as species  
31 conservation, habitat restoration, ecosystem services management, or invasion ecology. Network emerging  
32 properties could also be used to test the effects of large scale drivers of global change upon ecosystem  
33 structure and stability.

## 34 **Community ecology across heterogeneous landscapes**

35 Understanding how species use resources across landscapes is essential for the design of effective  
36 management strategies to support biodiversity and ecosystems services. By using conceptual or mathematical  
37 models, theoretical ecology has greatly improved our understanding of the dynamic principles which govern  
38 the way populations and communities respond to landscape processes (Forman 1995, MacArthur and Wilson  
39 2001, Loreau et al. 2003). To date, patch-matrix models rooted in meta-community (Leibold et al. 2004) or  
40 island biogeography theory have largely focused on species responses to the amount and configuration of  
41 remnant habitats within a hostile matrix (Tschardt et al. 2012, Hadley and Betts 2016) (Fig. 1A). Central  
42 tenets of these models are that species dispersal (i.e. the flow of individuals) occurs mainly between patches  
43 and that the focal population mostly relies on resources occurring within a specific habitat. As it is becoming  
44 increasingly clear that many species utilize a range of different habitats of varying qualities (Ricketts 2001,  
45 Tews et al. 2004, Driscoll et al. 2013), landscape ecology has moved beyond the dichotomy of patch-matrix  
46 models to explicitly incorporate landscape heterogeneity (Wiens et al. 1993, Fischer and Lindenmayer 2006,  
47 Cushman et al. 2010, Brudvig et al. 2017). Yet, while the meta-ecosystem concept has provided fundamental  
48 insights into the dynamics and functioning of ecosystems from local to regional scales (Loreau et al. 2003),  
49 there is still a gap between theory and empirical research and few methods have linked species and habitats  
50 in real landscapes (Gounand et al. 2017)

51 The field of landscape ecology has made significant inroads toward understanding community  
52 responses to landscape processes at multiple spatial scales (Turner 2005, Fahrig et al. 2011). This empirical  
53 research has driven the field of applied ecology forward by providing a solid evidence base for managers and  
54 policy makers (Tschardt et al. 2005, 2012, Mayer et al. 2016). However, most of these studies are based on  
55 another dichotomy, i.e. a focal local habitat vs. the surrounding landscape. Often the species community of  
56 interest is only sampled in one habitat and related to the landscape by using the proportion of suitable or  
57 unsuitable habitats (Fig. 1A). When landscape heterogeneity is taken into account, it is usually quantified  
58 using metrics that collapse complex processes into single indices (Frazier and Kedron 2017). Many examples  
59 of this approach in applied ecology exist (Clough et al. 2014) and recent advances in ecosystem services  
60 research have successfully applied the same approach to study key functions such as seed dispersal,

61 biocontrol (Schellhorn et al. 2015) or pollination (Kennedy et al. 2013). One downside of this research,  
62 however, is the lack of a mechanistic understanding of the links between multiple habitats and community-  
63 level processes, indicating the need for broader conceptual frameworks of spatial patterns.

64 Network approaches based on graph theory have been increasingly applied to the problem of  
65 describing complex and dynamic community level changes in ecology (Bascompte and Jordano 2007, Minor  
66 and Urban 2008, Memmott 2009, Blonder et al. 2012, Burkle et al. 2013, Albert et al. 2017, Gilarranz et al.  
67 2017, Harvey et al. 2017). The network paradigm is based on the representation of emerging properties of  
68 studied systems as oriented graphs: any system is traced back to a set of nodes (its constituent units) linked  
69 by edges corresponding to the relationships between nodes. This allows for a straightforward quantitative  
70 formalization of systems by computing mathematical descriptors of such graphs. In this way, network tools  
71 have already been applied to elucidate landscape processes, i.e. habitat patches have been represented as  
72 nodes and linked via dispersal to model connectivity at multiple spatial scales (Burns and Zotz 2010, Dale  
73 and Fortin 2010, Gonzalez et al. 2011). While these pioneering approaches have enabled the link between  
74 habitat configuration and species dispersal, they have failed both to upscale from species to community level,  
75 and to consider multiple habitat types simultaneously.

## 76 **Beyond the focal habitat: Introducing the species-habitat network**

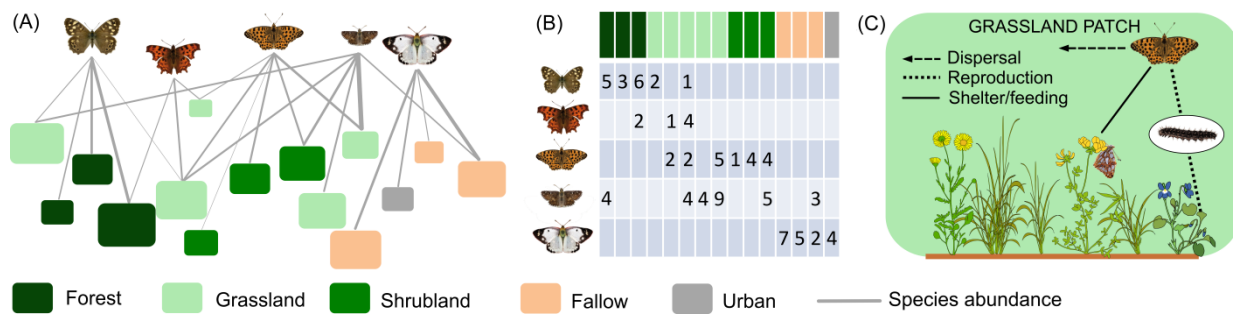
77 Traditionally, patch-mosaic models have defined landscapes as complex and heterogeneous mosaics,  
78 constituted of many interacting discrete habitat patches. More recently, several gradient models of landscape  
79 structure have challenged the mosaic paradigm (Fischer and Lindenmayer 2006), suggesting that landscape  
80 heterogeneity should be modelled using multiple, continuous environmental gradients (Cushman et al. 2010).  
81 In both cases, explicitly accounting for species resource use requires the sampling of target species in  
82 multiple sites across the landscape. These ideas have led us to consider the whole landscape as a unit to  
83 quantify and analyse community response to landscape processes (Fig. 1B). Integrating and analysing  
84 species use of multiple sites within a landscape may seem a daunting task, especially because the number of  
85 species-sites links scale exponentially with the number of species and sites sampled. Fortunately, tools  
86 developed from ecological network theory can be used to analyse and describe such complex interactions. In  
87 particular, we advocate the modelling of species-habitat interactions as bipartite networks (Box 1), analogous

