

11 **Abstract**

12 **Aim:** Ongoing climate change is currently modifying the geographical location of
13 areas that are climatically suitable for species. Understanding a species' ability to
14 successfully shift its geographical range would allow us to assess extinction risks and
15 predict future community compositions. We investigate how habitat configuration
16 impedes or promotes climate-driven range shifts, given different speeds of climate
17 change and dispersal abilities.

18 **Location:** Theoretical, but illustrated with European examples.

19 **Methods:** We model how a species' ability to track a directional shift in climatic
20 conditions is affected by: i) species' dispersal abilities; ii) speed of climatic shift; and
21 iii) spatial arrangement of the habitat. Our modeling framework includes within-
22 and between-patch population dynamics and uses ecologically realistic habitat dis-
23 tributions and dispersal scenarios (verified with data from a set of European mam-
24 mal species), and, as such, is an improvement of classical range shift models.

25 **Results:** In landscapes with a homogeneous distribution of suitable habitats, all
26 but the least dispersive species will be able to range shift. However, species with
27 high dispersal ability will have lower population densities after range shift. In het-
28 erogeneous landscapes species' ability to range shift is far more variable and heavily
29 dependent on the habitat configuration. This means that landscape configuration
30 in combination with the speed of climate change and species dispersal abilities give
31 rise to non-linear effects on population sizes and survival after a climatic shift.

32 **Main conclusions:** : Our analyses point out the importance of accounting for the

33 interplay of species dispersal and the landscape configuration when estimating future
34 climate impact on species. These results link ecologically important attributes of
35 both species and their landscapes to outcomes of species range shift, and thereby
36 long-term persistence of ecological communities.

37 **Key words**

38 dispersal, landscape configuration, range shift, speed of climate change, habitat distribu-
39 tion

40 **Introduction**

41 One of the most important factors determining how species are distributed around the
42 globe is their tolerance of climatic conditions (Thomas, 2010). However, ongoing climate
43 change is currently changing the locations of areas that are climatically suitable for species
44 (Loarie et al., 2009), and there is clear evidence that these changes are indeed inducing
45 shifts in the distributions for a wide variety of organisms (Parmesan and Yohe, 2003; Chen
46 et al., 2011; Lenoir and Svenning, 2015). There are also several examples of species that
47 have not been able to track changes in climatic conditions (Maclean and Wilson, 2011),
48 thereby facing the risk of eventually going extinct. Therefore species' capabilities of
49 successfully tracking the changing climate have far-reaching consequences for biodiversity
50 (Thuiller et al., 2005).

51 For most ecosystems around the world habitat loss, degradation and fragmentation
52 are primary causes of species declines (Fahrig, 2003; Joern Fischer, 2006). Climate change
53 is predicted to increasingly interact with, and often intensify, the effects of these factors
54 (Doerr et al., 2011). Ultimately, the survival of a population facing a changing climate
55 depends on its ability to either adapt to the new conditions (Hoffmann and Sgrò, 2011;
56 Sentis et al., 2015) or successfully disperse and colonize new geographical areas (Travis
57 et al., 2013). Understanding how species distributions and persistence are likely to be
58 affected by climate change, in combination with factors affecting dispersal and colonization
59 success, is critical to inform effective conservation strategies in a changing world (Gillson

60 et al., 2013).

61 Landscapes, natural as well as human-modified, can be viewed as geographical areas
62 with suitable and unsuitable habitats for a given species combined in different densities
63 and configurations. Since species dispersal is a process that connects discrete habitat
64 patches together, the amount of habitat is naturally important for a successful colonization
65 event, but so is the distribution of the habitat patches in the landscape (Villard et al., 1999;
66 Baguette et al., 2013). In fragmented landscapes the amount of habitat and landscape
67 connectivity are often linked to each other (Villard and Metzger, 2014) but the relationship
68 is by no means a necessity (Wang et al., 2014) as the same amount of habitat can be
69 distributed in various ways and thereby give different degrees of structural connectivity
70 in the landscape. When the landscape gets re-structured due to land-use modifications,
71 e.g., becomes more fragmented, the negative effects of lower structural connectivity is
72 especially pronounced for species with certain characteristics, such as strong adaptation
73 to the historic landscape configuration (i.e., species whose habitats historically have been
74 abundant and less fragmented) or low dispersal ability (Martin and Fahrig, 2016). Climate
75 change may in turn cause both habitats and the matrix to decrease in quality (Martin
76 and Fahrig, 2016), potentially leading to interaction effects between land-use and climate
77 change (Pielke, 2005). Landscape configuration, the species dispersal ability, and quality
78 of the new habitat jointly contribute to the realized connectivity (i.e. how structural
79 connectivity is experienced by a given species) and ultimately determines the outcome of
80 species dispersal (Baguette et al., 2013; Borthagaray et al., 2014).

81 Species' ability to track a changing climate is also dependent on how fast the climatic
82 shift is progressing (Schloss et al., 2012), and there can be profound differences in the
83 rate of change between biomes (Stocker et al., 2013; Loarie et al., 2009). Species that are
84 able to disperse longer distances and at a faster pace should be better able to track a fast
85 shift in climatic conditions compared to a species with slower and more limited dispersal
86 (Walther et al., 2002; Angert et al., 2011), with implications for biodiversity and other
87 features of community structure. Even though long distance dispersal often is rare, and
88 survival and establishment commonly correlate negatively with the distance dispersed,
89 long distance dispersal can have profound effects on species spread and survival (Nathan,
90 2006) .

91 Simulating biodiversity scenarios under climate change has so far largely relied on
92 species distribution models, SDM, (Guisan and Zimmermann, 2000; Thomas et al., 2006),
93 where statistical correlations between species' current distribution and a set of environ-
94 mental variables are used to make predictions of future distributions. However, the ac-
95 curacy of these models have been extensively debated (Thuiller et al., 2013; Araújo and
96 Peterson, 2012; Wiens et al., 2009) owing to limitations such as species dispersal often
97 being considered unlimited or non-existent (Peterson et al., 2001; Thuiller et al., 2005)
98 and the exclusion of population dynamics (Zurell et al., 2009). To address this limitations
99 there has been a recent development of "hybrid models" which combine the classical SDM
100 approach with, for example, simple dispersal or population dynamic models (Ehrlén and
101 Morris, 2015). Zurell et al. (2016) recently tested the predictive performance of models

102 for range dynamics differing in their complexity, and found a clear advantage for models
103 including dynamic approaches. There have also been several advanced software tools de-
104 veloped for simulating species migration rates (Collingham et al., 1996) and range shifts
105 (Midgley et al., 2010; Schumaker, 2013). These models are primarily developed for sim-
106 ulating dispersal of plant species, hence have successfully been used for that purpose
107 (Pérez-García et al., 2017).

108 We developed a theoretical modeling framework to address the implications of habitat
109 configuration more broadly, and link the results to real life scenarios. Our framework
110 allowed us the flexibility to choose the type of population dynamic model and to impose
111 different types of habitat distribution. We used this framework to investigate the joint
112 impact of species dispersal, habitat configuration in landscapes, and the speed of climatic
113 shift on species' abilities to colonize and survive in new climatically suitable areas. We
114 illustrate the implications of our results using the landscapes that four European mammal
115 species' will encounter during climatically driven range shifts.

116 **Methods**

117 We modeled how species' ability to track a directional shift in climatic conditions was
118 jointly affected by: i) spatial arrangement of suitable habitats in the landscape; ii) char-
119 acteristics of species' dispersal abilities (shape of dispersal kernel); and iii) speed of the
120 climatic shift. We explored how these factors affect the patch occupancy and overall

121 abundance of the range-shifting population.

122 **Landscape generation**

123 We first produced a set of artificial landscapes with clear differences in habitat aggre-
124 gation. We generated landscapes using a method based on spectral density, following
125 the methodology described in Lindström et al. (2011), to produce neutral point pattern
126 landscapes (NPPL). The NPPLs are primarily defined by three parameters: the number
127 of patches (n), a continuity parameter (γ) and a contrast parameter (δ). The continuity
128 parameter determines the spatial autocorrelation over multiple scales, i.e., if areas with
129 similar patch density are located close to or far from each other. The contrast parameter
130 defines the size of the difference between areas with dense or sparse habitat distribution,
131 i.e., is a measure of density dispersion. For a detailed description of the method see Lind-
132 ström et al. (2011). As we here focus on the aggregation of habitats in the landscapes we
133 kept δ constant and analyzed two values of γ . The combinations we used were [$\gamma=0$, $\delta=$
134 3] and [$\gamma=2$, $\delta= 3$], which produce landscape types that have their habitat organized in a
135 clearly homogeneous (evenly distributed over the whole landscape) versus heterogeneous
136 (clearly aggregated) manner. We hereafter refer to those combinations as homogeneous
137 and heterogeneous landscapes respectively. Note that each habitat is a point and thus does
138 not have a specific area, and therefore the aggregation stems from how close that patches
139 (points) are in space. The number of habitat patches distributed in each landscape was
140 1000.

