

Evolution of local adaptations in dispersal strategies

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Abstract

1

2 The optimal probability and distance of dispersal largely depend on the risk to end up
3 in unsuitable habitat. This risk is highest close to the habitat's edge and consequently,
4 optimal dispersal probability and distance should decline towards the habitat's border.
5 This selection should lead to the emergence of spatial gradients in dispersal strategies.
6 However, gene flow caused by dispersal itself is counteracting local adaptation. Using
7 an individual based model we investigate the evolution of local adaptations of dispersal
8 probability and distance within a single, circular, habitat patch. We compare evolved
9 dispersal probabilities and distances for six different dispersal kernels (two negative ex-
10 ponential kernels, two skewed kernels, nearest neighbour dispersal and global dispersal)
11 in patches of different size. For all kernels a positive correlation between patch size and
12 dispersal probability emerges. However, a minimum patch size is necessary to allow for
13 local adaptation of dispersal strategies within patches. Beyond this minimum patch area
14 the difference in mean dispersal distance between center and edge increases linearly with
15 patch radius, but the intensity of local adaptation depends on the dispersal kernel. Except
16 for global and nearest neighbour dispersal, the evolved spatial pattern are qualitatively
17 similar for both, mean dispersal probability and distance. We conclude, that inspite of the
18 gene-flow originating from dispersal local adaptation of dispersal strategies is possible if a
19 habitat is of sufficient size. This presumably holds for any realistic type of dispersal kernel.

20

21 *Keywords:* dispersal distance, dispersal probability, dispersal kernel, spatial pattern,
22 individual-based model

23 1 Introduction

24 The evolution of dispersal strategies has become an important topic in theoretical ecology
25 (e.g. Hamilton and May 1977; Comins et al. 1980; Hovestadt et al. 2001; Hanski et al.
26 2004). From an individual's perspective dispersal may be motivated by a number of
27 reasons, e.g. avoiding competition for resources (either inter- or intraspecific; Lambin
28 et al. 2001), minimising kin competition (e.g. Hamilton and May 1977; Comins 1982; Kisdi
29 2004), avoiding inbreeding (e.g. Motro 1991) or coping with the temporal variability of
30 resource availabilities (Levin et al. 1984; Travis and Dytham 1999). Generally, individuals
31 should disperse as long as they expect a higher fitness away from their natal habitat (Frank
32 1986; Metz and Gyllenberg 2001; Poethke and Hovestadt 2002; Dytham 2003). However,
33 dispersal is associated with costs and depending on landscape configuration dispersal may
34 carry a substantial risk: as long as habitat is abundant, dispersal is not very risky, but
35 when suitable patches become scarce and widely spread, dispersers are likely to end up in
36 unsuitable habitat: the matrix (Hastings 1983; Travis and Dytham 1999). Consequently,
37 we can predict the adaptation of dispersal strategies to general landscape characteristics
38 (Hovestadt et al. 2001).

39 In natural landscapes, the quality, density and distribution of habitat is typically vari-
40 able across space. Obviously, the optimal dispersal strategy will depend on the actual
41 position within a heterogeneous landscape. Selection should therefore favour local adap-
42 tation of dispersal strategies, at least as long as offspring disperses into a similar spatial
43 context. However, dispersal is also the factor responsible for gene flow and fundamentally
44 operating against local adaptation (Haldane 1956; Case and Taper 2000). The question
45 then arises under which conditions spatial patterns in dispersal strategies can evolve.