88 to those describing antagonistic or mutualistic interactions (Bascompte and Jordano 2007). Bipartite  
89 networks are networks in which two types of nodes exist, and interactions are analysed only between nodes  
90 of different types. In the most simple case, habitat types and the species occurring within each habitat  
91 constitute the two types of nodes. The links between species and habitats are represented by the number of  
92 individuals occurring in a certain habitat at any given moment. The flexibility of the proposed approach  
93 allows habitat nodes to be further defined as individual sites where the community was sampled (Burns and  
94 Zotz 2010). This definition of a node can incorporate the underlying spatial processes associated with  
95 differences in landscape composition and configuration. That is, each individual site could affect network  
96 topology and stability depending on its attributes such as habitat quality, disturbance or connectivity. When  
97 species do not occupy readily identifiable habitat patches, a continuous variation in habitat quality and  
98 available resources around the sampling points can replace a discrete habitat categorization. Once the nodes  
99 are defined, the links need to be carefully formulated as they can affect the ecological interpretation of the  
100 species-habitat network. The operational definition of a link is the occurrence/abundance of a particular  
101 species in a certain location (Box 1). The focal species community would usually belong to the same trophic  
102 level sharing a similar functional role. Examples could include lichens, pollinators, ground-dwelling  
103 predatory arthropods, insectivorous mammals, etc.

104

105 **Box 1 Sampling a species-habitat network**

Any heterogeneous landscape and the species using its resources can be visualized as a bipartite network. In this example, we will consider the butterfly species occurring across an agricultural landscape in a temperate region. In the example, we sample the butterfly species occurring at 15 sites belonging to five habitats (forest, grassland, shrubland, fallow and urban area) within a landscape mosaic (1.5 x 1.5 km) (Figure IA).



**Figure I** (A) A species-habitat network of 15 sites of varying size and quality belonging to five habitats in which a butterfly community is sampled, (B) data matrix that can be derived from the sampling, and (C) example of types of species-habitat link.

The 15 sites may represent different qualities (e.g. size, tree cover or management) and spatial configurations. If species do not occupy readily identifiable habitat patches (e.g. forest-shrub gradient), a continuous variation in habitat quality and available resources around the sampling points can replace the discrete habitat categorization. The nodes in the network are represented by the butterfly species and the sampling sites. The numbers indicate the link strength (number of individuals in each site) (Figure IB). The number of sampling sites is selected to be representative of the resources and habitat diversity. In the example, the butterfly-habitat network is built using the cumulative abundance from three rounds of sampling (spring, early summer and summer) using a transect walk method. In a transect walk, butterflies are recorded in a fixed width band (typically 5 m wide) within each site. Particular attention should be paid to the functional interpretation of the links. If we consider one grassland in this network (Figure IC), a butterfly species is recorded in that site because individuals can use multiple resources (e.g. host plants for reproduction, nectar for adult feeding or plants for roosting or shelter) or simply because individuals are using that site as a stepping stone for dispersal. Hence, the choice of the sampling method will dictate the interpretation of the ecological data. In this case a transect walk

emphasizes the weight of adult feeding over reproduction. On the other hand, an alternative sampling focused on butterfly larvae and host plants can inform about species habitat use for reproduction (Dainese et al. 2017). This idea can be expanded to any taxa that use resources across heterogeneous landscapes.

106

## 107 **Building species-habitat networks**

108 Several studies have shown that individual species and community responses to landscape processes depend  
109 on the spatial scale over which the landscape metrics are quantified (Steffan-Dewenter et al. 2002, Fahrig et  
110 al. 2011). The selection of the appropriate spatial extent is thus the first key issue that needs to be addressed  
111 when building a species-habitat network. The spatial extent in which the community is sampled should be  
112 selected according to species' foraging ranges (e.g. for mobile organisms) or propagule dispersal (e.g. for  
113 sessile organisms) and to the ecological hypotheses underpinning the study. This issue is similar to the  
114 selection of buffer radii when adopting a traditional approach to quantify landscape composition or  
115 configuration. Once the spatial extent is defined, the species communities need to be sampled across the  
116 landscape. In most cases, the most pragmatic solution would be to adopt a 'habitat-centric' approach where  
117 the number of sampled sites is proportional to the habitat area. It is important to stress that as the spatial  
118 extent of the habitat mosaic used by the species is generally large (e.g. 1-10 km for mobile organisms), it is  
119 likely that most surveyed species-habitat networks would be subunits of much larger networks (Jordano  
120 2016).

121 While the definition of species as nodes is usually straightforward, the way in which habitats are  
122 defined as nodes can be more complex (Frazier and Kedron 2017). Spatial grain and habitat classification  
123 can affect the topology (and hence interpretation) of the network. In modified landscapes, different habitats  
124 are often organized in patches, which can be defined as discrete areas with a definite shape, size and  
125 configuration. The focal species community may be used to guide the identification of habitat types that are  
126 functionally relevant. From an operational point of view, we suggest that habitat nodes are defined according  
127 to the dominant vegetation (e.g. crop, forest, semi-natural grasslands, etc.), accounting for differences in  
128 structure and function for different communities. However, a species-habitat network does not necessarily

129 require a patchy habitat structure and a representation of landscape heterogeneity using continuous gradients  
130 can also be incorporated in this framework (Fischer and Lindenmayer 2006).