141 Population dynamics

142 In each habitat patch the population dynamics were described by a modified Ricker equa-
143 tion (Ricker, 1954)

$$N_i(t + 1) = N_i(t)e^{r_i(t)(1-\frac{N_i(t)}{K_i(t)})^c} \quad (1)$$

144 where $N_{i,t}$ is the population density in patch i at time t ; $r_{i,t}$ is the intrinsic rate of
145 increase in patch i at time t ; $K_{i,t}$ is the carrying capacity for patch i at time t ; and c
146 is a parameter that affects the population's responsiveness, i.e., whether the population
147 shows over-compensatory or under-compensatory dynamics in response to K . K is set
148 to 1000 individuals to ensure a low risk of extinction since we study mainly change in
149 population density. The dynamics parameter c is set to 0.1 such that the population
150 has under-compensatory dynamics to avoid complicating dynamic behavior such as chaos
151 and cycles as well as instability of the numerical methods. The intrinsic growth rate r
152 is defined by the number of births and deaths in a population. In order to incorporate
153 demographic stochasticity into the model we let $r_{i,t}$ vary between time steps and different
154 habitat patches. We modeled the stochasticity by modifying the number of births in
155 patch i at time t using a Poisson probability function (expected value $r_b = 1.85$), while
156 the number of deaths was held constant ($r_d = 0.75$) (Melbourne and Hastings, 2008). We
157 chose not to allow the r -value to vary further in order to limit parameter space, but our
158 preliminary analyses showed limited effects of realistic variations in the r -value.

159 Species dispersal

160 After reproduction individuals moved between patches and this dispersal process was
161 described with a distance dependent model similar to that of Lindström et al. (2009). For
162 each individual dispersing from patch i a sample was made from a distribution of arrival
163 probabilities. The probabilities of movement of individuals from patch i to patch j was
164 defined by a dispersal kernel of which the probability mass was given by

$$P_{ij} = \begin{cases} \frac{e^{-\left(\frac{d_{ij}}{a}\right)^b}}{\sum_{j=1}^n e^{-\left(\frac{d_{ij}}{a}\right)^b}} & \text{for } j = 1, 2, \dots, n \text{ and } i \neq j \\ 0 & \text{if } i = j \end{cases} \quad (2)$$

165 where d_{ij} is the distance between patch i and j ; a and b are parameters determining
166 the shape and width of the dispersal kernel; and n is the total number of patches. The
167 dispersal kernel is normalized by dividing by the sum of all possible destinations (Lind-
168 ström et al., 2009). The proportion of a population that disperses from patch i to patch
169 j at time t is given by $N_{i,t} \times \sigma$ where σ defines the proportion of the total population
170 dispersing. Here we set σ to 0.5 (in order to reflect a behavior in a medium dispersive
171 populations), and b to 1 (in order to model the dispersal kernel as an exponential dis-
172 tribution) and a is the parameter used to vary the width of the tail of species' dispersal
173 kernels. A species dispersal kernel is a function that describes the probability of a species
174 dispersing different distances (Nathan, 2006).

175 We let a take the values 0.002, 0.032, 0.064 and 2.048 – hereafter referred to as dispersal

176 group 1–4 respectively, where group 1 has the most thin-tailed dispersal kernel (i.e. no
177 Long Distance Dispersal (LDD) events (Nathan, 2006; Hovestadt et al., 2001)), and group
178 4 the most fat tailed kernel (many LDD events, for a visual description see Fig. 1). The
179 population density in patch i at time $t + 1$ with regard to dispersal between patches was
180 therefore

$$N_i(t + 1) = N_i(t)(1 - \sigma) + \sum_{j=1}^n P_{ji}(N_j(t) \times \sigma) \quad i \neq j \quad (3)$$

181 **Simulation of the climatic shift**

182 To simulate a climatic shift we started by assuming that the species had its optimal
183 climatic conditions at a certain point in the landscape. We also assumed that the species
184 distribution was centered at that point. We assigned the maximum carrying capacity of
185 the species to the climatically optimal position in the landscape and then let the carrying
186 capacity decline with increased distance from that position. The decline was modeled as
187 a normal distribution. Note that in our model the carrying capacity is only determined
188 by the climate. In order to incorporate some stochasticity environmental noise, ε , was
189 added to the carrying capacities of the patches, modeled as white noise with mean 1 and
190 standard deviation 0.05 following Lögberg and Wennergren (2012).

191 Two landscapes, with 500 patches each and the desired aggregation, were generated
192 and then positioned adjacent each other. This means there were 1000 habitat patches
193 in the whole landscape, and of these we let the 500 patches in the starting landscape be

194 inhabited from start. The 500 starting patches were seeded with 100 individuals each and
195 the populations were allowed to settle for the initial 100 time steps before we started to
196 simulate the climatic shift. The climatic shift was simulated as a sliding window where
197 the suitable climatic conditions move in a steady pace from south to north the landscape
198 over time. The climatic shift was simulated at three different speeds: the complete shift
199 took place over 20, 80 or 160 time steps which we here after refer to as fast, medium and
200 slow speed respectively. The simulated speeds of climatic shift corresponds to 2.5, 0.625
201 and 0.3125 km/year respectively, assuming that each theoretical landscape corresponds to
202 a 50x50km grid-cell. These values are within the range observed in empirical data (Loarie
203 et al., 2009). Finally, after the climatic shift has stopped the populations were allowed to
204 settle for 100 time steps before the simulation was halted.

205 The simulations were performed in MATLAB (R2014b, The MathWorks, Natick, MA,
206 USA). For each combination of speed of climatic shift (fast, medium and slow), species
207 dispersal abilities (dispersal group 1, 2, 3 and 4) and habitat aggregation (homogeneous,
208 heterogeneous) 30 replicates were produced. Replicates varied in the distribution of habi-
209 tat patches, the noise added to species growth rates r and patch carrying capacities K .
210 This resulted in 720 simulations in total. For a schematic description of the simulation
211 flow see Fig. 2.

212 **Analysis of population change**

213 We followed and recorded the changes in population densities in all habitat patches before,
214 during, and after the climatic shift. The results were presented as the average density of
215 the global population at the end of the simulation taken over the 30 landscape replicates.
216 We additionally calculated the habitat occupancy (the fraction of habitat patches with
217 surviving populations) before, during and at the end of each climatic shift. Note that
218 the number of habitat patches occupied at the beginning of simulation was 500, and this
219 refers to whole initial global population, i.e. when 500 patches are occupied the fraction
220 of the habitats occupied is 1. This means that the fraction could become larger than 1
221 as novel parts of the landscape could be colonized at a faster pace compared to the pace
222 with which initial habitats were emptied.

223 **Differentiation of heterogeneous landscapes**

224 In the heterogeneous landscapes the habitats were aggregated according to $\gamma=2$
225 (see section Landscape generation). As a result of the aggregation a technical issue arose:
226 when habitats are aggregated large areas in the landscape have no (or very few) habitats.
227 This leads to high variation in population density, depending on where the center of
228 habitat aggregation is placed relative to the climate optimum. An aggregation close to
229 the climate optimum will result in a higher net carrying capacity for the landscape, which
230 in turn will give a higher net population in the landscape. To analyze the effects of these

231 differences in placement of the aggregates on species survival and density, we divided the
232 heterogeneous landscapes into three classes based on the fraction of habitat positioned
233 in middle third of the landscape: landscape of type A - 0–23%, type B - 24–43% and
234 type C- 44–100% of total habitat positioned in the middle of the landscape (for example
235 landscapes, see Fig. 6). We analyzed how the population density changes during and
236 after the climatic shift in these different landscape configurations.

