

# Journal of Animal Ecology

The relative importance of local and regional processes to  
metapopulation dynamics

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**Running title:** Local & regional metapopulation drivers

**Author contributions:** TAD designed the study and performed the analyses. All authors contributed to manuscript writing.

**Acknowledgments:** We thank the coordinators and volunteers who participated in the Åland island survey since 1993. The research was funded by the Academy of Finland (grant 309581 to OO), the Research Council of Norway (SFF-III grant 223257), and the European Research Council (Independent Starting grant no. 637412 'META-STRESS' to MS). The Research Centre for Ecological Change is funded by the Jane and Aatos Erkkö Foundation.

**Conflict of interest:** The authors have no conflicts of interest to declare.

**Keywords:** Patch occupancy, Spatial network structure, Species distribution, Metapopulation, Graph theory, Connectivity

**Data accessibility:** *R* code is available on figshare at <https://doi.org/10.6084/m9.figshare.7667096>.

## 1 Abstract

- 2 1. Metapopulation dynamics – patch occupancy, colonization, and extinction  
3 – are the result of complex processes at both local (e.g., environmental  
4 conditions) and regional (e.g., spatial arrangement of habitat patches) scales.  
5 A large body of work has focused on habitat patch area and connectivity  
6 (area-isolation paradigm). However, these approaches often do not incorporate  
7 local environmental conditions, or fully address how the spatial arrangement  
8 of habitat patches (and resulting connectivity) can influence metapopulation  
9 dynamics.
- 10 2. Here, we utilize long-term data on a classic metapopulation system – the  
11 Glanville fritillary butterfly occupying a set of dry meadows and pastures in  
12 the Åland islands – to investigate the relative roles of local environmental  
13 conditions, geographic space, and connectivity in capturing patch occupancy,  
14 colonization, and extinction. We defined connectivity using traditional measures  
15 as well as graph theoretic measures of centrality. Using boosted regression  
16 tree models, we find roughly comparable model performance among models  
17 trained on environmental conditions, geographic space, or patch centrality.
- 18 3. In models containing all of the covariates, we find strong and consistent  
19 evidence for the roles of resource abundance, longitude, and centrality (i.e.,  
20 connectivity) in predicting habitat patch occupancy and colonization, while  
21 patch centrality (connectivity) was relatively unimportant for predicting  
22 extinction. Relative variable importance did not change when geographic  
23 coordinates were not considered and models underwent spatially-stratified  
24 cross validation.
- 25 4. Together, this suggests that the combination of regional scale connectivity  
26 measures and local-scale environmental conditions are important for predicting  
27 metapopulation dynamics, and that a stronger integration of ideas from  
28 network theory may provide insight into metapopulation processes.

## 29 Introduction

30 Species often occupy only a portion of potential habitat within their geographic  
31 range (MacArthur, 1984). This is especially true when species occupy small  
32 and fragmented habitats within a landscape, resulting in temporally dynamic  
33 occurrence across the set of interconnected habitat patches i.e., a metapopulation  
34 (Hanski, 1994a, 1999b). A large body of theory has emerged from the metapopulation  
35 concept at scales from examinations of entire metapopulations (Gotelli, 1991;  
36 Gilarranz & Bascompte, 2012), semi-independent networks (Hanski *et al.*, 2017),  
37 individual habitat patches (Ovaskainen & Hanski, 2003; Ovaskainen, 2017), and  
38 individuals within habitat patches (Ovaskainen & Hanski, 2004). The continued  
39 interest in metapopulations has produced many testable hypotheses concerning  
40 patch occupancy and dynamics (Ovaskainen & Saastamoinen, 2018), and how  
41 these quantities relate to metapopulation structure (Thomas, 1994; Hanski, 2001).

42 Naturally, there are many variables that interact to produce species occurrence in  
43 a given habitat patch (Guisan & Thuiller, 2005; Elith & Graham, 2009). However,  
44 despite this complexity, habitat patch area has emerged as a consistently good  
45 predictor of metapopulation dynamics (Hanski, 1994a; Thomas & Harrison, 1992;  
46 Hill, Thomas & Lewis, 1996). Habitat patch area, and associated area-isolation  
47 paradigm (Hanski, 1994a), has been linked to enhanced species persistence (Etienne,  
48 2004) and colonization (Fleishman *et al.*, 2002), while also decreasing the probability  
49 of local extinction (Fleishman *et al.*, 2002; Hanski, 1994b; Day & Possingham,  
50 1995). Much of this rests on the assumption that larger habitats can support  
51 larger populations and represent a larger target for incoming propagules from  
52 nearby patches (Ovaskainen & Saastamoinen, 2018); an assumption with mixed  
53 support (Bowman, Cappuccino & Fahrig, 2002; Rabasa, Gutiérrez & Escudero,  
54 2008; Anderson & Meikle, 2010). Despite a focus on patch area, other variables

55 are certainly related to metapopulation dynamics (Mortelliti, Amori & Boitani,  
56 2010). For instance, the spatial position of habitat patches has been linked with  
57 patch occupancy (Ims, Petter Leinaas & Coulson, 2004; MacKenzie *et al.*, 2017),  
58 as patches in certain areas may be more likely to be colonized (or rescued) by  
59 immigration (Eriksson *et al.*, 2014). Spatial position may additionally serve as a  
60 proxy for some unmeasured aspect of habitat quality or environmental constraints  
61 on species occurrence. Further, local dynamics may be driven by ecological interactions  
62 and resource limitation, such that patch occupancy in a given habitat patch  
63 could be a result of interactions with competitors (Connor & Simberloff, 1979;  
64 Hamel *et al.*, 2013), resource limitation (Dennis & Eales, 1999; Dennis, Shreeve &  
65 Van Dyck, 2003), or natural enemies (Steffan-Dewenter & Schiele, 2008). Lastly,  
66 metapopulation dynamics could be a result of habitat patch connectivity driven  
67 by physical distance of the patches and/or by the dispersal ability of the focal  
68 species, suggesting that spatial network statistics may explain patch occupancy  
69 (Gilarranz & Bascompte, 2012; Grilli, Barabás & Allesina, 2015).

70 Measures of habitat patch importance in spatial networks have been developed  
71 largely outside of the realm of metapopulation ecology, despite measuring similar  
72 – and sometimes equivalent – properties (see (Urban *et al.*, 2009) and Box 1).  
73 So what benefit do we obtain from using measures from graph theory in place  
74 of, or in addition to, existing measures of the importance of a habitat patch  
75 to the metapopulation, such as patch contribution to metapopulation capacity  
76 (Ovaskainen & Hanski, 2003)? Measures of centrality attempt to quantify flow  
77 of information or individuals between habitat patches, but centrality itself can be  
78 measured in many different ways. That is, measures can be quite local (focused  
79 only on the immediate connections of a given habitat patch with other patches  
80 in the immediate vicinity) or global (incorporating information on the spatial

81 distribution of all habitat patches in the network and the connections between  
82 them). This is advantageous as ecological processes may occur at both of these  
83 scales simultaneously. One clear example of the potential benefits of using graph  
84 theoretic centrality measures in place of existing connectivity measures is in the  
85 case of 'stepping stone' habitat patches (Bodin & Saura, 2010), which serve to  
86 connect two habitat patches which otherwise would not be connected by dispersal.  
87 In graph theory, betweenness centrality measures the number of shortest paths  
88 between all pairs of habitat patches in the network which go through a given  
89 habitat patch. This essentially measures, at the network scale, the importance  
90 of a habitat patch as a potential stepping stone. The further integration of  
91 metapopulation ecology and graph theory will greatly advance our understanding  
92 of metapopulation dynamics (Urban *et al.*, 2009).

93 But how important are measures of connectivity – either from graph theory or  
94 from metapopulation ecology – relative to aspects of habitat patch quality, spatial  
95 position, or patch area? Numerous studies have explored the relationship of each  
96 of these factors to metapopulation dynamics (e.g., Hanski (1994a); Fleishman *et al.*  
97 (2002); Prugh *et al.* (2008)), but few have weighed the relative effects of different  
98 covariate groups (but see Rabasa, Gutiérrez & Escudero (2008); Fleishman *et al.*  
99 (2002)). Understanding the relative importance of each of these variable sets  
100 on metapopulation dynamics is a pressing need, as some things change (local  
101 environmental conditions) and some things tend to stay the same (spatial arrangement  
102 of habitat patches). Failing to account for this could lead to inaccurate predictions  
103 concerning metapopulation persistence or misidentification of habitat patch conservation  
104 targets. It is also important to note that habitat patch quality, spatial position, and  
105 habitat patch centrality – which putatively determine metapopulation dynamics –  
106 likely interact to produce spatial variation in habitat patch occupancy, colonization,

107 and extinction processes. For instance, resource limitation may only control patch  
108 occupancy in a given habitat if enough individuals are present and able to disperse  
109 to the habitat. This density-dependence would result in an interaction between  
110 resource availability and habitat patch isolation. As such, approaches capable of  
111 estimating the relative importance of local (e.g., environmental conditions) and  
112 regional (e.g., spatial arrangement of patches) factors are needed to advance our  
113 understanding of metapopulation dynamics.