131 Finally, understanding how and why the topology of the networks changes over time, and how these  
132 changes affect species resource use across the landscape, can help to predict the consequences of human  
133 impacts upon community dynamics (Blonder et al. 2012). Incorporating a temporal perspective, however,  
134 requires careful thought of the timing (when) and spacing (how frequently) of the sampling. For instance, a  
135 longitudinal design with repeated observations within or across years can inform the degree of temporal  
136 variability in the species-habitat use (Laliberté and Tylianakis 2010). In the case of species-habitat networks  
137 at equilibrium, system stability to perturbations can be further investigated using both empirical and  
138 simulation models (May 1972, Memmott et al. 2007, Thébault and Fontaine 2010).

### 139 **Use and limitations of the framework**

140 There are several important conditions to note when operationalising species-habitat networks. First, users  
141 must ensure that the data inputs are realistic and relevant to the community sampled to ensure meaningful  
142 results are obtained through the network analysis. For sessile organisms such as lichen or plant species,  
143 occurrence directly links to resource use and habitat preference (Burns and Zotz 2010). On the contrary for  
144 mobile organisms that use multiple resources, species occurrence can assume different ecological meanings  
145 (Kremen et al. 2007). If we consider a specific habitat, a species can be recorded at that site because  
146 individuals can use multiple resources (e.g. host plants for reproduction, preys, nesting site or structure for  
147 roosting or shelter) or simply because individuals are using that site as a stepping stone for dispersal. Hence,  
148 depending on the species traits and the sampling method chosen the species-habitat networks can capture  
149 different community properties (Box 1).

150 Second, not all taxa can be appropriately described by species-habitat networks. One situation where  
151 the framework is unlikely to be applicable is when average species dispersal in the community is too large  
152 (e.g. large mammals or birds) compared with the feasibility of field sampling.

153 Third, the species-habitat networks may be limited in use when the landscape structure is  
154 characterized by high habitat heterogeneity at a spatial scale much smaller than the average species dispersal.



155 For instance, sampling insect communities in highly complex forest landscapes such as those in tropical  
156 regions might be challenging. On the contrary, human-altered landscapes with high contrast between habitat  
157 types provide ideal conditions to apply the framework.

158 Fourth, the required sampling effort is likely to be relatively higher than traditional observational  
159 landscape studies. However, sampling a greater number of sites will more likely capture the intrinsically high  
160 complexity of community response to landscape processes, which is pivotal to adequately address particular  
161 ecological questions. Additionally, while species-level is the obvious unit to consider in this context, species  
162 may also be grouped using functional traits to reduce network dimensionality (Eklöf et al. 2013). As for most  
163 empirical ecological interaction networks, species-habitat networks would suffer to some extent from under-  
164 sampling. Hence, limitations imposed by sampling incompleteness need to be carefully explored (Vizentin-  
165 Bugoni et al. 2016). Robust estimates of the actual number of individuals of mobile species occurring across  
166 a landscape mosaic require an adequate sampling effort that needs to be explicitly evaluated (Jordano 2016).

#### 167 **Tools for analysing species-habitat networks**

168 The appeal of a network approach is that they enable very powerful visualizations via a common language  
169 that defines most processes in terms of nodes and links. Most existing metrics used to study properties of  
170 bipartite ecological networks can easily be adapted to the study of species-habitat networks. These metrics  
171 can be broadly divided in two groups: emergent properties of the whole network and node-level metrics that  
172 measure the role of single nodes (i.e. single habitat sites or species) in the network (Dormann et al. 2009)  
173 (Fig. 2). As metric choice will depend on the nature of the question, we advocate a hypothesis-driven  
174 approach whereby users decide *a priori* which metrics will address which research question.

175 In bipartite networks, *nestedness* is a central property that describes network structure. Studies  
176 evaluating beta-diversity have long recognized that species turnover among sites can be decomposed into  
177 nestedness and turnover components (Baselga 2010, Cardoso et al. 2014). When sites with lower diversity  
178 contain a subset of the species of sites with higher diversity, the beta-diversity is dominated by the  
179 nestedness component (Fig. 2A). Scaling up from pairwise habitat comparisons to the network level, a  
180 network is said to be nested when the communities of sites that have a few links (i.e. species) are a subset of  
181 the communities of sites with more links (Atmar and Patterson 1993). In a nested species-habitat network,

182 the entire system will likely be affected if the most species-rich habitat or site is removed. In contrast, the  
183 removal of species-poor habitats that only interact with a few habitat generalists, is unlikely to have  
184 significant ripple effects.

185 In a bipartite network it is also possible to identify modules. A module comprises a set of habitat  
186 sites and species that interact more with each other than with other sites and species outside the module (Fig.  
187 2B). *Modularity* measures the strength of division of a network into modules. Often, networks with a  
188 modular structure are expected to have a lower risk of collapse due to their buffering capacity to system  
189 perturbations (Dormann et al. 2017, Gilarranz et al. 2017). However, the loss of specific sites may also affect  
190 the associated species in the same module due to low redundancy. Hence, both *nestedness* and *modularity*  
191 can have profound conservation implications (Dormann and Strauss 2014).

192 A common way to assess those implications is to look at network *robustness*. The *robustness* of a  
193 network can be a key metric for conservation prioritization of high value sites and ecosystem management  
194 (Sole and Montoya 2001), as it is defined as the network resilience to the loss of nodes. For instance, simple  
195 simulations removing habitat randomly or in realistic sequences are one way to quantify community  
196 robustness to habitat loss (Fig. 2C). While particular species-habitat networks might be robust to random  
197 removals of habitats, they may also be highly sensitive to targeted habitat loss.