237 **Which parameters control the speed of range shifts?**

238 In order to further disentangle the role of the different variables (dispersal kernel width,
239 speed of climatic shift and landscape configuration) we used a regression tree approach,
240 which recursively partitions the predictor variables to explain the variation in the response
241 variable. Regression trees assess whether a response variable is associated with variation in
242 a number of explanatory variables, can represent more complex interactions than multiple
243 regression or ANOVA, and are robust to nonlinear relationships (De'ath and Fabricius,
244 2000; Brose et al., 2005). As the response variable we used the fraction of the population
245 remaining at the end of the simulations divided by the population size when it had settled
246 right before the climatic shift started, i.e. after the initial 100 time steps. We chose
247 this response variable as the populations settled at varying densities depending on their
248 dispersal ability and the landscape configuration. In the regression tree we used four
249 classes of landscapes: homogeneous and the three classes of heterogeneous landscapes
250 (see above). For these analyses we use the *rpart* package in R (Version 3.2.2; R Core

251 Team 2015).

252 **Results**

253 All three factors - habitat configuration, width of the species dispersal kernel and speed
254 of climatic shift - had a clear effect on the survival success of local populations following
255 a changing climate. In landscapes with a homogeneous distribution of habitat patches
256 there was an abrupt shift at an intermediate level of dispersal; above this threshold a
257 high proportion of the local populations survive, and below it the entire population goes
258 extinct (Fig. 3). The same trend was also present in more heterogeneous landscapes
259 although the transition was smoother with more intermediate levels of survival (Fig.4).
260 In both cases the shift became less abrupt when the speed of climatic shifts was slower
261 (from left to right in Fig. 3 & 4). The number of local populations persisting (number of
262 occupied habitat patches) was on average highest when species had intermediate or more
263 fat-tailed dispersal kernels, but the densities of the surviving populations decreased when
264 the dispersal kernel changed from intermediate to fat-tailed (Fig. 3 & 4).

265 Looking at how the densities of the surviving populations changed over time as the
266 climatic shift progressed, we saw that there was a large difference in the variability of
267 densities in homogeneous (Fig. 5) but especially in heterogeneous landscapes (Fig. 6).
268 In heterogeneous landscapes species can have both higher or lower densities compared to
269 those in homogeneous landscapes. When the climatic shift progressed faster, population

270 densities decreased at a faster pace (red areas in Fig. 5 & 6). After the shift was completed,
271 species with a sufficiently high dispersal ability were able to reverse the earlier density
272 decline and recover, whereas species with the lowest dispersal ability went extinct. Even
273 when species did survive, they were not certain to recover to the same levels as before the
274 shift, as seen in particular for species of dispersal group 4 (species with the most fat-tailed
275 dispersal kernel analyzed here).

276 We classified heterogeneous landscapes into three types: A, B and C, in which an
277 increasing proportion of habitat lies in the middle of the landscape to be crossed, see
278 Methods). The landscapes of type A and B show the highest variation in global popu-
279 lation density after the populations had settled but before the climatic shift started Fig.
280 S3). Those landscape types also showed high variation after the climatic shift and final
281 settlement. The most striking difference between the types of heterogeneous landscapes is
282 that type A showed a clear trend of decreasing densities during the shift and also a clear
283 recovery, while types B and C did not. Note that in some cases there was an increase in
284 global population density after the climatic shift.

285 The regression tree analysis confirmed that the species dispersal ability was the factor
286 having the largest effect on the fraction of the both population persisting after the climatic
287 shift (Table 1) and the global population density (Table 2). After dispersal ability the
288 actual distribution of the habitat played a major role for the fraction of habitat patches
289 occupied.

290 Discussion

291 Our analyses highlight interacting effects of landscape configuration, dispersal kernel
292 shape, and speed of climate change on the persistence of populations during and after a
293 climatic shift. The idea that the ability of species to reach new climatically suitable areas
294 will be hampered by fragmentation and habitat loss has been widely studied (Thomas
295 et al., 2004). While previous focus has mainly been on the amount of habitat, we here
296 show that the realized distribution of suitable habitat is crucial. This affects conserva-
297 tion planning decisions, e.g. which areas to protect or restore, in particular since climate
298 change induce both decreased habitat availability and quality (Martin and Fahrig, 2016).

299 The difference in landscape configurations ranging from homogeneous to heteroge-
300 neous habitat distribution is also a range from low to high levels of habitat aggregation.
301 Our analyses show that in landscapes where habitats are heterogeneously distributed,
302 landscapes with the same level of aggregation show highly variable trends. A high level
303 of habitat aggregation means that large, contiguous parts of the landscape contain no
304 suitable habitat. The densities and persistence of the local populations are therefore de-
305 pendent on the actual location of the habitat aggregates. If aggregates are situated far
306 away from where the species has its optimal carrying capacity the persistence will be low.
307 This because the habitat in the aggregate will have low climatic suitability, and thus low
308 carrying capacity. On the other hand, if the aggregates are located in areas with climates
309 close to the species climatic optimum, then population densities, and hence persistence,

310 will be high. Note, however, that there can be situations where few habitats are found
311 close to the species climatic optimum. In these cases, as climate change proceeds, the op-
312 timum moves its position and can, during the shift, reach areas where the habitat density
313 is high. Thus, the climatic shift can in some cases have a positive effect on population
314 density. Alternatively, the new position of the optimal climate could be situated in an
315 area where little habitat is available. This further strengthens the argument that the
316 distribution of habitats is more important than the amount of habitat alone, and that a
317 continuous and well-connected distribution of suitable habitat throughout the landscape
318 is a lower risk option for conservation strategies providing higher predictability.

319 Our results also show that species with the second lowest dispersal ability indeed ben-
320 efit from a habitat distribution where the amount of suitable habitat patches is high in
321 the middle of the landscape, i.e. the part the species disperses over before reaching the
322 new climatic suitable areas. Earlier studies on how protected areas for biodiversity con-
323 servation should be placed in the landscape, have shown the importance of well-connected
324 dispersal pathways (dispersal chains) for species persistence (Phillips et al., 2008), and
325 how this is particular important for species with limited dispersal ability (Williams et al.,
326 2005).

327 However, species dispersal often has a cost: a dispersing individual or propagule might
328 not find suitable habitat (Bonte et al., 2012). Therefore, while fat-tailed dispersal kernels
329 can ensure a greater survival rate for a metapopulation as a whole by increasing the chance
330 of reaching new patches, they can also result in lower population densities. Here we show

331 that for species with fat-tailed dispersal kernels (LDD more common) the population
332 is capable of moving with the range shift, but may still not reach the same densities
333 after the climatic shift has stopped. This is due to the fact that much of the population
334 moves to areas further away from the climatic optimum, and thereby the global species
335 population will have lower density than a species with a more thin-tailed dispersal kernel.
336 An intermediate dispersal ability has been found to maximize the survival of a specialist,
337 long-lived plant under climate change (Pérez-García et al., 2017). Our work supports
338 the existence of such a 'mid-distance optimum' for population parameters that reflect a
339 range of life-histories. Having a fat-tailed dispersal kernel therefore does not necessarily
340 optimize survival for species experiencing climate change in homogeneous or in highly
341 aggregated landscapes. Instead, the optimal dispersal kernel is tightly coupled to the
342 spatial distribution of habitat available for the species to occupy in areas with good
343 climatic conditions.

344 Some species are dependent on larger consecutive areas of suitable habitat in order
345 to have viable populations, e.g. species that need large home ranges or have limited
346 dispersal abilities (Lindenmayer and Fischer, 2013; Hanski, 2011). Although this is not
347 explicitly modeled here, areas with different geographical extents will possess different
348 viabilities due to the similar carrying capacities, and reproduction rates, in adjacent
349 habitat patches. One could assume that larger aggregates of habitat would jointly have
350 a higher quality by functioning as single larger habitat patches. However, for this to be
351 beneficial for species, the habitat aggregations must be located in areas with good climatic

352 conditions. This is a situation in which a Single Large habitat aggregation could be inferior
353 to Several Small habitat patches (reawakening the SLOSS debate). Dividing conservation
354 protection between a large number of smaller habitat patches increases extinction rates
355 within patches, and requires accurate estimates of local extinction rates (McCarthy et al.,
356 2011; Donaldson et al., 2017). However, in the context of climate change, a large number
357 of smaller habitat patches maximizes the ability of species with a broad range of dispersal
358 capacities to undergo range-shifts.