114 Here, we address two current shortcomings in examinations of metapopulation  
115 dynamics. First, we provide a clear link between graph-theoretic measures (i.e.,  
116 centrality) to connectivity as defined in metapopulation ecology. Second, we  
117 examine the relative influence of geographic position, habitat (e.g., resource availability),  
118 and patch connectivity on metapopulation dynamics. To do this, we utilize data  
119 from a classic well-studied ecological metapopulation, the Glanville fritillary metapopulation  
120 in the Åland islands (Ojanen *et al.*, 2013; Hanski *et al.*, 2017). While numerous  
121 studies have examined the influence of patch-level *or* network-level covariates on  
122 metapopulation processes, weighing the relative importance of different covariate  
123 groups is far more rare, despite the potential for synergistic effects (see Table  
124 1). Our aim is to quantify the contributions of patch area, spatial location,  
125 local habitat-level variables, and connectivity (i.e, patch centrality in the dispersal  
126 network) on patch occupancy (fraction of times a patch was occupied), colonization,  
127 and extinction. In doing so, we highlight the similarities between measures of  
128 connectivity and centrality (Box 1), and explore whether measures derived from  
129 metapopulation theory and graph theory are correlated, or whether they measure  
130 fundamentally different aspects of the network properties (Minor & Urban, 2007;  
131 Urban *et al.*, 2009). Further, we provide evidence for the importance of local  
132 habitat conditions and connectivity in driving metapopulation dynamics, suggesting

133 that the combination of local environmental conditions with measures of dispersal  
134 connectivity may best explain metapopulation dynamics (see Table 1). The continued  
135 integration of graph theoretic measures and flexible statistical approaches that  
136 allow estimation of relative variable importance will enhance our understanding  
137 of the relative roles of geography, environment, and dispersal to metapopulation  
138 dynamics.

### Box 1: Linking metapopulation statistics and graph theory

The development of theory related to metapopulations and spatial graphs – despite the striking similarities in application – has been largely separate (but see (Urban *et al.*, 2009; Dale & Fortin, 2010)). This has led to the development of statistics different in name, but identical (or quite similar) in application. For instance, habitat patch connectivity ( $S_i$ ; Equation 1) is a measure from metapopulation ecology, and quantifies the total immigration potential into a given habitat patch (Hanski, 1999a). This considers the receiving patch area scaled by some constant  $im$ , a negative exponential dispersal kernel ( $e^{-\alpha d_{ij}}$ ), and the influence of the donor patch area raised to an emigration term ( $A_j^{em}$ ).

$$S_i = \sum_{j \neq i} A_i^{im} e^{-\alpha d_{ij}} A_j^{em} \quad (1)$$

If we consider the links between habitat patches in the spatial network as potential dispersal pathways, the edge between two patches in the network can be defined according to that same negative exponential dispersal kernel, and patch area can be included in these link weights if the influence of habitat patch area on immigration and emigration is well understood (Hanski *et al.*, 2017). Then, a measure from graph theory, weighted degree centrality (sometimes referred to as



*strength*) is quantified by summing the edges going into a given habitat patch. This is equivalent to connectivity measures as developed in metapopulation ecology, dependent on how patch area is incorporated, and whether degree centrality is calculated on a directed graph (i.e., dispersal pathways between two nodes are non-equal). Further, degree centrality is not the only form of centrality in graph theory, and each different formulation of centrality captures some unique aspect of centrality. Degree centrality inherently captures local dynamics, as it is concerned with direct connections of a given habitat patch. However, other measures utilize information on the entire network and connections between other nodes. For example, betweenness centrality measures the importance of habitat patches as bridges between other habitat patches, which is important to conservationists and managers when designing reserves, especially for migratory species (Fall *et al.*, 2007). Further, betweenness centrality may better capture the tendency for patches to maintain connections between patches too far apart to be connected. Meanwhile, closeness centrality, which measures the mean shortest path distance between a patch to all other habitat patches, may capture spatial aggregation of habitat patches, with the potential to be a better predictor of metapopulation dynamics than more local measures of connectivity (e.g., degree centrality).

Another example of this is the close relationship between the contribution of a habitat patch to overall metapopulation capacity ( $\lambda_i$ ), developed in the study of metapopulations, and eigenvector centrality from graph theory. While not directly analogous, both use a eigenvector decomposition of the dispersal network to estimate the importance of each habitat patch to the overall structure of the spatial network. Using the Åland metapopulation as an example, we see the clear positive relationship between habitat patch contribution to metapopulation capacity

(Ovaskainen, 2003; Grilli, Barabás & Allesina, 2015) and eigenvector centrality (Figure 1). A more direct example, though less often used currently, is the hub score (Kleinberg, 1999), which is nearly identical to metapopulation capacity. The only difference is that metapopulation capacity is calculated on the dispersal matrix ( $\mathbf{M}$ ) and the hub score is calculated on the positive definite matrix obtained by multiplying the matrix by its transpose ( $\mathbf{M} \times \mathbf{M}^T$ ).

The theory developed for the study of networks – even solely the development of theory related to spatial graphs – is more general and more broadly utilized than the theory of metapopulations (Newman, 2003; Barthélemy, 2011), despite the fact that metapopulations are clear examples of spatial graphs. The application of approaches from graph theory may provide further insight into metapopulation structure and resulting metapopulation dynamics.

141

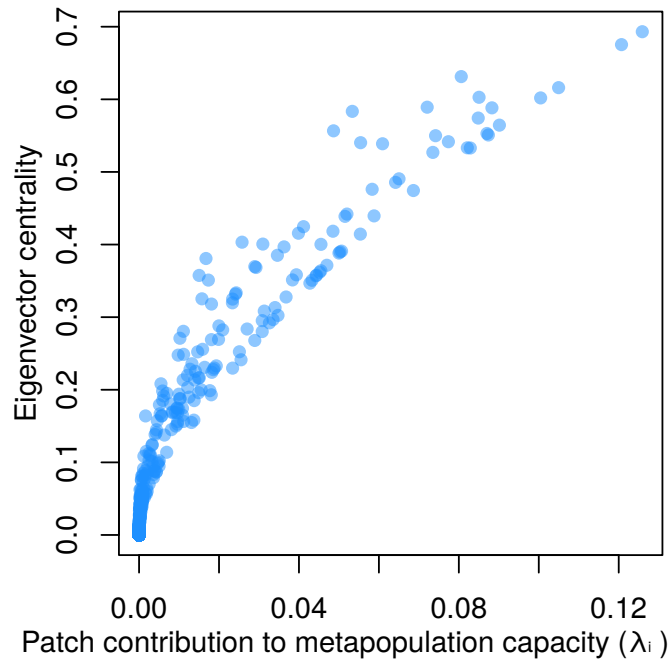


Figure 1: A strong positive relationship exists between patch contribution to metapopulation capacity ( $\lambda_i$ ) and eigenvector centrality. Each point corresponds to a habitat patch in the Åland island metapopulation system. Eigenvector centrality was based on a dispersal network formed assuming an exponential decay in dispersal probability between patches ( $\alpha = 1$  and  $p = 0.001$ , as described further in the *Spatial network formation* section).

## 142 **Methods**

### 143 **Glanville fritillary metapopulation**

144 In the Åland islands, a set of nearly 5000 habitat patches have been monitored  
145 annually since 1993. The habitat in the Åland Islands is highly fragmented and  
146 the butterfly has a classic metapopulation structure with a high rate of population  
147 turnover – i.e., extinctions and re-colonizations (Hanski, 1999b, 2011). However,  
148 as some habitat patches were not surveyed for the entire duration of the study, we  
149 restrict our analyses to patches surveyed between 2000 - 2017, resulting in a total  
150 of 4652 habitat patches distributed broadly across the Åland islands. However,  
151 for patches for which environmental data was available prior to 2000, we included  
152 these years to estimate the mean environmental conditions. Each habitat patch is  
153 a dry meadow or pasture occupied by one or more host plant species – *Plantago*  
154 *lanceolata* or *Veronica spicata* – which serve as a larval food source and oviposition  
155 resource to the butterfly of interest, *Melitaea cinxia*.