198 Understanding network *selectiveness* is central to assess the extent of habitat generalization  
199 (Blüthgen et al. 2006). An unselective network is characterized by having sites used proportionally to their  
200 size (green line in Fig. 2D), while selective networks are characterized by species using preferred sites,  
201 irrespective of site area (blue line in Fig. 2D). This metric can provide information about the consequences of  
202 different land-use change scenarios for species communities.

203 Species-habitat network analysis can also provide insights into the roles of specific habitat sites or  
204 species in the network. While some of these metrics can be derived from classic community ecology, the  
205 network approach enables scaling up to whole communities. First, the influence of one site upon another site  
206 can be assessed using *apparent influence* metrics (Muller et al. 1999). This index quantifies how much one  
207 habitat site contributes to sustaining the species present in another site (Fig. 2E). Interestingly, this index is  
208 not symmetrical (influence of node *a* upon *b* can be high, while the influence of node *b* upon *a* can be low)

209 and more complex relations can be added, like adding time directionality in cases when the phenology of the  
210 habitat is known (e.g. flower phenology).

211 Another useful metric is node *strength* (Bascompte et al. 2006). This metric captures, for example, a  
212 single site's importance taking into account how much the species depend on this site. A site can have high  
213 *strength* if it supports a high number of species with high dependency (i.e. specialist) on it (node *a* in Fig.  
214 2F). Alternatively, sites that only host a few generalist species (node *b*) have low *strength* playing a minor  
215 role in the landscape (Collado et al. 2018).

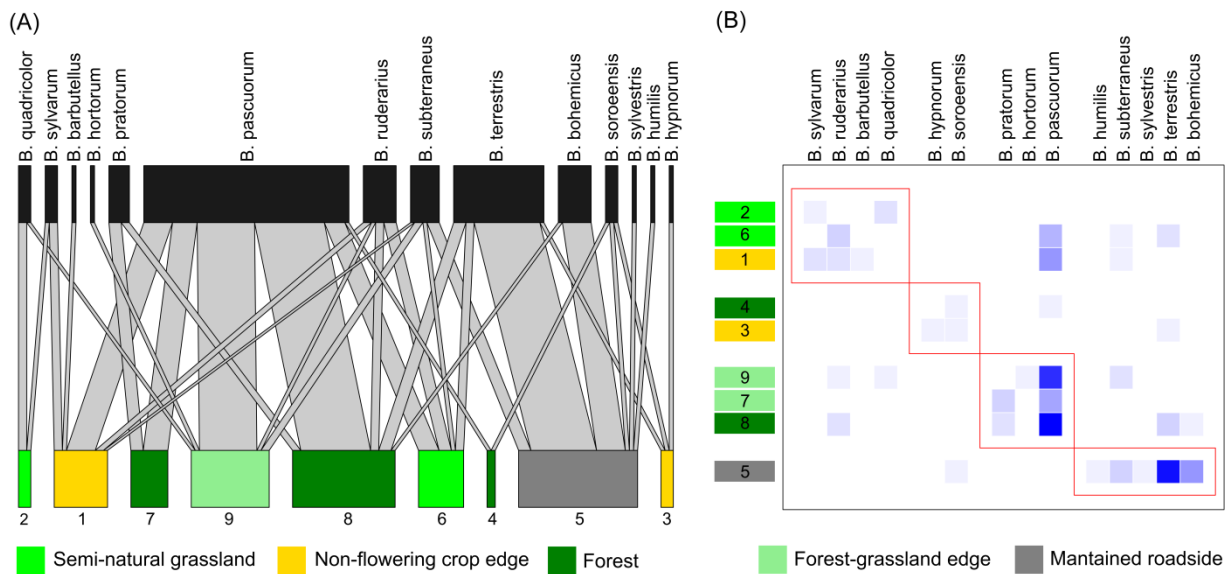
216 We can also see the contribution of particular nodes to network level metrics like modularity or  
217 nestedness. The example of modularity is the most enlightening as modularity algorithms can also assess the  
218 role of each node in the network (Olesen et al. 2007). For example, using among-module *connectivity* (*c*) we  
219 can identify hub species connecting different modules (Fig. 2G). This can help to identify key-stone sites or  
220 species that can affect the robustness of the whole network. As for the whole network, habitat *generality* or  
221 *preference* can be also considered at the node level, using selectivity metrics (Fig. 2H) (Neu et al. 1974).

222 Overall, the characterization of nodes as individual habitat sites can be used to address questions  
223 regarding the extent to which particular network properties are related with ecological properties of the site  
224 (e.g. habitat quality, resources, area or isolation). Here, we have provided examples of a few commonly used  
225 metrics, while several comprehensive reviews of different metrics are available (Blüthgen et al. 2006,  
226 Dormann et al. 2009, Dormann and Strauss 2014). In Box 2, we present a worked example of species-habitat  
227 network using a published dataset.

228

## 229 Box 2. Analysing species-habitat networks: a worked example

Here, we illustrate a simple example of our approach by re-analysing a published dataset (Hill and Bartomeus 2016). The data comprises all bumblebee species sampled in multiple sites along 10 landscapes of 4 km<sup>2</sup> (2 x 2 km) in Sweden. To exemplify how to apply common metrics, we will focus on a single landscape and build a species-habitat network. Even with a simple visualization as a bipartite network (Figure IIA), some ecological information can be obtained.