359 The speed of climate change is highly uncertain (Stocker et al., 2013) and will differ
360 between biomes (Loarie et al., 2009). Interestingly, the speed of climate change had limited
361 effect on the survival of local populations and both the landscape configuration and species
362 dispersal ability were usually more important. Our results show it is feasible for all but
363 the species with the lowest dispersal abilities to cross homogeneous landscapes, even
364 under the fastest speed of climate change that we simulated. However, for species with
365 restricted dispersal ability, the speed of climatic shift will have a large effect on persistence.
366 This means that species that are sensitive to isolation effects, for example forest species
367 reluctant to cross non-forest habitat, will be particularly prone to extinction in areas of
368 rapid climate change (Melles et al., 2011). This trend has also been observed in marine
369 systems. For example in ocean of southeast Australia, species with high dispersal capacity
370 and ecological generalism have expanded their range (Sunday et al., 2015), whereas other
371 species faced a higher risk of being stuck in unsuitable areas as climate changes.

372 Of importance for conservationists and other stakeholders is to be able to identify

373 circumstances under which a species is likely to be particularly vulnerable to extinction
374 (or become an invasive). Fig. 7 summarizes the combinations of dispersal abilities for
375 species and landscape configurations and highlights those that are of particular conser-
376 vation concern. It is evident that species' dispersal patterns play a major role in range
377 shifts, but also that combinations of landscape and dispersal ability can result in unintu-
378 itive outcomes. For example, under the medium speed of climatic shift, landscape type
379 heterogeneous C (most of the suitable habitats are located in the middle third of the
380 landscape) and species from dispersal group 2 (the second most narrow dispersal kernel),
381 results in a much lower global population density than under higher or lower speeds. But
382 also, if the habitat distribution is different, say the landscape is of type A instead, the
383 same dispersal type species will have a different population level response. One can also
384 see that for some combinations the final population size is much larger after the climatic
385 shift (large dots in Fig. 7), with possible implications for the species to become a prob-
386 lematic invasive (for a summary of potential mechanisms, see Hellmann et al., 2008).
387 One example of this is that a species in dispersal group 3 increases its population after a
388 high speed climatic shift if a large amount of habitat is positioned where the new climatic
389 optimum is, but will have a severely decreased population if habitat is more limited.

390 In order to evaluate the relevance of our theoretical modeling approach to conservation
391 we compared our results to empirical data from four European mammals; siberian flying
392 squirrel *Pteromys volans*, chamois *Rupicapra rupicapra*, European hare *Lepus europeaus*,
393 and brown bear *Ursos arctos*. The species dispersal kernels were calculated from natal

394 dispersal distances (Whitmee and Orme, 2013), and are within the range of those used
395 in the theoretical analyses (Fig. 1, see SI Appendix 1 for details). We allowed each
396 50x50km grid-cell in the European study area to correspond to a theoretical landscape
397 as defined in the Methods (for details see SI Appendix 1). In each 50km grid-cell, the
398 1km grid-cells in which vegetation is suitable for the study species are considered to be
399 habitat patches. 50km grid-cells adjacent to the current range, that become climatically
400 suitable from 1961-1990 to 2071-2100 were taken from calculations in (Morrison, L., et
401 al. , (accepted), "Species traits suggest European mammals facing the greatest climate
402 change are also least able to colonise new locations", Diversity and Distributions), using
403 the Representative Concentration Pathway 4.5 and CNRM-CM5 global climate model.
404 We calculated the Clark-Evans habitat aggregation indices (Clark and Evans, 1954) in
405 each 50km grid-cell that could be colonized, and compared these to Clark-Evans indices
406 in the theoretical landscapes. The indices for empirical landscapes ranged between 0.31
407 - 1.50 (average value 0.84), and indices for theoretical landscapes ranged between 0.56 -
408 1.18 (average 0.83) (SI Appendix 1, Fig. S2). The simulated speeds of climatic shift of
409 20, 80 or 160 time steps correspond to 2.5, 0.625 and 0.3125 km/year respectively. These
410 values indicate that the parameters used in our theoretical study are representative of
411 real-world range-shift scenarios, and that the approach could be used to address specific
412 conservation questions. Theoretical landscapes that have Clark-Evans indices that match
413 the empirical landscapes have diverse population densities, and the color of the empirical
414 landscapes is shaded light or dark depending corresponding to the areas in the inset

415 graphs (Fig. 8). When the Clark-Evans index of landscape aggregation is below 0.9, the
416 arrangement of habitat patches can result in drastically different population densities.
417 For the mammals studied, approximately half of the 50km grid-cells they could soon
418 colonise have habitat aggregations that could result in either very high, intermediate, or
419 zero population densities, depending on the specific habitat distribution. The European
420 hare (dispersal group 2) has the potential to have the highest population densities in
421 colonised grid-cells, whereas most habitat configurations would result in relatively much
422 lower population densities for the Brown bear (dispersal group 4).

423 A complicating aspect for conservation actions is that species are not sole actors in
424 ecological communities but rather depend on other species for survival (e.g., prey species,
425 mutualistic interactions). The synchrony in movements of interacting species during a
426 climatic shift will determine future biodiversity scenarios - a species highly able to dis-
427 perse and colonize under shifting climate may not be able to do so if, for example, their
428 prey species has more limited dispersal and colonization capabilities ('biotic mismatch')
429 (Chivers et al., 2017). In more homogeneous landscapes this variation in density will
430 likely be less pronounced. In this situation, as patches of relatively good quality can
431 easily be reached even by species with lower levels of dispersal ability, and therefore bi-
432 otic interactions are more likely to be kept intact. Our analyses further emphasize that
433 predicting biotic mismatch will depend not only on species' dispersal abilities, but also
434 on landscape configuration, since species with different habitat requirements experience
435 landscape connectivity differently (Taylor et al., 1993). Also, if climate change progresses

436 rapidly, dispersal-limited species might be trapped in habitats with low climatic suitabil-
437 ity, with negative repercussions for any species that depends on them for their ecological
438 interactions.

439 We have showed that the actual distribution of habitat patches, not only the distances
440 between them, is crucial for species to survive during climate change. This is borne out
441 by the fact that even for the species that move furthest and fastest, the landscape struc-
442 ture can block movement completely. Within the range of parameters we investigated,
443 which reflect the range of landscape characteristics and dispersal abilities of European
444 mammals, all but the poorest dispersers can successfully cross landscapes where habitats
445 are relatively evenly distributed. The future is less certain for all species in heterogeneous
446 landscapes where suitable habitats are unevenly distributed.

447 Our results pinpoint the importance of taking into account factors like fragmentation,
448 land-use, and dispersal barriers across large geographical scales when performing biodi-
449 versity predictions and developing conservation strategies in the light of climate change.
450 While the speed and amplitude of climate change is something we cannot change in the
451 short-term, the configuration of the landscape in many cases is. Restoration of destroyed
452 habitats as well as thoughtful organization of green infrastructure elements (Benedict and
453 McMahon, 2006) may be a possible solution for lowering the risks in the short-term.

454 **Acknowledgments**

455 This research was funded by the ERA-Net BiodivERsA, part of the 2011 BiodivERsA call
456 for research proposals. RE and A.Es acknowledge the ERA-Net BiodivERsA, with the
457 national funder FCT, through the project BIODIVERSA/00003/2011. A.Ek. acknowl-
458 edge funding from Swedish Research Council grant number 2016-04919. A.Es. has a
459 postdoctoral contract funded by the project CN-17-022 (Principado de Asturias, Spain).
460 Catarina Meireles compiled data on dispersal kernels and habitat tolerances for European
461 mammals. We thank Alyssa Cirtwill and György Barabas for useful comments on the
462 manuscript.

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592 namics. – *Glob. Chang. Biol.* 22: 2651–2664.

593 **Supporting Information**

594 SI-ConditionsSuccessfulRangeShifts.pdf

595 **Author contribution**

596 AEk and UW originally formulated the ideas presented in this article. JÅ coded the
597 theoretical model and performed the simulations. JÅ and AEk performed the analyses of
598 the simulated data. RE and AEs obtained the empirical species data and performed the
599 analyses of them. JÅ and AEk wrote the first draft of the manuscript and all authors
600 contributed extensively to the preparation of the final version.