156 The dry meadows and pastures have been surveyed for the presence and numbers  
157 of larval groups during fall (Hanski, 1999b, 2011). This is possible as the females  
158 of the Glanville fritillary butterfly lay clutches of eggs, the larvae live gregariously,  
159 and at the end of the summer the larvae build a conspicuous “winter nest” at  
160 the base of the host plant inside which they diapause overwinter in groups of  
161 mainly full sibs (Kuussaari *et al.*, 2004; Fountain *et al.*, 2018). Each fall all of  
162 the potential habitat patches are surveyed for the presence of these larval nests  
163 (see (Ojanen *et al.*, 2013) for details of the survey). Based on control surveys  
164 it has been estimated that the presence of the butterfly is not detected in up  
165 to 15% of occupied patches with non-detection mainly occurring in very small  
166 populations (Hanski *et al.*, 2017). Based on the long term data we know that

167 all local populations are more or less ephemeral, due to being very small and  
168 commonly having just a single or a few larval groups in a given year (Hanski,  
169 1999b, 2011).

## 170 **Patch occupancy, colonization, and extinction**

171 Occupancy was quantified as the fraction of times a habitat patch was occupied  
172 by *M. cinxia* during the survey. This provides insight into how often a given habitat  
173 patch contributed to metapopulation dynamics, as more frequently occupied patches  
174 are likely more important to enhancing metapopulation persistence and providing  
175 propagules to other nearby patches. The spatial distribution of patch occupancy  
176 clearly identifies hotspots of habitat patches which maintain the metapopulation  
177 (Figure 2).

178 Colonization rate captures how fast a habitat patch becomes re-colonized after  
179 a local extinction. We quantified colonization probability as the number of times  
180 that *M. cinxia* was present when it did not occur in the previous sampling period  
181 divided by the total number of possible colonization events (i.e., the number of  
182 sampling periods where the species was absent, not considering the most recent  
183 sampling period). Extinction probability was measured in a similar manner,  
184 calculated as the number of times a species was recorded as absent when it  
185 was observed in that patch in the prior sampling period, divided by the total  
186 number of potential extinction events. Patches with high turnover – those that  
187 are colonized and go extinct often – may simply be sinks for propagules from more  
188 persistent patches. On the other hand, these patches may contribute strongly  
189 to metapopulation persistence if they serve as temporary spillover habitats or  
190 provide dispersal connections with more distant patches (Howe, Davis & Mosca,  
191 1991; Hanski & Simberloff, 1997).

192 The full number of habitat patches ( $n = 4652$ ) was used for analyses of patch  
193 occupancy. Habitat patches that were never occupied ( $n = 2595$ ), and those  
194 that remained occupied for the entire sampling duration ( $n = 21$ ) were removed  
195 from calculation of colonization and extinction, resulting in 2057 and 4631 habitat  
196 patches, for examinations of colonization and extinction, respectively.

## 197 **Defining the spatial network**

198 Habitat patches exist in a mosaic of inhospitable habitat to *M. cinxia*, and links  
199 between habitat patches represent potential dispersal pathways. Based on previous  
200 research (Hanski *et al.*, 2017) we considered dispersal probability to decay exponentially  
201 with geographic distance between habitat patches. We constructed a network  
202 based on this exponential decay ( $\alpha = 1 \text{ km}^{-1}$ ), and removed links below a threshold  
203 dispersal probability ( $p = 0.001$ ). We examine the sensitivity of the resulting  
204 dispersal network structure in the Supplemental Material, finding no appreciable  
205 difference in patch connectivity estimates (see Figure S1). Patch area may influence  
206 dispersal probability and subsequent links between habitat patches in the network  
207 (Hanski, 2001; Hanski *et al.*, 2017). We incorporated the influence of patch area  
208 on the structure of the dispersal network by modifying the negative exponential  
209 dispersal kernel, where links between two habitat patches were defined as a function  
210 of the area of both patches ( $A_i$  and  $A_j$ ), both of which were raised to constants  
211 obtained from previous studies (Hanski *et al.*, 2017), which represent the relationships  
212 between patch area and immigration ( $im = 0.3$ ) and emigration ( $em = 0.3$ ) rates  
213 (see Equation 1). This is discussed further in Box 1, which conceptually links  
214 measures of centrality to existing concepts in metapopulation ecology. We found  
215 qualitatively similar results when habitat patch area was not allowed to influence  
216 dispersal links (see Supplemental Materials).

## 217 **Variables influencing patch occupancy, colonization, and extinction**

218 We divided variables into four different groups, in order to compare model performance  
219 among variable groups, while also considering a full model including all variables.  
220 We also consider every combination of the variable groups in the Supplemental  
221 Materials, providing even further support for our conclusions. The variable groups  
222 consisted of *patch area* (a baseline model which only considers the log-transformed  
223 habitat patch area), *habitat* (containing local patch level environmental variables),  
224 *spatial* (containing spatial position of each habitat patch), and *network* (containing  
225 measures of patch centrality). Expected relationships between variable groups and  
226 metapopulation dynamics are provided in Table 1, and each of the variable groups  
227 are outlined in Table 2, with each variable described below.

228 Patch area was estimated during sampling, with the median patch area being  
229 approximately 0.6 ha. The spatial location of each habitat patch was mapped with  
230 GPS during the survey (Ojanen *et al.*, 2013). Grazing pressure was estimated as  
231 the estimated fraction of the habitat patch subjected to grazing pressure based on  
232 observations of damaged plants or the presence of grazers (e.g., ungulates). We  
233 quantified resource availability as the mean abundance, and the summed mean  
234 abundance of the two host plants (*Plantago lanceolata* and *Veronica spicata*),  
235 where abundance of each host plant was estimated based on an ordinal scale  
236 between 0 and 3, with larger values corresponding to a greater plant abundance.  
237 Previous findings in a rodent herbivore metapopulation suggest that temporal  
238 variability in resources can influence metapopulation dynamics (Fernández, Román  
239 & Delibes, 2016). We explore this in the Supplemental Materials by calculating  
240 the standard deviation in total resource availability (the summed abundance of  
241 both host plants). We find little evidence that variability in resource abundance  
242 influences metapopulation dynamics (see Supplemental Materials for further analyses

243 and discussion), suggesting that species life history may play a large role in estimating  
244 the relative importance of spatial and environmental variables on metapopulation  
245 dynamics (Fernández, Román & Delibes, 2016). Resource quality may be reduced  
246 as a function of infection by a powdery mildew pathogen, which has been found  
247 to reduce *M. cinxia* larval development over the summer (Rosa *et al.*, 2018) and  
248 influence overwintering survival (Laine, 2004). Mildew infection was estimated by  
249 quantifying the fraction of times mildew pathogen was detected in each habitat  
250 patch.

251 Habitat patch importance in the spatial network was estimated using patch  
252 centrality measures. Specifically, we examined four common centrality measures,  
253 each capturing different aspects of habitat patch importance in the dispersal  
254 network (**M**; equations for each connectivity measure are provided in the Supplemental  
255 Materials). First, weighted degree centrality – also called *strength* – measures  
256 the summed links (dispersal pathways) for each habitat patch. This measures  
257 the immediate connections to neighboring patches. Next, we considered closeness  
258 centrality, which incorporates the structure of the overall network, measuring the  
259 average shortest path distance between each habitat patch to all other habitat  
260 patches. Habitat patches with large closeness values would be well connected to  
261 other patches in the context of the entire network, while degree centrality measures  
262 habitat patch importance in a neighborhood context. Next, we considered betweenness  
263 centrality, which measures the number of shortest paths between habitat patches  
264 that go through a given habitat patch. This is important, as habitat patches with  
265 high betweenness may serve as stepping stones between two otherwise unconnected  
266 habitats. Lastly, we measured eigenvector centrality, which measures the importance  
267 of habitat patches as defined by the importance of connected habitat patches. That  
268 is, a habitat patch may not be strongly connected to many other habitats, but be



269 connected to a patch that is quite well connected to other patches (i.e., serves an  
270 important role in the metapopulation). This could occur when a patch is spatially  
271 removed from much of the spatial network, but connected to nearby patches which  
272 are more well connected to other habitat patches.

### 273 **Boosted regression tree models**

274 Boosted regression tree (BRT) models were used to assess how patch area, geographic  
275 space, habitat-level variation, and patch centrality influence *M. cinxia* occupancy  
276 and colonization using the `gbm` R package (with contributions from others, 2017).  
277 This modeling approach has been used previously for prediction (Elith, Leathwick  
278 & Hastie, 2008; De'Ath, 2007), in part because it allows for non-linear responses  
279 and variable interactions. Since the regression tree is hierarchical, "upstream"  
280 splits based on one variable influence "downstream" splits, which automatically  
281 models variable interactions. Further, the process of *boosting* enhances learning on  
282 complex data, as the process produces many regression trees with a small number  
283 of splits, each of these "weak learners" iteratively build on previous trees to account  
284 for the remaining variation. This approach removes the need to partition variance  
285 among submodels, as the goal is not to examine the components of variance  
286 explained, but to assess overall model performance with the inclusion or exclusion  
287 of particular variable sets.