46 In this paper we use an individual-based model to investigate the evolution of dispersal
47 probability and dispersal distance of asexual annual plants within a single circular patch
48 located in a hostile matrix. In contrast to Hamilton and May (1977), Comins et al. (1980),
49 and Rousset and Gandon (2002), who implement dispersal costs as an external factor, in

50 our model the structure of the landscape determines the costs of dispersal due to the loss
51 of offspring dispersing into the matrix (Hovestadt et al. 2001). The evolutionary pressure
52 is mainly exerted by the risk to disperse offspring across the edge of a habitat. This
53 should select for decreased dispersal probability and dispersal distance in small patches
54 or in large patches near the border to the matrix. In the latter case however, gene
55 flow may counteract selection. Therefore, population size and accessibility of habitat
56 should play a crucial role in the emergence of locally adapted dispersal strategies. The
57 topic has already been addressed by Travis and Dytham (1999), who demonstrated that
58 local adaptation of dispersal strategies can emerge in a complex landscape. However,
59 their model consisted of demes with local, non-spatial population dynamics. In addition,
60 Travis and Dytham (1999) did not aim at a systematic investigation of the effect of patch
61 respectively population size on the evolution of dispersal distance and was limited to only
62 one type of dispersal kernel.

63 Our goal is to understand under which conditions the emergence of locally adapted
64 dispersal strategies becomes possible and to compare the evolutionary outcome for differ-
65 ent dispersal kernels in a very simple landscape, which separates our study from the one
66 by Travis and Dytham (1999).

67 **2 Material and Methods**

68 We use an individual-based model, in which space is modelled as a two dimensional grid
69 (Berec 2002) of square landscape cells which can be either habitat or matrix. Each habitat
70 cell can support only one adult plant which is placed in the cell's center. Therefore the
71 spatial scale depends on the plant's size. Within an unbounded world of matrix cells we
72 placed a single circular habitat patch of variable radius (25, 50, 75, 100, 125 and 150 cells)
73 (Figure 1). We use six dispersal kernels in this study: two negative exponential kernels
74 (NE and NE+), two skewed kernels (S and S+) as well as nearest neighbour (NN) and
75 global dispersal (G) (see below and Table 1).

76 Each time step of the model represents a reproduction cycle of annual parthenogenetic
77 plants. Three different procedures are executed during each time step, i.e. (i) reproduc-
78 tion, (ii) dispersal and (iii) post-dispersal competition.

79 **(i) Reproduction:** For simplicity, density-independent mortality of seeds or seedlings
80 is not explicitly modelled. Thus each plant is considered to be a point source for
81 seedlings rather than seeds. Each mother produces a constant number of five ($m=5$)
82 descendants. Each descendant is characterised by two continuous genetic characters
83 G_d and G_p . G_p is coding for the propensity to disperse, whereas G_d codes for the
84 mean dispersal distance. For simulation experiments with kernels characterised by
85 dispersal distance only (S and NE, see below), G_p is without function and conse-
86 quently selectively neutral. The same holds for G_d in simulation experiments with
87 kernels G and NN, which are only defined by a dispersal probability.

88 Seedlings inherit the genes for G_d and G_p from their mother but genes mutate with
89 a probability of 0.001 during this process. In case of a mutation G_d is altered
90 by multiplying its value with a random value from the uniform interval $[0.9, 1.1]$.
91 This keeps G_d positive and creates mutation steps proportional to the value of
92 the genetic character. G_p is altered by adding a random value from the uniform
93 interval $[-0.025, 0.025]$. Its values are kept within the interval $[0, 1]$ by truncation.
94 In each simulation run the values of G_d and G_p in the start population are uniformly
95 distributed within the interval $[0, 200]$ and $[0, 1]$ respectively.

96 **(ii) Dispersal:** During the dispersal process all offspring are distributed according to
97 their parent's dispersal strategy (dispersal distance (G_d) and/or dispersal probability
98 (G_p)). Whenever a dispersing offspring ends up in a matrix cell, it dies. There are
99 no energetic or allocation costs associated with the decision to disperse (G_p) or a
100 specific mean dispersal distance G_d , i.e., the cost of dispersing seeds over a long
101 distance is similar to short distance dispersal.