601 **Biosketch**

602 Jonatan Årevall is a PhD student at Linköping University, particularly interested in ex-
603 amining interactions between population dynamics, landscape characteristics and species
604 dispersal behavior, and how these together can affect population distributions. He is
605 also interested in applying these results to increase the efficiency of green infrastructure
606 projects in order to accommodate biodiversity in the future.

607 **Figure legends**

608 **Figure 1.** Shows dispersal kernels used in the model (colored lines) and the dispersal
609 kernels for four European mammal species (dotted lines). The mammals are from bottom
610 to top *Pteromys volans*, *Rupicapra rupicapra* and *Lepus europaeus* (lines are overlapping),
611 and finally *Ursus arctos*. The x-axis show distances as landscape units (50km).

612

613 **Figure 2.** Schematic description of the range shift simulation. In this example a land-
614 scape with totally 1000 habitat patches heterogeneously distributed is produced (1). The
615 landscape is a combination of two landscapes consisting of 500 patches each; each black
616 dot in the figure corresponds to one habitat patch. Then the one half of the landscape
617 (here the lower part, which in a species range shift scenario would corresponds to the
618 south part) is populated with 100 individuals in each patch (2). Thereafter the pop-
619 ulation reproduce within and disperse between patches. The population dynamics are
620 allowed to settle for 100 time steps. Maximum carrying capacity is positioned where the
621 climatic optimum are and decreases with distance from that optimum (3). The climatic
622 shift starts and is modelled such that the climatic optimum moves from south to north in
623 the landscape (4). The climate change is halted and population is allowed to settle before
624 final population size and patch occupancy is recorded (5).

625

626 **Figure 3.** The fraction of surviving local populations after the climatic shift has taken

627 place as a function of the width of species dispersal kernel. The results are shown for
628 landscapes where the suitable habitats are homogeneously distributed. For each land-
629 scape type three different climatic scenarios are presented panel a) shows the highest,
630 b) shows the medium, c) lowest speed of the climatic shift. Darker color of the symbols
631 represents higher population densities in surviving populations.

632

633 **Figure 4.** The fraction of surviving local populations after the climatic shift has taken
634 place as a function of the width of species dispersal kernel. The results are shown for
635 landscapes where the suitable habitats are heterogeneously distributed. For each land-
636 scape type three different climatic scenarios are presented panel a) shows the highest,
637 b) shows the medium, c) lowest speed of the climatic shift. Darker color of the symbols
638 represents higher population densities in surviving populations.

639

640 **Figure 5.** Shows the average densities of the local populations during simulations in
641 homogeneous landscapes; the solid black line shows the average over 1000 replicated
642 landscapes, the outer lines show standard deviation. Red areas show the time when
643 the climatic shift is occurring, blue areas before and after the shift. The first row shows
644 results from simulating climatic scenario A, the second scenario B, and the third scenario
645 C. The different columns show different dispersal patterns (group 1-4 from left to right).

646

647 **Figure 6.** Shows the average densities of the local populations during simulations in

648 heterogeneous landscapes; the solid black line shows the average over 1000 replicated
649 landscapes, the outer lines shows standard deviation. Red areas show the time when the
650 climatic shift is occurring, blue areas before and after the shift. First row shows results
651 from simulating climatic scenario A, second scenario B and third scenario C. The different
652 columns show different dispersal patterns (group 1-4 from left to right).

653

654 **Figure 7.** Figure summarizing the interaction of the different factors; speed of climatic
655 shift (low, medium and high), species dispersal ability (dispersal group 1, 2, 3 and 4 goes
656 from low to high in that order) and landscape configuration, and their role for changed
657 population density after a climatic shift. The size and color of the dots correspond to
658 the change in global population density between start of the climatic shift and end of the
659 simulation (global population density at shift start / global population density at the end
660 of the simulation); the largest dark blue dots means the population has doubled its global
661 density, smallest light red dots mean that the population has declined to near extinction.
662 The panels in the lower row are describing landscapes with different distributions of habi-
663 tat patches (homogeneous; heterogeneous of type A – 0 to 23% of the suitable habitats
664 located in the middle third of the landscape; heterogeneous of type B – 24 to 43 %, to ,
665 heterogeneous of type C – 44 to 100%) , and the species disperse from left to right in the
666 landscapes.

667

668 **Figure 8.** Maps of the current and projected climatic and habitat suitability of a)

669 *Pteromys volans*, b) *Rupicapra rupicapra*, c) *Lepus europeaus*, d) *Ursos arctos*. Grid-cells
670 in map are approximately 50km x 50km, and are those used by atlases to map species
671 distributions. Grey cells are the ones predicted to be climatically suitable for the mam-
672 mal in 1961-1990 using SDMs. Colored cells are the cells that are expected to become
673 climatically suitable in 2071-2100. The recessed graphs show results from the theoretical
674 simulations for the dispersal group each empirical species belongs to; on the y-axis is the
675 global population density (for visualization the numbers are divided by 1000) and on the
676 x-axis is the Clark-Evans aggregation index for the corresponding simulation. The colors
677 of the cells in the map for the empirical data correspond to the range of Clark-Evans
678 aggregation index for the distribution of suitable habitats in that cell falls into, and the
679 key is given in the recessed graphs. *Pteromys volans* and *Rupicapra rupicapra* belong to
680 dispersal group 2 and thus only one recessed graph is shown. *Lepus europeaus* to dispersal
681 group 3, and *Ursos arctos* to dispersal group 4.