288 For each of the four covariate groups and the full model containing all covariates,  
289 models were trained, cross-validated, and evaluated for performance five times  
290 (each on a different random subset of 80% of the data) to examine the consistency  
291 of model performance and covariate relative importance. Models were trained  
292 using a maximum of 50,000 trees, with a learning rate of 0.001 (Elith, Leathwick &  
293 Hastie, 2008), Gaussian error structure, and an interaction depth of 3, which allows

294 for interactions between covariates. All models were internally cross-validated  
295 (5-fold) to determine the optimal number of regression trees.

296 Models were trained on 80% of the data, and the remaining 20% was used  
297 to assess model performance. Accuracy was quantified using Spearman's rank  
298 correlations between predicted values from the trained model and the empirical  
299 estimates of occupancy, colonization or extinction for each habitat patch in the  
300 20% of the data which was used for testing (i.e., those data that were not used  
301 for model training). In the Supplemental Materials, we further quantify accuracy  
302 using Pearson's correlation and root mean square error (RMSE).

303 It is possible that spatial autocorrelation in metapopulation dynamics could lead  
304 to model overfitting when trained on spatial coordinate data. This would inflate  
305 the relative contribution of latitude and longitude in the full models, and lead to  
306 the spatial submodel appearing to perform well, when in fact it is simply fitting to  
307 spatial variation. While this could be informative if system-specific prediction was  
308 the goal, the ability of the model to extrapolate would be compromised. To explore  
309 the effect of spatial predictors on model transferrability, we also performed the  
310 cross validation by dividing the data spatially into five longitudinal folds (models  
311 were trained on four, and used to predict the remaining data).

312 The relative importance of each predictor variable in the full model containing  
313 all the covariates was estimated by quantifying the relative improvement to model  
314 fit as a result of the inclusion of a given covariate into the model, weighted by  
315 the number of trees in which the covariate occurred (Elith, Leathwick & Hastie,  
316 2008; De'Ath, 2007). The resulting relative contribution values are scaled between  
317 0 and 100, with larger numbers corresponding to higher variable importance, and  
318 the relative importance of all covariates summing to 100. To assess how important

319 covariates influenced model predictions, we examined partial dependence plots,  
320 which capture the influence of a given variable on occupancy or colonization after  
321 accounting for other covariates (Elith, Leathwick & Hastie, 2008). Data and code  
322 to reproduce the analyses is provided at <https://doi.org/10.6084/m9.figshare.7667096>.

## 323 Results

324 Boosted regression tree model performance differed as a function of covariate  
325 group, with models trained on patch area generally performing the worst, and the  
326 model including all covariates performing best (Figure 3). The remaining models  
327 – consisting of local habitat variables, geographic location, or patch centrality –  
328 performed approximately equivalently (Figure 3). Considering all combinations  
329 of submodels, we find that the full model typically performed best, though in  
330 some cases the inclusion of patch area in the full model actually reduces model  
331 performance slightly, as does the geographic coordinates of the habitat patches (see  
332 Supplemental Materials). This suggests that the most important covariate sets  
333 to estimating metapopulation dynamics are local environmental conditions and  
334 habitat patch centrality (connectivity) measures (see Supplemental Materials for  
335 an expanded discussion). Model performance generally decreased when data were  
336 spatially stratified during 5-fold cross validation (open circles in Figures 3 and 4),  
337 suggesting the existence of a spatial signal in patch area, habitat characteristics,  
338 and spatial network structure. This spatial signal could exist through spatial  
339 autocorrelation, or because the effect of the covariate on metapopulation dynamics  
340 differs across space. Despite the existence of a spatial signal that influenced all  
341 submodels (e.g., the *habitat* model in Figure 3), the model including all variables  
342 tended to still outperform the submodels, and relative variable importance in  
343 these models was essentially unchanged by the cross-validation approach (Figure

344 4). However, the *habitat* model tended to perform just as well as the full model  
345 when models were spatially cross-validated, suggesting the importance of the local  
346 habitat on metapopulation dynamics (Figure 3).

347 Model performance and ranking were insensitive to the measure of model performance  
348 used (see Supplemental Materials). For models of extinction probability, the  
349 model containing local habitat covariates performed quite well, and submodels  
350 were relatively unaffected by the spatially stratified cross validation (Figure 3).  
351 Together, our findings suggest that patch occupancy, colonization, and extinction  
352 may be estimated to an approximately equal extent from detailed data on local  
353 habitat patch quality (*habitat* model) or more regional measures of patch connectivity  
354 (*network* model), but that joint effects between variables necessitate the inclusion  
355 of both local scale habitat variables and regional scale patch connectivity.

## 356 **Variables influencing patch occupancy, colonization, and extinction**

357 While many of the models trained on different covariate groups performed nearly  
358 equivalently (Figure 3), the relative importance of covariates in the full model  
359 under random cross-validation suggests that resource availability, longitude, and  
360 degree centrality were the dominant contributors to model performance (Figure  
361 4). When latitude and longitude were not included in the spatially cross-validated  
362 models, the key predictors remained quite similar (i.e., resources and degree centrality).  
363 Eigenvector centrality, a measure of connectivity which incorporates information  
364 on connections of patches which a focal node is connected to, became more important  
365 in the spatially cross-validated models, potentially as a result of this measure  
366 capturing aspects of the spatial positions of the habitat patches. However, eigenvector  
367 and degree centrality tend to be highly correlated ( $r = 0.48$ ,  $p < 0.001$ ), and are  
368 both similarly related to metapopulation dynamics (Figure S6).

369 The partial dependence plots of each covariate in the full model suggest that  
370 resource availability and degree centrality both were positively related to occupancy  
371 and colonization (Figure S6). However, while resource availability was important  
372 and non-linearly related to extinction probability prediction, no measure of patch  
373 centrality (connectivity) improved the model substantially. The importance of  
374 patch centrality to patch occupancy and colonization relates to the amount of  
375 immigration to a given patch, which is naturally related to patch colonization  
376 probability (Hanski, 1991, 1999b), and could also reduce extinction risk through  
377 rescue effects (Eriksson *et al.*, 2014; Ovaskainen, 2017). However, this effect  
378 appeared weak, as models of extinction containing patch centrality only marginally  
379 outperformed a model containing only patch area (Figure 4), and no patch centrality  
380 measure was in the top three predictive variables in the full model (Figure S6).  
381 When patch area was not allowed to influence patch centrality measures, patch area  
382 became more important in estimating metapopulation dynamics. However, patch  
383 centrality measures still retained an important role in estimating metapopulation  
384 dynamics as well (see Supplemental Materials).

385 Interestingly, the summed resource abundance was more important than the  
386 abundance of either host plant (*P. lanceolata* and *V. spicata*) in isolation, suggesting  
387 the importance of considering the entire resource community instead of simply  
388 the most dominant host plant (*P. lanceolata*). Further, this value of resource  
389 abundance was the top predictor in all three full models of patch occupancy,  
390 colonization, and extinction (Figure 4), suggesting a pronounced effect of resource  
391 availability on metapopulation dynamics. The stronger relative effect of total  
392 resource abundance instead of the abundance of either host plant may relate to  
393 variable feeding preferences of individuals in a population, or behavioral flexibility  
394 in host plant utilization. That is, even if both resource plants were equally suitable

395 resources, low abundance of one resource does not negate the presence of another  
396 suitable resource, making the summed resource abundance a clearer measure of  
397 resource availability for the butterflies.

## 398 **Discussion**

399 Metapopulation dynamics were best captured when both local environmental conditions  
400 and regional scale effects of habitat patch arrangement were considered. Secondly,  
401 while degree centrality – which is equivalent to how connectivity is typically  
402 defined in metapopulation studies – was largely the most important connectivity  
403 measure, other connectivity measures which incorporate more information about  
404 the surrounding network were also important (e.g., eigenvector centrality in models  
405 of occupancy and colonization). Together, this suggests that future research  
406 should incorporate multiple scales of information to understand metapopulation  
407 dynamics. Further, the joint effects of local and regional variables served to  
408 enhance model prediction, as evidenced by the substantial improvement in the full  
409 model relative to models including habitat, spatial, or network variables separately.  
410 Models incorporating local habitat variables, patch centrality, and geographic  
411 location performed nearly equivalently in estimating metapopulation dynamics,  
412 suggesting that the performance of more ecologically meaningful (habitat variables)  
413 models was roughly equivalent to less ecologically meaningful (spatial patch location)  
414 models. This is potentially due to systematic spatial variation in patch quality, the  
415 existence of strong dispersal limitation, or simply a model overfit to spatial data  
416 (see Supplemental Materials). Weighing the relative importance of all covariates  
417 in the full model, we consistently found that resource availability and degree  
418 centrality were important in estimating patch occupancy, colonization, and extinction  
419 probability (though patch area was comparably as important as patch centrality for

420 extinction probability estimation). While network statistics may provide equivalent  
421 performance as more system-specific covariates for predicting patch occupancy  
422 and colonization, it is the combination of spatial processes, resource availability  
423 (Hanski *et al.*, 2017), and patch centrality (connectivity) that, in concert, best  
424 capture overall metapopulation dynamics.