**Figure II** (A) Visual representation of the species-habitat network in one landscape where nine sites were sampled, and (B) plots showing the modules composing the network (red outline) with species abundance in each site (blue shading)

For example, *B. pascuorum* is the most abundant species and is connected to most habitats, especially to semi-natural habitats and the maintained roadside is the most species-rich site. To facilitate conservation decision-making, we can calculate different metrics depending on the conservation aim. First, we show that this network is significantly more nested than expected by chance (observed NODF= 20.84,  $p < 0.001$ ), i.e. species-poor sites tend to only host generalists that are also present in species-rich sites. If the aim is to protect the highest number of species with the minimum effort, a conservation strategy focusing only on the few most species-rich sites might be the best option. It is also possible to identify modules (Figure IIB), and calculate among-module (*c*) connectivity which in turn provides information about the role of each node in the network structure. Here, sites 6, 8 and 9 (*c* values close to 0.6) tend to act as connectors among different

modules, and should thus be prioritized for conservation if the aim is to preserve the integrity of the network as a whole. To prioritize conservation, another option is to calculate site *strength* ( $S$ ). The maintained roadside is the site with the highest *strength* ( $S= 4.36$ ), because it hosts a large number of species and individuals that have a high dependence on this habitat. Finally, from a species perspective, we may be interested in habitat preferences. The *selectivity* ( $d'$ ) index gives us information about the degree of habitat specialization of each species. With low values of  $d'$ , species such as *B. humilis* and *B. soroensis* are among the most selective in this network. Since habitat specialists tend to be more vulnerable to extinction than generalists, these species should be the first included in conservation efforts (complete code to reproduce this and other analyses is available in the Supplementary Material).

## 230 **Implications for ecosystem management and policy**

231 Land-use change is massively reshaping terrestrial ecosystems worldwide, and is recognized as a key driver  
232 of biodiversity loss with negative consequences on ecosystem functioning (Cardinale et al. 2012). An urgent  
233 question is to understand how to manage whole landscapes to maximize biodiversity conservation or  
234 ecosystem services delivery (Mendenhall et al. 2016). The flexibility of the proposed approach is that it can  
235 easily be applied across a range of ecological fields such as species conservation, habitat restoration,  
236 ecosystem services management, or invasion ecology (Memmott et al. 2007). Here, we provide four  
237 important research directions that could be addressed by adopting species-habitat networks:

238 *a) Conservation prioritization.* Conservation actions often face the trade-off between maximum protection of  
239 the environment and a limited budget. Site *strength* values in a landscape or in a protected area network can  
240 be used to prioritize which sites to conserve to maximize the biodiversity of any target taxon.

241 *b) Land-use change and community stability.* Conservationists often aim to achieve maximum biodiversity  
242 representation, without an explicit focus on the long-term stability. Seminal works (May 1972) and more  
243 recent studies (Thébault and Fontaine 2010, Gilarranz et al. 2017) on ecological networks have tried to use  
244 architectural patterns such as *modularity* to understand the mechanisms underlying the stability of  
245 communities. Similarly, we can investigate if certain species-habitat structures confer stability to the system  
246 in order to predict the *robustness* of species-habitat interactions to habitat perturbations.

247 *c) Maximizing biodiversity-based ecosystem services.* Landscape interventions to support ecosystem services  
248 often require the introduction of new habitats (e.g. hedgerows, mass-flowering crops) across a landscape. For  
249 instance, pollinators and pest control agents are known to be enhanced by the proximity to semi-natural areas  
250 (Ricketts et al. 2008, Schellhorn et al. 2015, Grass et al. 2016). Simulations using different crop  
251 configurations and green infrastructures can be used to maximize the positive *influence* among sites. For  
252 example, placing early mass flowering crops in the right configuration may maximize ecosystem service  
253 delivery, without imposing negative effects on natural habitats (Magrach et al. 2017).

254 *d) Impact of invasive species.* Landscapes are often invaded by alien species with a strong impact on native  
255 communities and ecosystem functioning. Here, the application of the species-habitat network will help to  
256 better understand the native community response to alien invasions across gradients of landscape  
257 composition and configuration. Incorporating a temporal perspective will elucidate how alien species move  
258 and use resources across the landscape. For instance, *modularity* or *selectivity* can provide key information  
259 on species spill-over and potential competition between natives and aliens.

260         The dichotomy of focal habitat versus the surrounding landscape overlooks the diversity of processes  
261 that characterise real-world landscapes. Species-habitat networks enable characterization of not only species  
262 or habitat-level dynamics, but also the emerging properties of those landscapes, going beyond the traditional  
263 landscape patch-mosaic model (Wiens 1995). By sampling multiple networks along relevant environmental  
264 gradients, these emerging properties can be used to test the effects of large scale drivers of global change  
265 upon ecosystem structure and stability (Schleuning et al. 2012). One key advantage of the application of the  
266 species-habitat network is that the scale of the derived ecological information will match the scale of  
267 landscape management interventions. The versatility, visualization power and easy interpretation of these  
268 networks will enable the application of the species-habitat network concept to a wide array of real-world  
269 problems concerning biodiversity conservation and ecosystem service enhancement at different spatial  
270 scales.

## 271 **Acknowledgements**

272 We are grateful to P. Paolucci (Padova) for the drawings included in the figures.

273 **Data Accessibility**

274 All code and data for creating the practical example included in the supplementary material is available at  
275 [https://ibartomeus.github.io/hab-sp\\_ntw/demo.html](https://ibartomeus.github.io/hab-sp_ntw/demo.html).