682

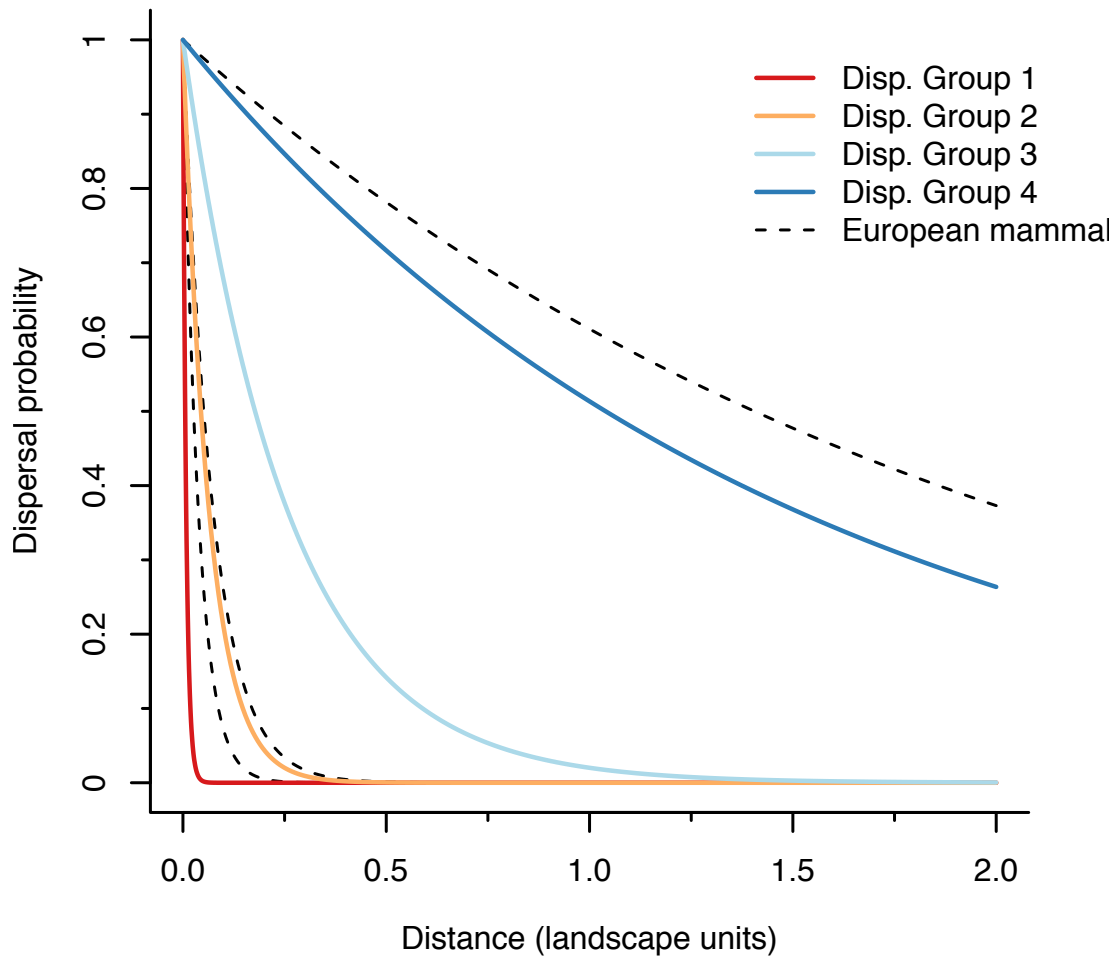


Figure 1

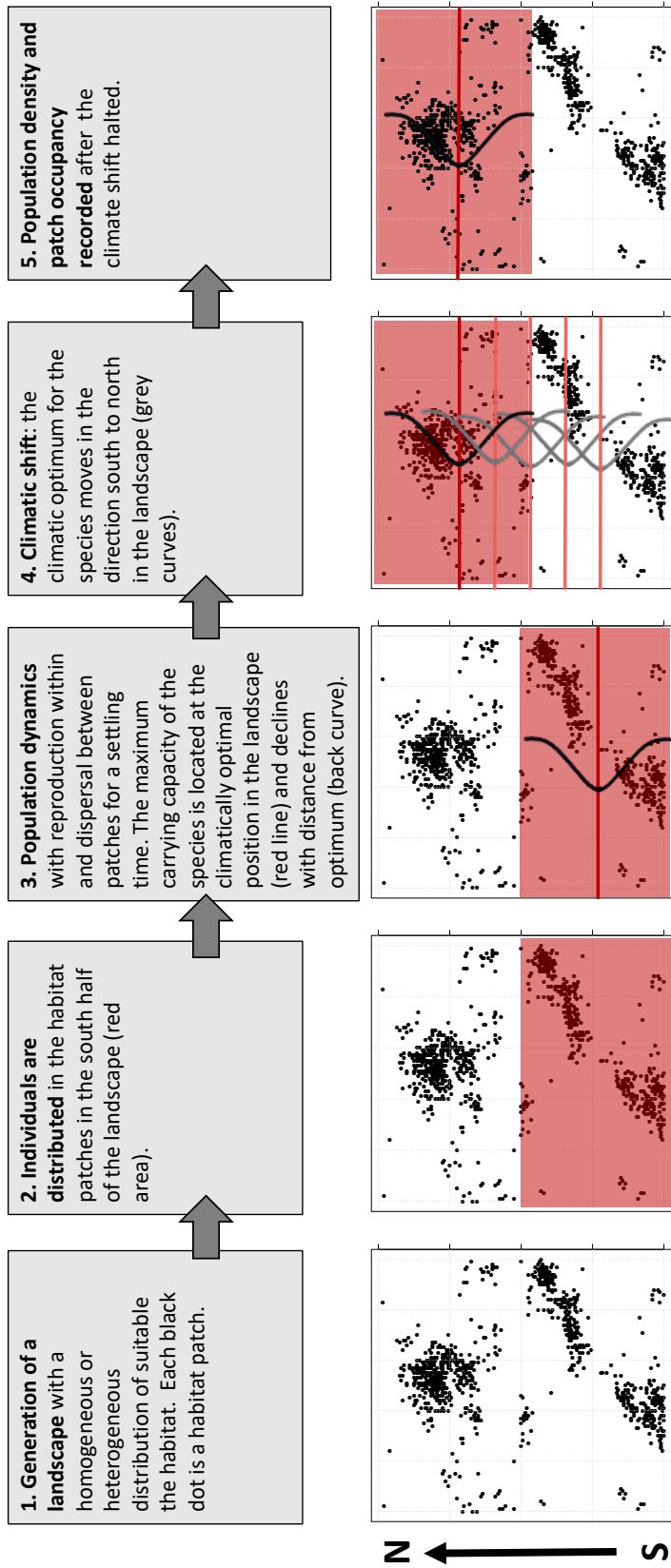


Figure 2

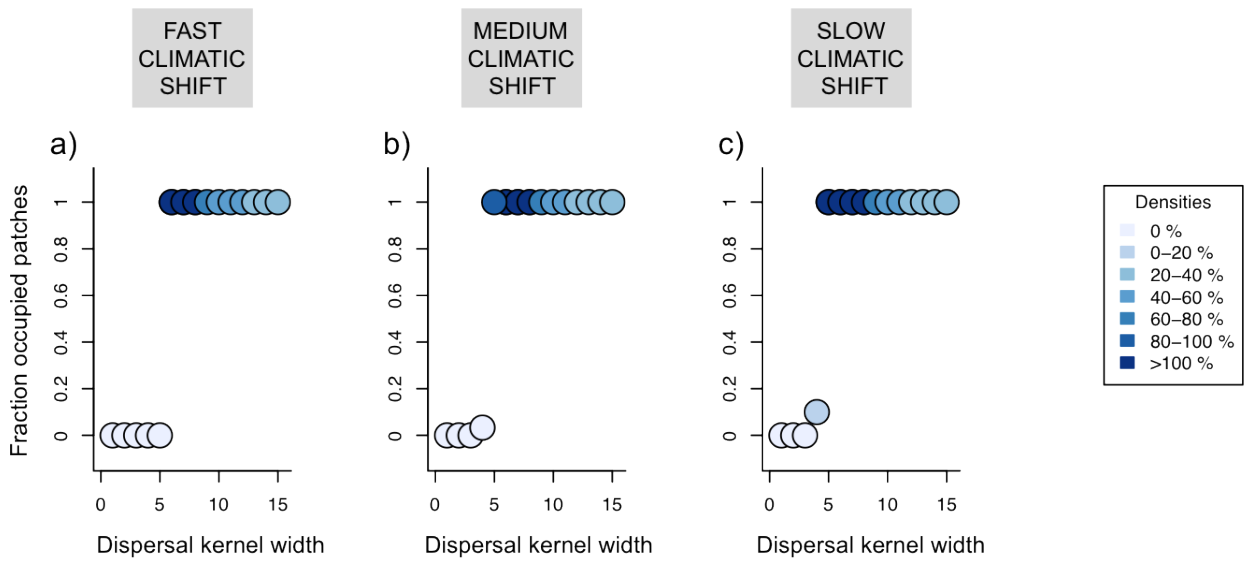


Figure 3

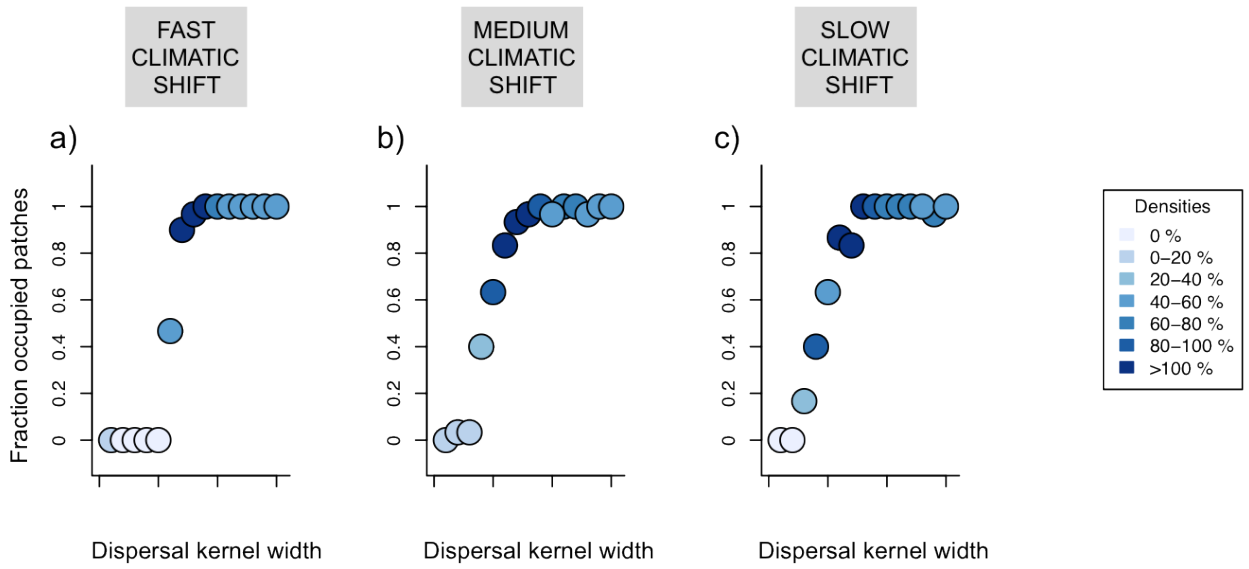


Figure 4

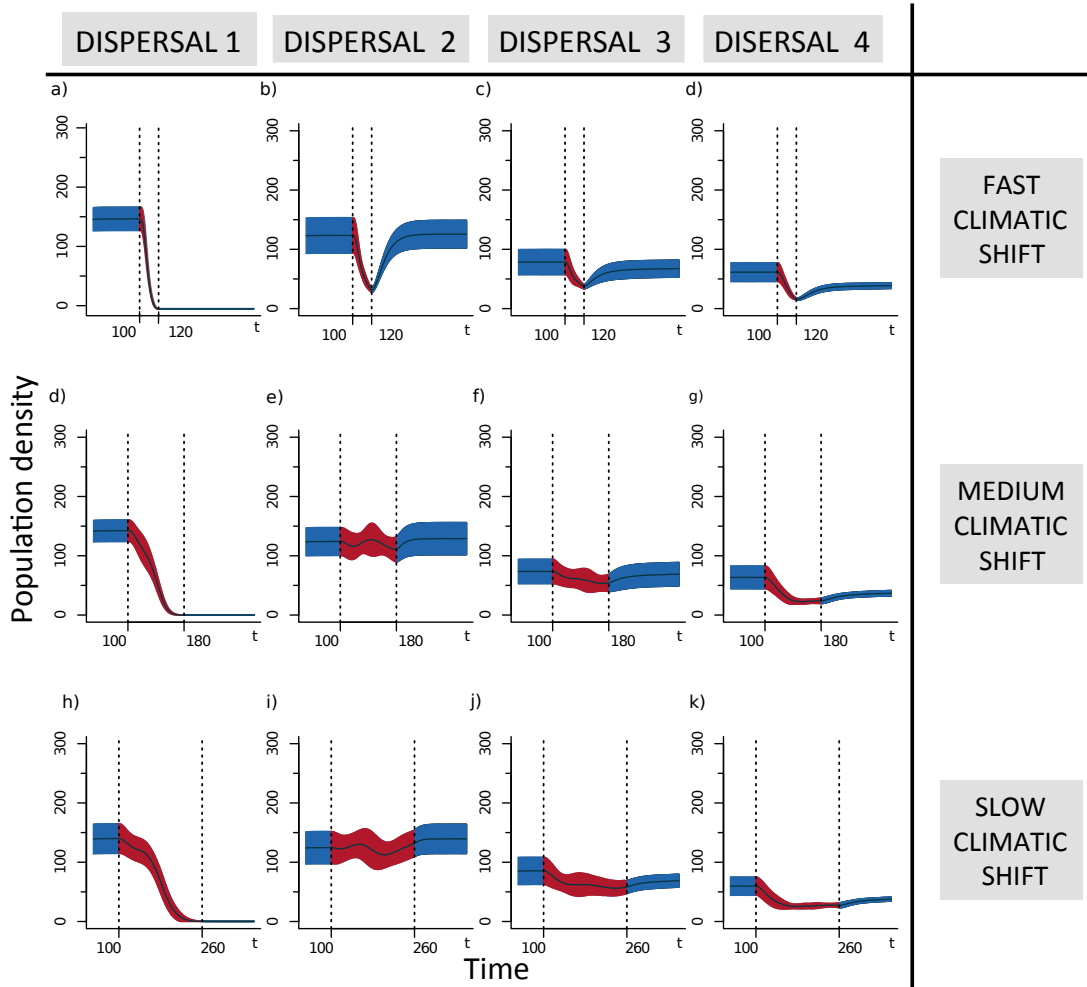


Figure 5

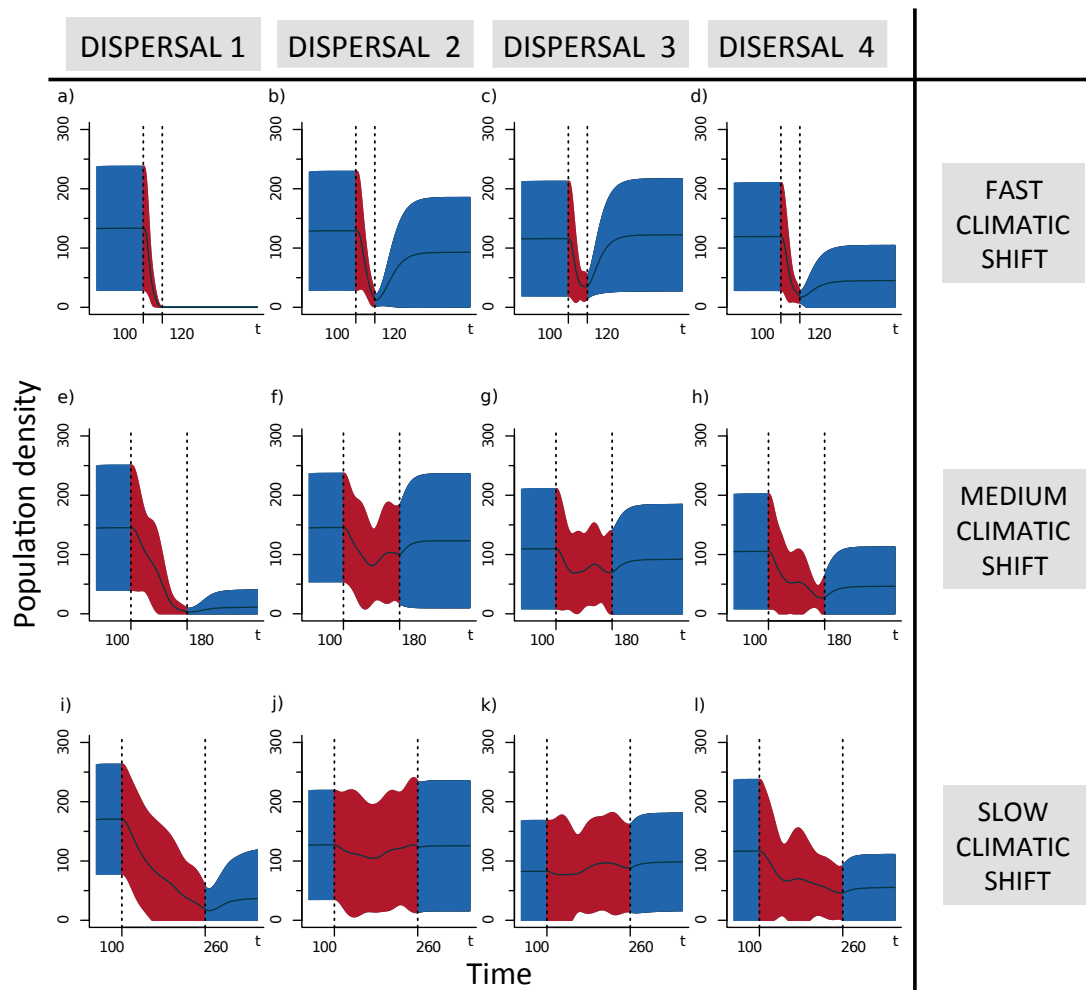


Figure 6

Table 1: Regression tree explaining the number of patches occupied at the end of the simulation. Entities with * indicate terminal branches.

Split	Factor	Number obs.	Mean # occ. patches
0)	Root (all data)	720	399
1)	DispGroup =1	180	32
2)	LandscapeType=2,6A,6B	152	16
4)	LandscapeType=2	90	1 *
4)	LandscapeType=6A,6B	62	37
8)	ShiftSpeed < 120	39	12 *
8)	ShiftSpeed ≥120	23	79 *
2)	LandscapeType=6C	28	119
5)	ShiftSpeed < 50	14	0.1 *
5)	ShiftSpeed ≥50	14	238 *
1)	DispGroup=2,3,4	540	521
3)	DispGroup=2	180	465
6)	LandscapeType=6A,6B	64	410 *
6)	LandscapeType=2,6C	116	494 *
3)	DispGroup=3,4	360	549
7)	DispGroup=3	180	532 *
7)	DispGroup=4	180	566 *

Table 2: Regression tree explaining the global population density at the end of the simulation. Entities with * indicate terminal branches.