425 The relative importance of network statistics to model performance suggests that  
426 metapopulation dynamics are strongly influenced by the structure of the network  
427 of habitat patches and the dispersal connections between them. This supports  
428 previous findings that patch centrality, independent of habitat patch quality, can  
429 approximate patch occupancy patterns (Hanski, 1991, 2011). However, these  
430 studies have largely focused on the role of patch area as it influences centrality,  
431 a connection which may take a variety of functional forms (Anderson & Meikle,  
432 2010; Hambäck & Englund, 2005) given density-dependence in dispersal processes.  
433 We find that excluding the influence of patch area on centrality measures does tend  
434 to increase the influence of patch area estimates relative to patch centrality, and  
435 reduces the predictive accuracy of the *network* submodel greatly, suggesting that  
436 taking patch size when estimating dispersal connections between habitat patches  
437 is important (see Supplemental Materials). By the same token, the importance of  
438 resource availability suggests an important role for local patch quality on metapopulation  
439 dynamics, and the importance of habitat patch geographic position suggests that  
440 dispersal limitation and historical patch occupancy can influence resulting metapopulation  
441 dynamics. Lastly, the relative unimportance of patch connectivity to extinction  
442 probability may provide a further signal of the importance of scale, as occupancy  
443 and colonization may be more dependent on regional scale processes connecting  
444 habitat patches to one another, while extinction may be far more dependent on  
445 local environmental conditions, such as resource availability (Franzén & Nilsson,

2010) (but see (Rabasa, Gutiérrez & Escudero, 2008)). That is, while connectivity may rescue populations from extinction, patch extinction probability may ultimately be more a function of local environmental conditions than patch connectivity.

Apart from considering both local patch-scale processes and regional processes simultaneously, it is important to consider how dynamic or successional habitats can influence metapopulation dynamics (Hodgson, Moilanen & Thomas, 2009). That is, patch occupancy, colonization, and extinction were calculated under the assumption that the habitat did not change substantially, and that mean quantities accurately captured patch quality. We partially addressed the issue of dynamic environments by considering variation in resource abundance, which was found to be unimportant to estimating metapopulation dynamics (see Supplemental Material). Apart from dynamic habitats, numerous layers of complexity have been added to the existing patch area - connectivity paradigm, including incorporating informed or aggregated dispersal (Conradt *et al.*, 2000; Smith & Peacock, 1990), matrix habitat quality (Kuussaari, Nieminen & Hanski, 1996; Ricketts, 2001), and genetic information (Fountain *et al.*, 2018; Lamy *et al.*, 2012). The question then becomes, which of these additional layers are among the most important? If prediction of patch occupancy, colonization, and extinction is equally possible using data on spatial position compared to models incorporating patch level habitat variation or genetic data, it seems worthwhile to assess both the reasons behind the similarity, as well as the overall goal of the research. That is, additional layers become unnecessary if prediction of metapopulation dynamics is the goal, as simple measures of habitat patch centrality – even in the absence of habitat patch area – predict dynamics comparably to more highly parameterized models incorporating patch-level covariates. This is not to say that future research on the environmental, spatial, and genetic factors affecting metapopulation dynamics is



472 not warranted. Quite the contrary. However, it would be useful to weigh the effect  
473 of these additional layers relative to basic models incorporating only information  
474 on patch area or network structure, as these simple models can provide benchmarks  
475 to assess the relative importance of additional factors.

476 Metapopulation ecology shares numerous conceptual and analytical commonalities  
477 with landscape ecology (DiLeo, Husby & Saastamoinen, 2018; Howell *et al.*, 2018)  
478 and network ecology (Box 1 and (Urban & Keitt, 2001; Urban *et al.*, 2009)).  
479 Bridging these disciplines can provide conceptual synthesis and lead to a better  
480 understanding of patch occupancy patterns (Urban & Keitt, 2001; Rozenfeld *et al.*,  
481 2008; Gilarranz & Bascompte, 2012; Zamborain-Mason *et al.*, 2017). We find  
482 that local scale habitat variables are equally capable of predicting metapopulation  
483 dynamics as regional scale measures of connectivity, but that the best performing  
484 models included both local and regional scale variables together. This result may  
485 not scale to other metapopulation systems. However, differences in the balance  
486 of local scale patch quality and regional scale patch connectivity in other systems  
487 may provide insight into the drivers of metapopulation dynamics. Species life  
488 history becomes important to consider as well, as the dynamics of a species with  
489 narrow environmental tolerance and large dispersal kernel will be much more  
490 controlled by local scale processes than regional connectivity. Overall, our findings  
491 suggest that multi-scale approaches to estimating patch occupancy are important,  
492 especially considering the use of patch occupancy models in conservation decisions  
493 (Lande, 1988; Hanski & Ovaskainen, 2000; Lipcius *et al.*, 2008). Lastly, the use  
494 of statistical tools allowing for non-linear relationships and variable interactions  
495 is important to weighing the relative variable importance. A focus on the ability  
496 to predict metapopulation dynamics is paramount given shifting environmental  
497 conditions and land use changes resulting in non-random habitat patch destruction,

498 deterioration, and alteration to dispersal links among habitat patches.

Accepted Article

## References

- Alexander, H.M., Foster, B.L., Ballantyne, F., Collins, C.D., Antonovics, J. & Holt, R.D. (2012) Metapopulations and metacommunities: combining spatial and temporal perspectives in plant ecology. *Journal of Ecology*, **100**, 88–103.
- Anderson, C.S. & Meikle, D.B. (2010) Genetic estimates of immigration and emigration rates in relation to population density and forest patch area in *Peromyscus leucopus*. *Conservation Genetics*, **11**, 1593–1605.
- Austin, D. (2006) How Google finds your needle in the webs haystack. *American Mathematical Society Feature Column*, **10**, 12.
- Barthélemy, M. (2011) Spatial networks. *Physics Reports*, **499**, 1–101.
- Bodin, Ö. & Saura, S. (2010) Ranking individual habitat patches as connectivity providers: integrating network analysis and patch removal experiments. *Ecological Modelling*, **221**, 2393–2405.
- Bowman, J., Cappuccino, N. & Fahrig, L. (2002) Patch size and population density: the effect of immigration behavior. *Conservation ecology*, **6**.
- Connor, E.F. & Simberloff, D. (1979) The assembly of species communities: chance or competition? *Ecology*, **60**, 1132–1140.
- Conradt, L., Bodsworth, E., Roper, T. & Thomas, C. (2000) Non-random dispersal in the butterfly *Maniola jurtina*: implications for metapopulation models. *Proceedings of the Royal Society of London B: Biological Sciences*, **267**, 1505–1510.
- Dale, M. & Fortin, M.J. (2010) From graphs to spatial graphs. *Annual Review of Ecology, Evolution, and Systematics*, **41**.