276 **References**

- 277 Albert, C. H. et al. 2017. Applying network theory to prioritize multispecies habitat networks that are robust  
278 to climate and land-use change. - *Conserv. Biol.* 31: 1383–1396.
- 279 Atmar, W. and Patterson, B. D. 1993. The measure of order and disorder in the distribution of species in  
280 fragmented habitat. - *Oecologia* 96: 373–382.
- 281 Bascompte, J. and Jordano, P. 2007. Plant-animal mutualistic networks: The architecture of biodiversity. -  
282 *Annu. Rev. Ecol. Evol. Syst.* 38: 567–593.
- 283 Bascompte, J. et al. 2006. Asymmetric coevolutionary networks facilitate biodiversity maintenance. -  
284 *Science* 312: 431–433.
- 285 Baselga, A. 2010. Partitioning the turnover and nestedness components of beta diversity. - *Glob. Ecol.*  
286 *Biogeogr.* 19: 134–143.
- 287 Blonder, B. et al. 2012. Temporal dynamics and network analysis. - *Methods Ecol. Evol.* 3: 958–972.
- 288 Blüthgen, N. et al. 2006. Measuring specialization in species interaction networks. - *BMC Ecol.* 14: 6–9.
- 289 Brudvig, L. A. et al. 2017. Evaluating conceptual models of landscape change. - *Ecography* 40: 74–84.
- 290 Burkle, L. A. et al. 2013. Plant-pollinator interactions over 120 years: loss of species, co-occurrence, and  
291 function. - *Science* 339: 1611–5.
- 292 Burns, K. C. and Zotz, G. 2010. A hierarchical framework for investigating epiphyte assemblages: networks,  
293 meta- communities, and scale. - *Ecology* 91: 377–385.
- 294 Cardinale, B. J. et al. 2012. Biodiversity loss and its impact on humanity. - *Nature* 486: 59–67.
- 295 Cardoso, P. et al. 2014. Partitioning taxon, phylogenetic and functional beta diversity into replacement and

- 296 richness difference components. - *J. Biogeogr.* 41: 749–761.
- 297 Clough, Y. et al. 2014. Density of insect-pollinated grassland plants decreases with increasing surrounding  
298 land-use intensity. - *Ecol. Lett.* 17: 1168–1177.
- 299 Collado, M. Á. et al. 2018. Bees use anthropogenic habitats despite strong natural habitat preferences. -  
300 bioRxiv: 278812.
- 301 Cushman, S. A. et al. 2010. The gradient paradigm: A conceptual and analytical framework for landscape  
302 ecology. - In: Cushman, S. A. and Huettmann, F. (eds), *Spatial Complexity, Informatics, and Wildlife*  
303 *Conservation*. Springer, pp. 83–108.
- 304 Dainese, M. et al. 2017. Landscape simplification weakens the association between terrestrial producer and  
305 consumer diversity in Europe. - *Glob. Chang. Biol.* 23: 3040–3051.
- 306 Dale, M. R. T. and Fortin, M.-J. 2010. From graphs to spatial graphs. - *Annu. Rev. Ecol. Evol. Syst.* 41: 21–  
307 38.
- 308 Dormann, C. F. and Strauss, R. 2014. A method for detecting modules in quantitative bipartite networks. -  
309 *Methods Ecol. Evol.* 5: 90–98.
- 310 Dormann, C. F. et al. 2009. Indices, graphs and null models: Analyzing bipartite ecological networks. - *Open*  
311 *Ecol. J.* 2: 7–24.
- 312 Dormann, C. F. et al. 2017. Identifying causes of patterns in ecological networks: Opportunities and  
313 limitations. - *Annu. Rev. Ecol. Evol. Syst.* 48: 559–84.
- 314 Driscoll, D. A. et al. 2013. Conceptual domain of the matrix in fragmented landscapes. - *Trends Ecol. Evol.*  
315 28: 605–613.
- 316 Eklöf, A. et al. 2013. The dimensionality of ecological networks (J Dunne, Ed.). - *Ecol. Lett.* 16: 577–583.
- 317 Fahrig, L. et al. 2011. Functional landscape heterogeneity and animal biodiversity in agricultural landscapes.  
318 - *Ecol. Lett.* 14: 101–112.



- 319 Fischer, J. and Lindenmayer, D. B. 2006. Beyond fragmentation: the continuum model for fauna research  
320 and conservation in human-modified landscapes. - *Oikos* 112: 473–480.
- 321 Forman, R. T. T. 1995. Some general principles of landscape and regional ecology. - *Landsc. Ecol.* 10: 133–  
322 142.
- 323 Frazier, A. E. and Kedron, P. 2017. Landscape metrics: Past progress and future directions. - *Curr. Landsc.*  
324 *Ecol. Reports* 2: 63–72.
- 325 Gilarranz, L. J. et al. 2017. Effects of network modularity on the spread of perturbation impact in  
326 experimental metapopulations. - *Science* 357: 199–201.
- 327 Gonzalez, A. et al. 2011. The disentangled bank: how loss of habitat fragments and disassembles ecological  
328 networks. - *Am. J. Bot.* 98: 503–16.
- 329 Gounand, I. et al. 2017. Meta-ecosystems 2.0: Rooting the theory into the field. - *Trends Ecol. Evol.* in press.
- 330 Grass, I. et al. 2016. Much more than bees-Wildflower plantings support highly diverse flower-visitor  
331 communities from complex to structurally simple agricultural landscapes. - *Agric. Ecosyst. Environ.*  
332 225: 45–53.
- 333 Hadley, A. S. and Betts, M. G. 2016. Refocusing habitat fragmentation research using lessons from the last  
334 decade. - *Curr. Landsc. Ecol. Reports* 1: 55–66.
- 335 Harvey, E. et al. 2017. Bridging ecology and conservation: from ecological networks to ecosystem function.  
336 - *J. Appl. Ecol.* 54: 371–379.
- 337 Hill, B. and Bartomeus, I. 2016. The potential of electricity transmission corridors in forested areas as  
338 bumblebee habitat. - *R. Soc. Open Sci.* 3: 160525.
- 339 Jordano, P. 2016. Sampling networks of ecological interactions. - *Funct. Ecol.* 30: 1883–1893.
- 340 Kennedy, C. M. et al. 2013. A global quantitative synthesis of local and landscape effects on wild bee  
341 pollinators in agroecosystems. - *Ecol. Lett.* 16: 584–599.