102 In our experiments we compare the performance of six frequently used dispersal

103 kernels (see Table 1 for a pictographic compilation):

- 104 1. Global (G): The destination cell of a disperser is drawn randomly from all
105 possible landscape cells. This kernel resembles the island model of Hamilton
106 and May (1977) with the modification, that our landscape is heterogeneous.
107 Only the dispersal probability (G_p) is subject to evolution. In contrast to the
108 other kernels this kernel requires a bounded landscape. Therefore, we restrict
109 the dimension of the landscape to 400 X 400 cells in all simulation experiments
110 implementing this kernel. The chance of a dispersing individual to arrive in a
111 habitat cell is determined by the number of habitat cells compared to the total
112 number of cells (equals p of Hamilton and May 1977).
- 113 2. Nearest Neighbour (NN): A disperser draws one of the eight adjacent cells at
114 random as destination (Travis and Dytham 1999). A similar kernel is suggested
115 by Comins (1982) for dispersal between discrete colonies of animals living on a
116 patchy resource, and seed and pollen distributions in continuous populations of
117 plants. Because the dispersal distance is fixed, only the propensity to disperse
118 (G_p) evolves.
- 119 3. Negative-exponential (NE): A disperser draws a direction and distance at ran-
120 dom. The dispersal distance is taken from a negative-exponential probability
121 density function (1) with mean $G_d = 1/\alpha$.

$$f(x) = \alpha e^{-\alpha x} \tag{1}$$

122 Dispersal probability is dependent on dispersal distance in this kernel and only
123 the dispersal distance (G_d) is subject to evolution. As distance is measured
124 from the center of a cell, a seedling remains philopatric if the dispersal distance
125 is short enough to deposit the seedling within the maternal cell. Levin et al.
126 (2003) states that this is probably the most common dispersal kernel in models
127 (e.g. Murrell et al. 2002; Streiff et al. 1999; Yao et al. 1999; Bullock and Clarke

128 2000; Hovestadt et al. 2000; Nathan et al. 2000; Bleher et al. 2002) and does
129 properly fit seed distributions in dense aggregations of plants like forests.

130 4. Negative-exponential plus dispersal probability (NE+): In this kernel the cal-
131 culation of dispersal distances follows the same rules as in kernel NE, except
132 that a dispersal move always starts at the maternal cell’s border, to ensure that
133 any dispersing seedling will fall into a cell different from its origin. The starting
134 point of a dispersal move is the intersection point of a randomly chosen direc-
135 tion and the maternal cell’s border. Hence, G_d (as a parameter of Equation 1)
136 in this kernel is the mean dispersal distance from the maternal cell’s border.
137 In contrast to kernel NE, a seedling disperses only with probability G_p . Both
138 genetic characters, G_p and G_d , evolve.

139 5. Skewed (S): Dispersal distances are drawn from a right-skewed probability
140 density function (2) with mean $G_d = 2/\alpha$, following Hanski (1994) and Appelt
141 and Poethke (1997):

$$p(x) = \alpha^2 x e^{-\alpha x} \quad (2)$$

142 By having its peak away from the source this kernel predicts more seeds to
143 travel beyond the immediate influence of the mother plant than with the nega-
144 tive exponential kernels. In contrast to leptokurtic distributions, like the “2Dt”
145 kernel suggested by Clark et al. (1999), it is determined by just one parameter
146 (α), and is not ‘fat-tailed’. Like with kernel NE only the dispersal distance,
147 determined by the genetic character G_d , undergoes evolutionary changes and
148 seeds that do not cross the maternal cell’s border, stay philopatric.

149 6. Skewed plus dispersal probability (S+): The process determining whether or
150 not to disperse is the same as in kernel NE+ and like with kernel (NE+) a
151 dispersal move starts at a cell’s border. The calculation of dispersal distances
152 complies the same distribution as in kernel S (Equation 2). Both genetic char-

acters, G_d and G_p , evolve.

154 **(iii) Post-dispersal competition:** After their offspring’s dispersal, all adult plants die.