- 522 Day, J.R. & Possingham, H.P. (1995) A stochastic metapopulation model with  
523 variability in patch size and position. *Theoretical Population Biology*, **48**,  
524 333–360.
- 525 De’Ath, G. (2007) Boosted trees for ecological modeling and prediction. *Ecology*,  
526 **88**, 243–251.
- 527 Dennis, R.L. & Eales, H.T. (1999) Probability of site occupancy in the large heath  
528 butterfly *Coenonympha tullia* determined from geographical and ecological data.  
529 *Biological Conservation*, **87**, 295–301.
- 530 Dennis, R.L., Shreeve, T.G. & Van Dyck, H. (2003) Towards a functional  
531 resource-based concept for habitat: a butterfly biology viewpoint. *Oikos*, pp.  
532 417–426.
- 533 DiLeo, M., Husby, A. & Saastamoinen, M. (2018) Landscape permeability and  
534 individual variation in a dispersal-linked gene jointly determine genetic structure  
535 in the Glanville fritillary butterfly.
- 536 Elith, J. & Graham, C.H. (2009) Do they? How do they? WHY do they differ?  
537 On finding reasons for differing performances of species distribution models.  
538 *Ecography*, **32**, 66–77.
- 539 Elith, J., Leathwick, J.R. & Hastie, T. (2008) A working guide to boosted  
540 regression trees. *Journal of Animal Ecology*, **77**, 802–813.
- 541 Eriksson, A., Elías-Wolff, F., Mehlig, B. & Manica, A. (2014) The emergence  
542 of the rescue effect from explicit within-and between-patch dynamics in a  
543 metapopulation. *Proc. R. Soc. B*, **281**, 20133127.
- 544 Etienne, R.S. (2004) On optimal choices in increase of patch area and reduction of

- 545 interpatch distance for metapopulation persistence. *Ecological Modelling*, **179**,  
546 77–90.
- 547 Fall, A., Fortin, M.J., Manseau, M. & O'Brien, D. (2007) Spatial graphs: principles  
548 and applications for habitat connectivity. *Ecosystems*, **10**, 448–461.
- 549 Fernández, N., Román, J. & Delibes, M. (2016) Variability in primary productivity  
550 determines metapopulation dynamics. *Proc. R. Soc. B*, **283**, 20152998.
- 551 Fleishman, E., Ray, C., Sjögren-Gulve, P., Boggs, C.L. & Murphy, D.D.  
552 (2002) Assessing the roles of patch quality, area, and isolation in predicting  
553 metapopulation dynamics. *Conservation Biology*, **16**, 706–716.
- 554 Fountain, T., Husby, A., Nonaka, E., DiLeo, M.F., Korhonen, J.H., Rastas, P.,  
555 Schulz, T., Saastamoinen, M. & Hanski, I. (2018) Inferring dispersal across  
556 a fragmented landscape using reconstructed families in the Glanville fritillary  
557 butterfly. *Evolutionary Applications*, **11**, 287–297.
- 558 Franzén, M. & Nilsson, S.G. (2010) Both population size and patch quality affect  
559 local extinctions and colonizations. *Proceedings of the Royal Society of London*  
560 *B: Biological Sciences*, **277**, 79–85.
- 561 Gilarranz, L.J. & Bascompte, J. (2012) Spatial network structure and  
562 metapopulation persistence. *Journal of Theoretical Biology*, **297**, 11–16.
- 563 Gotelli, N.J. (1991) Metapopulation models: the rescue effect, the propagule rain,  
564 and the core-satellite hypothesis. *The American Naturalist*, **138**, 768–776.
- 565 Grilli, J., Barabás, G. & Allesina, S. (2015) Metapopulation persistence in random  
566 fragmented landscapes. *PLoS computational biology*, **11**, e1004251.
- 567 Guisan, A. & Thuiller, W. (2005) Predicting species distribution: offering more  
568 than simple habitat models. *Ecology letters*, **8**, 993–1009.

- 569 Hambäck, P.A. & Englund, G. (2005) Patch area, population density and the  
570 scaling of migration rates: the resource concentration hypothesis revisited.  
571 *Ecology letters*, **8**, 1057–1065.
- 572 Hamel, S., Killengreen, S., Henden, J.A., Yoccoz, N. & Ims, R. (2013)  
573 Disentangling the importance of interspecific competition, food availability, and  
574 habitat in species occupancy: recolonization of the endangered Fennoscandian  
575 arctic fox. *Biological conservation*, **160**, 114–120.
- 576 Hanski, I. (1991) Single-species metapopulation dynamics: concepts, models  
577 and observations. *Metapopulation dynamics: empirical and theoretical*  
578 *investigations*, pp. 17–38. Elsevier.
- 579 Hanski, I. (1994a) Patch-occupancy dynamics in fragmented landscapes. *Trends*  
580 *in Ecology & Evolution*, **9**, 131–135.
- 581 Hanski, I. (1994b) A practical model of metapopulation dynamics. *Journal of*  
582 *Animal Ecology*, pp. 151–162.
- 583 Hanski, I. (1999a) Habitat connectivity, habitat continuity, and metapopulations  
584 in dynamic landscapes. *Oikos*, pp. 209–219.
- 585 Hanski, I. (1999b) *Metapopulation Ecology*, vol. ISSN 1746-3130. Oxford Series in  
586 Ecology and Evolution, Oxford, Egnland.
- 587 Hanski, I. (2001) Spatially realistic theory of metapopulation ecology.  
588 *Naturwissenschaften*, **88**, 372–381.
- 589 Hanski, I. & Ovaskainen, O. (2000) The metapopulation capacity of a fragmented  
590 landscape. *Nature*, **404**, 755.
- 591 Hanski, I., Schulz, T., Wong, S.C., Ahola, V., Ruokolainen, A. & Ojanen,  
592 S.P. (2017) Ecological and genetic basis of metapopulation persistence of the

- 593 Glanville fritillary butterfly in fragmented landscapes. *Nature communications*,  
594 **8**, 14504.
- 595 Hanski, I. & Simberloff, D. (1997) The metapopulation approach, its history,  
596 conceptual domain, and application to conservation. *Metapopulation biology*,  
597 pp. 5–26. Elsevier.
- 598 Hanski, I.A. (2011) Eco-evolutionary spatial dynamics in the Glanville fritillary  
599 butterfly. *Proceedings of the National Academy of Sciences*, **108**, 14397–14404.
- 600 Hill, J., Thomas, C. & Lewis, O. (1996) Effects of habitat patch size and isolation  
601 on dispersal by *Hesperia comma* butterflies: implications for metapopulation  
602 structure. *Journal of animal ecology*, pp. 725–735.
- 603 Hodgson, J.A., Moilanen, A. & Thomas, C.D. (2009) Metapopulation responses  
604 to patch connectivity and quality are masked by successional habitat dynamics.  
605 *Ecology*, **90**, 1608–1619.
- 606 Howe, R.W., Davis, G.J. & Mosca, V. (1991) The demographic significance of  
607 “sink” populations. *Biological Conservation*, **57**, 239–255.
- 608 Howell, P.E., Muths, E., Hossack, B.R., Sigafus, B.H. & Chandler, R.B. (2018)  
609 Increasing connectivity between metapopulation ecology and landscape ecology.  
610 *Ecology*, **99**, 1119–1128.
- 611 Ims, R.A. & Andreassen, H.P. (2005) Density-dependent dispersal and spatial  
612 population dynamics. *Proceedings of the Royal Society of London B: Biological  
613 Sciences*, **272**, 913–918.
- 614 Ims, R.A., Petter Leinaas, H. & Coulson, S. (2004) Spatial and temporal variation  
615 in patch occupancy and population density in a model system of an arctic  
616 Collembola species assemblage. *Oikos*, **105**, 89–100.

- 617 Kleinberg, J.M. (1999) Authoritative sources in a hyperlinked environment.  
618 *Journal of the ACM (JACM)*, **46**, 604–632.
- 619 Kuussaari, M., Nieminen, M. & Hanski, I. (1996) An experimental study of  
620 migration in the Glanville fritillary butterfly *Melitaea cinxia*. *Journal of animal*  
621 *Ecology*, pp. 791–801.
- 622 Kuussaari, M., Van Nouhuys, S., Hellmann, J.J. & Singer, M.C. (2004) Larval  
623 biology of checkerspots. *On the wings of checkerspots: a model system for*  
624 *population biology*. Oxford University Press, Oxford, pp. 138–160.
- 625 Laine, A.L. (2004) A powdery mildew infection on a shared host plant affects the  
626 dynamics of the Glanville fritillary butterfly populations. *Oikos*, **107**, 329–337.
- 627 Lamy, T., Pointier, J.P., Jarne, P. & David, P. (2012) Testing metapopulation  
628 dynamics using genetic, demographic and ecological data. *Molecular Ecology*,  
629 **21**, 1394–1410.
- 630 Lande, R. (1988) Demographic models of the northern spotted owl (*Strix*  
631 *occidentalis caurina*). *Oecologia*, **75**, 601–607.
- 632 Lipcius, R.N., Eggleston, D.B., Schreiber, S.J., Seitz, R.D., Shen, J., Sisson,  
633 M., Stockhausen, W.T. & Wang, H.V. (2008) Importance of metapopulation  
634 connectivity to restocking and restoration of marine species. *Reviews in*  
635 *Fisheries Science*, **16**, 101–110.
- 636 MacArthur, R.H. (1984) *Geographical ecology: patterns in the distribution of*  
637 *species*. Princeton University Press.
- 638 MacKenzie, D.I., Nichols, J.D., Royle, J.A., Pollock, K.H., Bailey, L. & Hines, J.E.  
639 (2017) *Occupancy estimation and modeling: inferring patterns and dynamics of*  
640 *species occurrence*. Elsevier.