- 342 Kremen, C. et al. 2007. Pollination and other ecosystem services produced by mobile organisms: a  
343 conceptual framework for the effects of land-use change. - *Ecol. Lett.* 10: 299–314.
- 344 Laliberté, E. and Tylianakis, J. M. 2010. Deforestation homogenizes tropical parasitoid–host networks. -  
345 *Ecology* 91: 1740–1747.
- 346 Leibold, M. A. et al. 2004. The metacommunity concept: a framework for multi-scale community ecology. -  
347 *Ecol. Lett.* 7: 601–613.
- 348 Loreau, M. et al. 2003. Meta-ecosystems: a theoretical framework for a spatial ecosystem ecology. - *Ecol.*  
349 *Lett.* 6: 673–679.
- 350 MacArthur, R. H. and Wilson, E. O. 2001. *The theory of island biogeography*. - Princeton University Press.
- 351 Magrach, A. et al. 2017. Plant-pollinator networks in semi-natural grasslands are resistant to the loss of  
352 pollinators during blooming of mass-flowering crops. - *Ecography*: in press.
- 353 May, R. M. 1972. Will a large complex system be stable? - *Nature* 238: 413–414.
- 354 Mayer, A. L. et al. 2016. How landscape ecology informs global land-change science and policy. -  
355 *Bioscience* 66: 458–469.
- 356 Memmott, J. 2009. Food webs: a ladder for picking strawberries or a practical tool for practical problems? -  
357 *Proc. R. Soc. B Biol. Sci.* 364: 1693–1699.
- 358 Memmott, J. et al. 2007. Global warming and the disruption of plant-pollinator interactions. - *Ecol. Lett.* 10:  
359 710–717.
- 360 Mendenhall, C. D. et al. 2016. Quantifying and sustaining biodiversity in tropical agricultural landscapes. -  
361 *Proc. Natl. Acad. Sci.* 113: 14545–14551.
- 362 Minor, E. S. and Urban, D. L. 2008. A graph-theory framework for evaluating landscape connectivity and  
363 conservation planning. - *Conserv. Biol.* 22: 297–307.
- 364 Muller, C. B. et al. 1999. The structure of an aphid-parasitoid community. - *J. Anim. Ecol.* 68: 346–370.

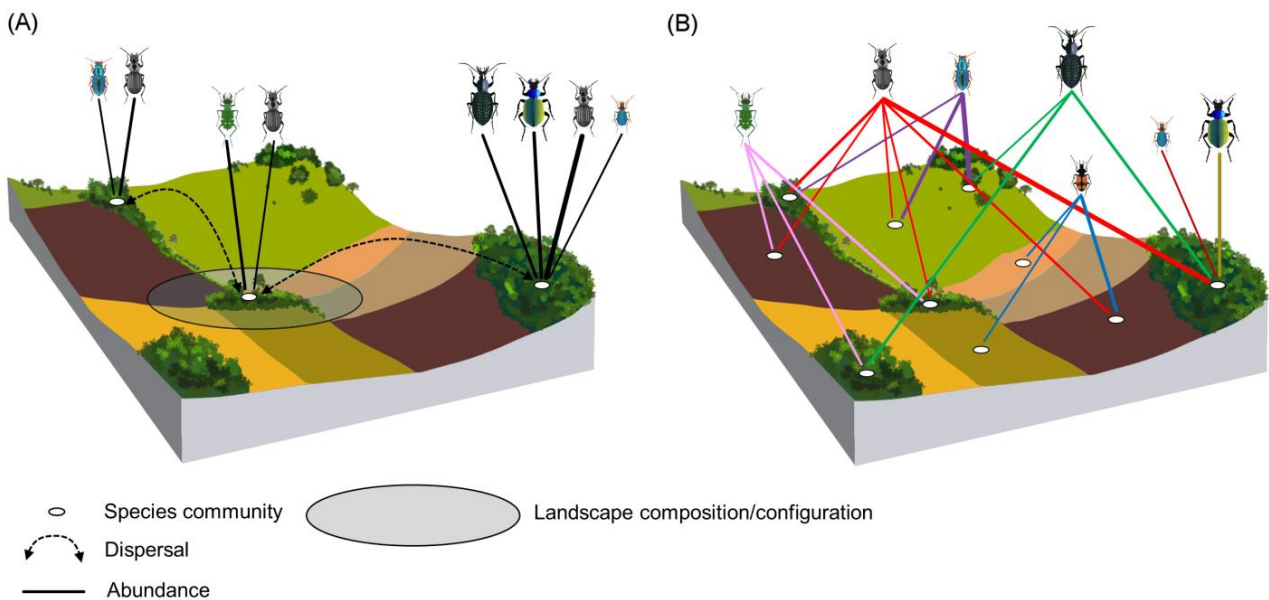
- 365 Neu, C. W. et al. 1974. A Technique for analysis of utilization-availability data. - *J. Wildl. Manage.* 38: 541–  
366 545.
- 367 Olesen, J. M. et al. 2007. The modularity of pollination networks. - *Proc. Natl. Acad. Sci. U. S. A.* 104:  
368 19891–6.
- 369 Ricketts, T. H. 2001. The matrix matters: effective isolation in fragmented landscapes. - *Am. Nat.* 158: 87–  
370 99.
- 371 Ricketts, T. H. et al. 2008. Landscape effects on crop pollination services: are there general patterns? - *Ecol.*  
372 *Lett.* 11: 499–515.
- 373 Schellhorn, N. A. et al. 2015. Time will tell: resource continuity bolsters ecosystem services. - *Trends Ecol.*  
374 *Evol.* 30: 524–530.
- 375 Schleuning, M. et al. 2012. Specialization of mutualistic interaction networks decreases toward tropical  
376 latitudes. - *Curr. Biol.* 22: 1925–1931.
- 377 Sole, R. V. and Montoya, M. 2001. Complexity and fragility in ecological networks. - *Proc. R. Soc. B Biol.*  
378 *Sci.* 268: 2039–2045.
- 379 Steffan-Dewenter, I. et al. 2002. Scale-dependent effects of landscape context on three pollinator guilds. -  
380 *Ecology* 83: 1421–1432.
- 381 Tews, J. et al. 2004. Animal species diversity driven by habitat heterogeneity/diversity: the importance of  
382 keystone structures. - *J. Biogeogr.* 31: 79–92.
- 383 Thébault, E. and Fontaine, C. 2010. Stability of ecological communities and the architecture of mutualistic  
384 and trophic networks. - *Science* 329: 853–6.
- 385 Tschamntke, T. et al. 2005. Landscape perspectives on agricultural intensification and biodiversity -  
386 Ecosystem service management. - *Ecol. Lett.* 8: 857–874.
- 387 Tschamntke, T. et al. 2012. Landscape moderation of biodiversity patterns and processes - eight hypotheses. -  
388 *Biol. Rev.* 87: 661–685.