Split	Factor	Number obs.	Mean pop. density
0)	Root (all data)	720	45056
1)	DispGroup=1,4	360	19086
2)	DispGroup=1	180	3616 *
2)	DispGroup=4	180	34555
4)	LandscapeType=2,6B,6C	147	26973*
4)	LandscapeType=6A	33	68329
6)	ShiftSpeed < 120	20	43689*
6)	ShiftSpeed ≥120	13	106236*
1)	DispGroup=2,3	360	71026
3)	ShiftSpeed < 50	120	28767*
3)	ShiftSpeed ≥50	240	92156
5)	DispGroup=3	120	67534
7)	LandscapeType=2,6C	73	55537*
7)	LandscapeType=6A,6B	47	86167*
5)	DispGroup=2	120	116778 *

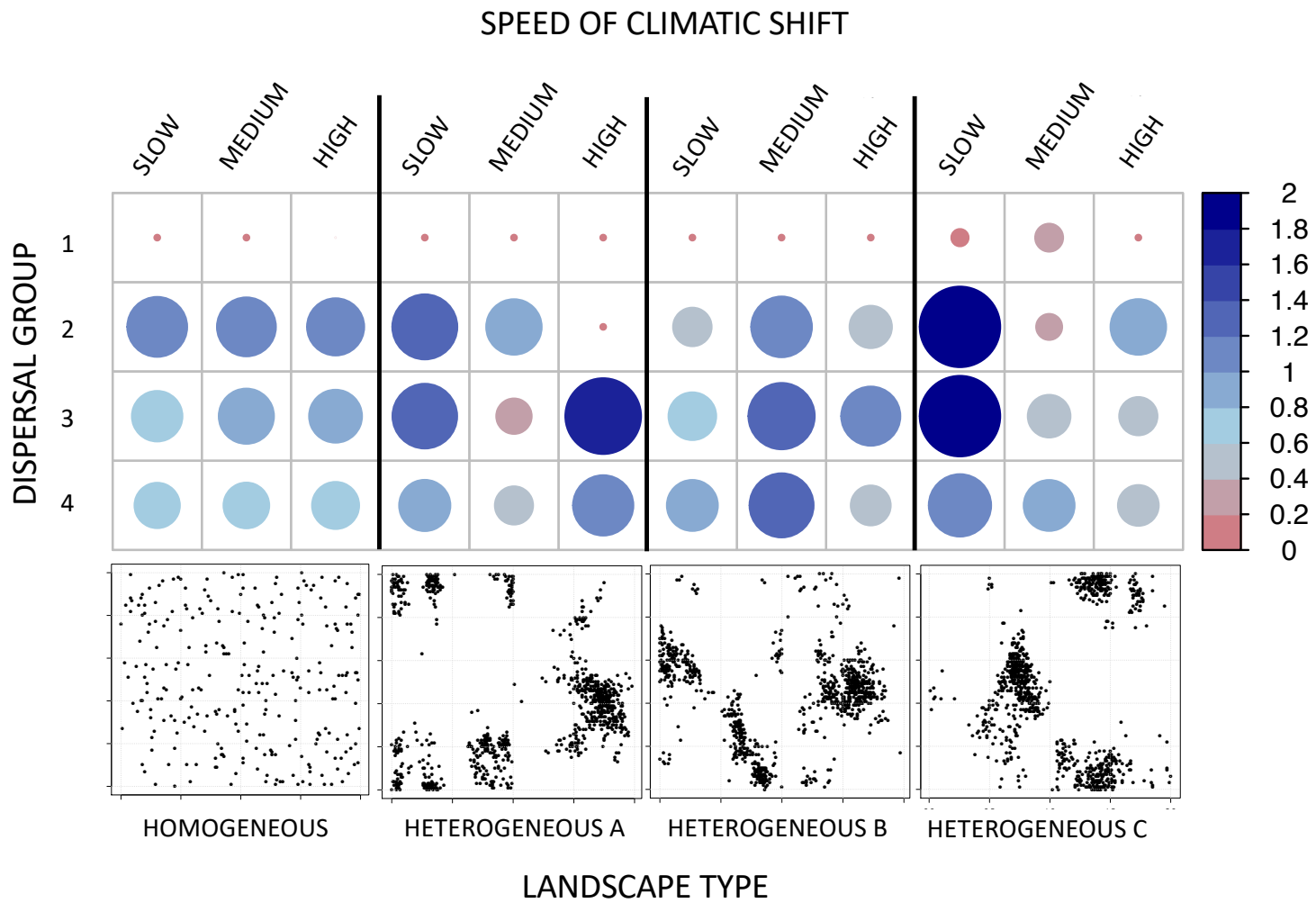


Figure 7

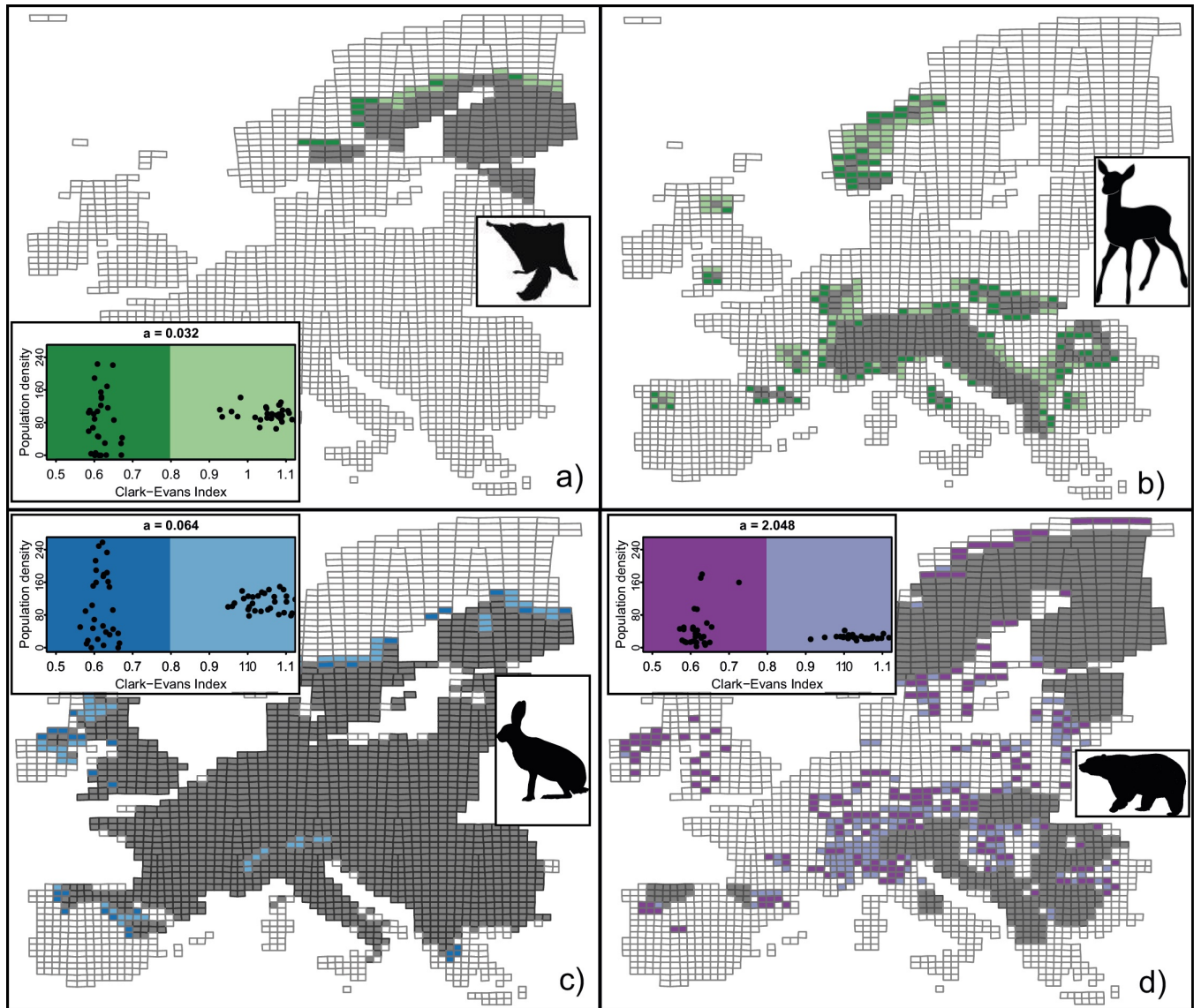


Figure 8