- 641 Menéndez, R. & Thomas, C.D. (2000) Metapopulation structure depends on  
642 spatial scale in the host-specific moth *Wheeleria spilodactylus* (Lepidoptera:  
643 Pterophoridae). *Journal of Animal Ecology*, **69**, 935–951.
- 644 Minor, E.S. & Urban, D.L. (2007) Graph theory as a proxy for spatially  
645 explicit population models in conservation planning. *Ecological applications*,  
646 **17**, 1771–1782.
- 647 Mortelliti, A., Amori, G. & Boitani, L. (2010) The role of habitat quality  
648 in fragmented landscapes: a conceptual overview and prospectus for future  
649 research. *Oecologia*, **163**, 535–547.
- 650 Newman, M.E. (2003) The structure and function of complex networks. *SIAM*  
651 *review*, **45**, 167–256.
- 652 Ojanen, S.P., Nieminen, M., Meyke, E., Pöyry, J. & Hanski, I. (2013) Long-term  
653 metapopulation study of the Glanville fritillary butterfly (*Melitaea cinxia*):  
654 survey methods, data management, and long-term population trends. *Ecology*  
655 *and Evolution*, **3**, 3713–3737.
- 656 with contributions from others, G.R. (2017) *gbm: Generalized Boosted Regression*  
657 *Models*. R package version 2.1.3.  
658 URL <https://CRAN.R-project.org/package=gbm>
- 659 Ovaskainen, O. (2003) Habitat destruction, habitat restoration and  
660 eigenvector–eigenvalue relations. *Mathematical biosciences*, **181**, 165–176.
- 661 Ovaskainen, O. (2017) The interplay between immigration and local population  
662 dynamics in metapopulations. *Annales Zoologici Fennici*, vol. 54, pp. 113–121.  
663 BioOne.

- 664 Ovaskainen, O. & Hanski, I. (2003) How much does an individual habitat fragment  
665 contribute to metapopulation dynamics and persistence? *Theoretical Population*  
666 *Biology*, **64**, 481–495.
- 667 Ovaskainen, O. & Hanski, I. (2004) From individual behavior to metapopulation  
668 dynamics: unifying the patchy population and classic metapopulation models.  
669 *The American Naturalist*, **164**, 364–377.
- 670 Ovaskainen, O. & Saastamoinen, M. (2018) Frontiers in Metapopulation Biology:  
671 The Legacy of Ilkka Hanski. *Annual Review of Ecology, Evolution, and*  
672 *Systematics*.
- 673 Prugh, L.R., Hodges, K.E., Sinclair, A.R. & Brashares, J.S. (2008) Effect of habitat  
674 area and isolation on fragmented animal populations. *Proceedings of the National*  
675 *Academy of Sciences*, **105**, 20770–20775.
- 676 Rabasa, S.G., Gutiérrez, D. & Escudero, A. (2008) Relative importance of  
677 host plant patch geometry and habitat quality on the patterns of occupancy,  
678 extinction and density of the monophagous butterfly *Iolana iolas*. *Oecologia*,  
679 **156**, 491–503.
- 680 Ricketts, T.H. (2001) The matrix matters: effective isolation in fragmented  
681 landscapes. *The American Naturalist*, **158**, 87–99.
- 682 Rosa, E., Woestmann, L., Biere, A. & Saastamoinen, M. (2018) A plant pathogen  
683 modulates the effects of secondary metabolites on the performance and immune  
684 function of an insect herbivore. *Oikos*.
- 685 Rozenfeld, A.F., Arnaud-Haond, S., Hernández-García, E., Eguíluz, V.M., Serrão,  
686 E.A. & Duarte, C.M. (2008) Network analysis identifies weak and strong links  
687 in a metapopulation system. *Proceedings of the National Academy of Sciences*,  
688 pp. pnas-0805571105.

- 689 Smith, A.T. & Peacock, M.M. (1990) Conspecific attraction and the determination  
690 of metapopulation colonization rates. *Conservation Biology*, **4**, 320–323.
- 691 Steffan-Dewenter, I. & Schiele, S. (2008) Do resources or natural enemies drive bee  
692 population dynamics in fragmented habitats? *Ecology*, **89**, 1375–1387.
- 693 Thomas, C. (1994) Extinction, colonization, and metapopulations: environmental  
694 tracking by rare species. *Conservation Biology*, **8**, 373–378.
- 695 Thomas, C. & Harrison, S. (1992) Spatial dynamics of a patchily distributed  
696 butterfly species. *Journal of Animal Ecology*, pp. 437–446.
- 697 Thomas, J., Bourn, N., Clarke, R., Stewart, K., Simcox, D., Pearman, G., Curtis,  
698 R. & Goodger, B. (2001) The quality and isolation of habitat patches both  
699 determine where butterflies persist in fragmented landscapes. *Proceedings of the*  
700 *Royal Society of London B: Biological Sciences*, **268**, 1791–1796.
- 701 Urban, D. & Keitt, T. (2001) Landscape connectivity: a graph-theoretic  
702 perspective. *Ecology*, **82**, 1205–1218.
- 703 Urban, D.L., Minor, E.S., Treml, E.A. & Schick, R.S. (2009) Graph models of  
704 habitat mosaics. *Ecology letters*, **12**, 260–273.
- 705 Zamborain-Mason, J., Russ, G.R., Abesamis, R.A., Bucol, A.A. & Connolly, S.R.  
706 (2017) Network theory and metapopulation persistence: incorporating node  
707 self-connections. *Ecology Letters*, **20**, 815–831.



Table 1: The potential directionality ('Sign') of each covariate group ('patch area', 'habitat', 'spatial', and 'network') on metapopulation dynamics. Metapopulation dynamics may be positively ( $\uparrow$ ) or negatively ( $\downarrow$ ) associated to the covariate group. The relationship between covariate group and metapopulation process (occupancy, colonization, or extinction) may be unclear or could be either positive or negative ( $\uparrow/\downarrow$ ). Lastly, the putative explanation for the relationship is provided in the 'Directionality' column.

Response	Model	Sign	Directionality
Occupancy	Patch area	$\uparrow$	Larger patches support larger populations
	Habitat	$\uparrow/\downarrow$	Mildew and grazing reduce occupancy, resources increase occupancy
	Spatial	$\uparrow/\downarrow$	Spatial patterns in historical introductions drive occupancy
	Network	$\uparrow$	Central patches are more likely to be occupied
Colonization	Patch area	$\uparrow$	Larger patches are bigger colonization targets
	Habitat	$\uparrow/\downarrow$	Mildew and grazing reduce colonization, resources increase colonization
	Spatial	$\uparrow/\downarrow$	Spatial patterns in historical introductions drive colonization
	Network	$\uparrow$	Central patches are more likely to receive immigrants
Extinction	Patch area	$\downarrow$	Larger patches have less extinction prone populations
	Habitat	$\uparrow/\downarrow$	Mildew and grazing enhance extinction, resources decrease extinction
	Spatial	$\uparrow/\downarrow$	Spatial patterns of occupancy influence extinction
	Network	$\downarrow$	Central patches are less likely to go extinct

Table 2: The identities of each of the covariates included in the submodels (e.g., habitat). All covariates were included in the full model, in order to estimate overall importance of each covariate. The measurement or estimation of each variable is described in more detail in the *Variables influencing occupancy and colonization* Methods section.

Group	Variable	Description
Patch area	log(Patch area)	Area of habitat patch in km <sup>2</sup>
Habitat	Resource availability	Total resources on ordinal scale (0-6)
	<i>Plantago lanceolata</i>	Plantago resources on ordinal scale (0-3)
	<i>Veronica spicata</i>	Veronica resources on ordinal scale (0-3)
	Grazing pressure	Estimated percentage of plants grazed
	Mildew infection	Fraction of time mildew pathogen found in given patch
Spatial	Latitude	Latitudinal coordinate of patch (decimal degrees)
	Longitude	Longitudinal coordinate of patch (decimal degrees)
Network	Betweenness centrality	Patch importance measure focused on <i>stepping stones</i>
	Closeness centrality	Importance measure based on the entire dispersal network
	Degree centrality	Local-scale importance of dispersal connections
	Eigenvector centrality	Importance estimated by connections to important patches

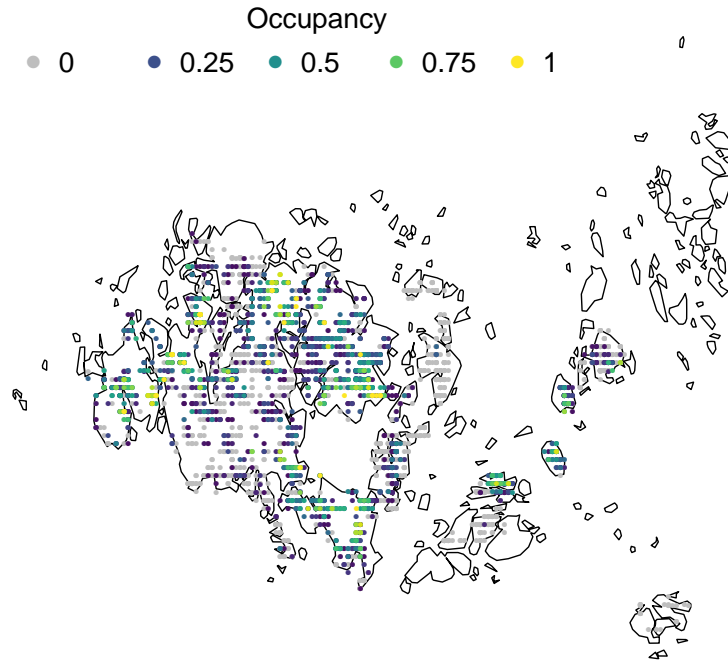


Figure 2: Maps of the Åland islands showing the distribution of sampled habitat patches as part of the monitoring effort, with habitat patches colored by the fraction of times the sampled patch was occupied between the period of 2000-2017. Patches in grey are those in which Glanville fritillary butterfly (*M. cinxia*) was never recorded.