155 For each cell a single seedling is randomly drawn among all its immigrants to es-
 156 tablish and reproduce in the next time-step. All other seedlings die, i.e. we do not
 157 consider the establishment of a seed bank. To test whether local adaptation has
 158 evolved in G_p and G_d , we separate the habitat into four areas: a circular area in
 159 the center (A1) and three consecutive rings (A2-A4) (other modes of partitioning
 160 do not alter the results presented in the following). Each of these areas includes
 161 an approximately equal number of cells. This implies that the rings get “thinner”
 162 towards the edge of the habitat (Figure 1).

163 The number of repeated simulation runs conducted is inversely proportional to the
 164 patch’s area. For a radius of 150 cells (70685 habitat cells in total) we only run
 165 one simulation, while for patches with a radius of 25 cells, 36 replicate simulation
 166 runs (36 x 1963 habitat cells = 70668 habitat cells in total). Hence, the evolu-
 167 tionary process in each landscape configuration is being evaluated on the basis of
 168 about an equal number of habitat cells. Simulations with one evolving trait ran for
 169 50000, for those with two traits 100000 time steps were simulated. We set longer
 170 simulation times for scenarios with two traits because multi-dimensional evolution-
 171 ary trajectories towards equilibrium usually take longer time. The small number
 172 of replicates in large habitats was determined by the substantial computation time
 173 needed. Mean values of G_d and G_p were averaged over all replicates of simulations
 174 of a landscape-kernel-combination.

175 3 Results

176 We first consider the evolution of the dispersal probability, i.e. the fraction of seedlings
 177 deposited outside the cell of origin. Dispersal probabilities depend on both, the size of
 178 the habitat patch and the dispersal kernel. Dispersal probability is by far the lowest

179 with global dispersal (G) but also shows the strongest increase with habitat patch size
180 (Figure 2a). Both exponential kernels (NE and NE+) and the skewed kernels (S and S+)
181 also exhibit an increase in dispersal probability with increasing patch size while nearest
182 neighbour dispersal (NN) is hardly sensitive to patch area. This difference in response
183 to patch size results in a decreasing difference in dispersal probabilities between different
184 kernels for increasing patch area. For small patches with a radius of 25 cells only 20 % of
185 the seeds are dispersed outside the mother's cell with kernel G compared to more than 70
186 % with kernel NE and about 90 % with kernel NE+, S and S+. For patches with a radius
187 of 150 cells evolutionarily stable dispersal probabilities are 50 % for global dispersers and
188 nearly 100 % for kernels S, S+ and NE+. A variance of less than 0.006 in the mean
189 dispersal probabilities across simulation runs even in the smallest patches indicates that
190 results are not strongly affected by random effects.

191 Mean dispersal distance is not an evolvable trait for either nearest neighbour dispersal
192 (NN) or global dispersal (G). For kernel NN it is fixed to the mean distance between
193 neighbouring cells (=1.21) and for global dispersal to approximately 200 cells, i.e. half
194 the dimension of the simulated landscape. For the two negative-exponential kernels (NE
195 and NE+) as well as the skewed kernels (S and S+) evolved mean dispersal distances
196 strongly respond to the size of the habitat patch. Even for small patches they are much
197 smaller than the patch radius. While evolved dispersal probabilities are higher for the
198 NE+ kernel, highest distances evolve with the NE kernel (Figure 2b). This contrasts to
199 the skewed kernels S and S+, where hardly any difference in mean dispersal distances
200 evolves between the two kernels. Furthermore, the mean dispersal distances of kernels S+
201 and S are about the same as with kernel NE+ (Figure 2b) in all patch sizes. To investigate
202 the influence of kin-competition we alter the number of individual offspring from $m=5$
203 to either $m=2$ or $m=10$. With $m=2$ the evolving dispersal probabilities respectively
204 distances drop in all kernels, whereas $m=10$ leads to an increase in the values of both
205 genetic characters.