- 389 Turner, M. G. 2005. Landscape ecology: What is the state of the science? - *Annu. Rev. Ecol. Evol. Syst.* 36:  
390 319–344.
- 391 Vizentin-Bugoni, J. et al. 2016. Influences of sampling effort on detected patterns and structuring processes  
392 of a Neotropical plant-hummingbird network. - *J. Anim. Ecol.* 85: 262–272.
- 393 Wiens, J. A. 1995. Landscape mosaics and ecological theory. - In: *Mosaic Landscapes and Ecological*  
394 *Processes*. Springer Netherlands, pp. 1–26.
- 395 Wiens, J. A. et al. 1993. Ecological mechanisms and landscape ecology. - *Oikos* 66: 369–380.
- 396

397 **FIGURES**

398

399 **Figure 1.** (A) Current spatial approach to study species community dynamics across heterogeneous  
400 landscapes. Meta-community ecology focuses on patches of one focal habitat embedded in a homogenous  
401 hostile matrix and linked through dispersal (black dotted arrows). Most empirical research in landscape  
402 ecology focuses on local habitat vs. landscape mosaic, where the landscape is quantified in terms of  
403 composition and/or configuration around a central point where the community is sampled (shadow buffer).  
404 Neither approach accounts for the interactions between multiple species and habitats outside the focal  
405 habitat. (B) The species-habitat network whereby the whole landscape is sampled and the species are  
406 quantified at multiple sites (line width proportional to species abundance). The landscape can be classified in  
407 patches according to the functional role of the different habitats for the target species community. If species  
408 do not occupy readily identifiable habitat patches, a continuous variation in habitat quality and available  
409 resources around the sampling sites can replace the discrete habitat categorization.



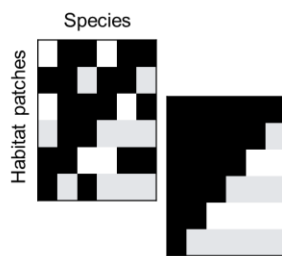
410

411

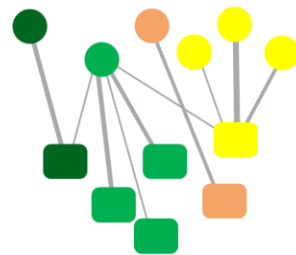
412 **Figure 2.** An untapped network toolbox for assessing species-habitat links. Bipartite network analysis is a  
413 mature field able to identify emerging properties of a system (A-D) as well as the roles that individual nodes  
414 (species or habitat sites) play in the network (E-H). Circles and rectangles represent species and habitat sites,  
415 respectively. Here, we present only a few examples of the metrics that can be computed (Blüthgen et al.  
416 2006, Dormann et al. 2009). See text for details.

Whole network topology

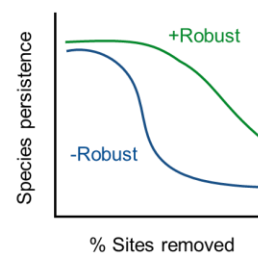
(A) Nestedness



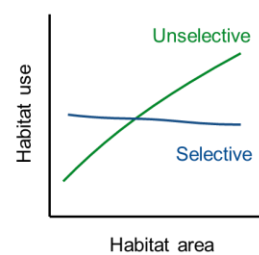
(B) Modularity



(C) Robustness

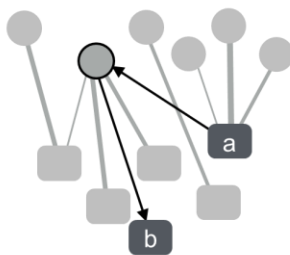


(D) Selectivity

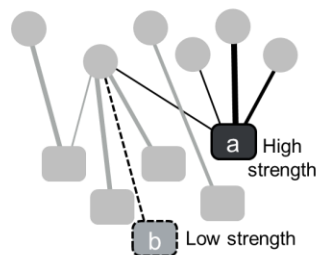


Role of single nodes

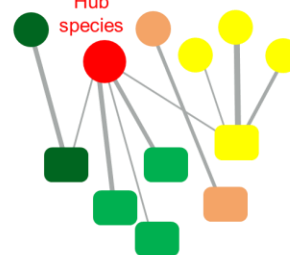
(E) Influence



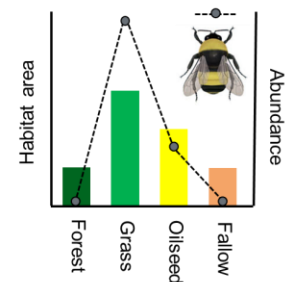
(F) Strength



(G) Connectivity ( $c$ )



(H) Selectivity ( $d'$ )



417