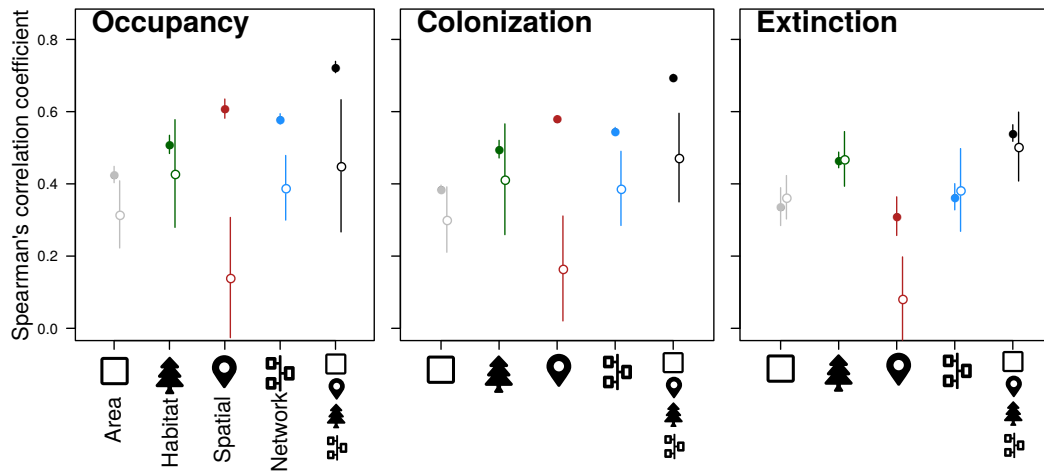


Figure 3: Model performance – defined as Spearman’s correlation coefficient between model-predicted values and empirical data from a subset of data not used to train the model – for each of the candidate models with both random cross-validation (closed circles) and spatially-stratified cross-validation (open circles). Plotted points correspond to average correlations across the ten cross-validated models, and bars correspond to standard deviation. Glyphs are from Font Awesome (<https://fontawesome.com/>).



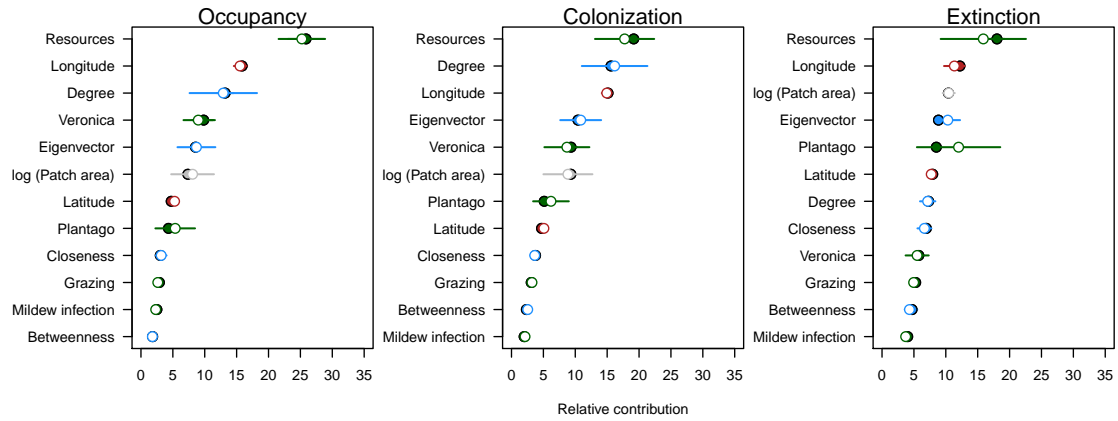


Figure 4: The trained boosted regression tree models revealed that resource availability, degree centrality, and longitude were important predictors of patch occupancy, colonization, and extinction. Variable relative importance remains quite similar with both random cross-validation (closed circles) and spatially-stratified cross-validation (open circles). Bars represent standard deviation across the set of five trained models on different subsets of data.

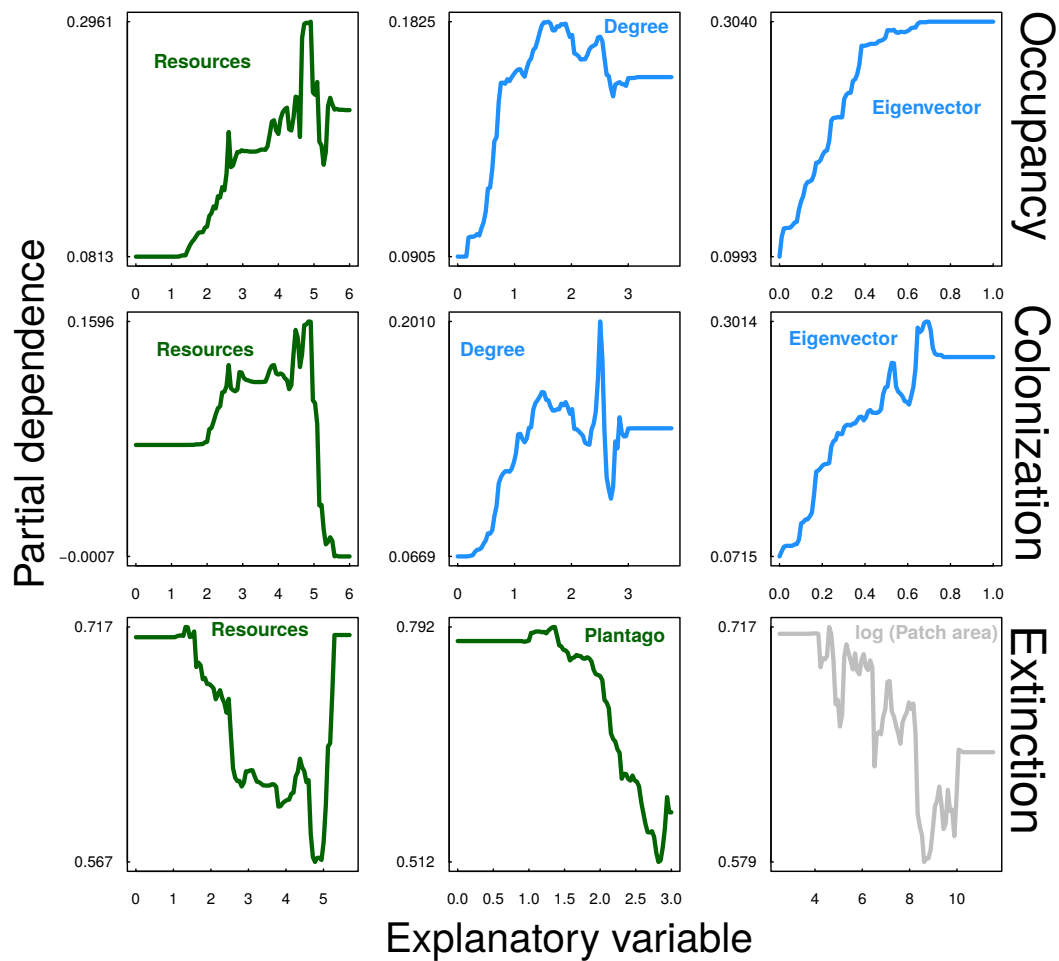


Figure 5: Partial dependence plots for the top three predictors in the boosted regression tree model of *M. cinxia* occupancy (top row), colonization (middle row), and extinction (bottom row), showing the relationships between each metapopulation process and the top three predictive variables in each model when models were cross validated by spatially stratification. The most important variables in the full models of occupancy, colonization, and extinction tended to be related to resource availability and connectivity.