206 We further check for the emergence of local adaptation in the distribution of dispersal

207 parameters (G_p and G_d) for each of the dispersal kernels. Obviously, there is no spatial
208 correlation between the mother's cell and the target cell of dispersed seedlings for global
209 dispersal. Consequently, no local adaptation can evolve for this dispersal kernel. For
210 the other five kernels (NN, NE, NE+, S and S+) the development of a spatial structure
211 critically depends on patch size. While we find no spatial structure in the experiments
212 with small habitat patches a pronounced structure evolves in the largest patches (Figures
213 3 and 4). Mean dispersal probability ($\overline{G_p}$) as well as mean dispersal distance ($\overline{G_d}$) of
214 individuals is always higher in the centre of the patches (area A1) than at the perimeter
215 (area A4). This difference is strongly dependent on patch size (Figure 5) and may exceed
216 30% in large patches.

217 To control for the effect of mutation rate we run simulations with either a tenfold
218 mutation rate or no mutations at all, but this has very little effect on our results. Only
219 in simulations where evolved values of G_p are close to 1 the results of simulations with no
220 mutations stay slightly below the values achieved with a mutation rate of 0.001 or 0.01.

221 4 Discussion

222 Our simulations clearly demonstrate the dual effect of patch size and dispersal mode
223 on the evolution of dispersal strategies. Depending on the dispersal kernel, different
224 evolutionary adjustments are possible: either by changes in the propensity to disperse, in
225 mean dispersal distance, or both. The evolving strategies are a result of a basic tradeoff
226 between reducing the loss of offspring dispersing into the matrix (Comins et al. 1980) and
227 the possibility to escape kin-competition (Hamilton and May 1977; Ezoe 1998; Kasuya
228 2000; Kisdi 2004). Other factors favouring dispersal are of minor importance in our model
229 because it lacks any environmental stochasticity.

230 For any dispersal kernel, the risk of losing offspring into the surrounding matrix will
231 always decline as patch size increases. Consequently we find a consistent increase in
232 dispersal probabilities with increasing patch area in all dispersal kernels except NN. The

233 risk of loosing offspring into the matrix also depends on the dispersal distance and is largest
234 for the kernels with the largest mean dispersal distance. This argument can explain why
235 with global dispersal, which has the highest mean dispersal distance, the lowest dispersal
236 probabilities evolved, and why this kernel is most sensitive to changes in patch size. With
237 respect to dispersal distance the order of kernels is NN, with a dispersal distance of
238 only one cell, followed by NE+, S, S+ (evolving similar dispersal distances), NE and G.
239 However, considering dispersal probability, the inverse order emerges (except for kernel
240 NN): G, NE, NN, followed by NE+, S and S+. It must be noted that the dispersal
241 probability for kernels NE and S is not an evolvable trait as such but the emergent result
242 of the evolution on mean dispersal distance ($\overline{G_d}$). It should also be noted that the highest
243 dispersal probabilities evolve in the only kernels with two parameters (NE+ and S+), i.e.
244 the kernels which allow the most flexible changes in dispersal strategy.

245 The results with kernel NN (nearest neighbour) do not fit into this general view.
246 Even though mean dispersal distance is the lowest with this kernel, evolved dispersal
247 probabilities are lower than with kernel NE+ and are hardly sensitive to changes in patch
248 area. Presumably, this is a consequence of the restricted ability to escape strong kin-
249 competition if dispersal is exclusively limited to the neighbouring cells (cf. Comins et al.
250 1980). This is confirmed by the effect of altering the number of individual offspring.
251 When m is reduced to 2, kin-competition for free space declines and consequently, the
252 evolving dispersal probabilities respectively distances drop in all kernels. In contrast, with
253 $m=10$ the increase in kin-competition leads to an increase in the values of both genetic
254 characters. For both the exponential and the skewed kernels, mean dispersal distance also
255 increases as patches become larger. It is striking that the mean values of G_d with kernel
256 NE are higher than those for kernel NE+ (compare Figures 4a and 4b). This is caused
257 by the evolutionary “challenge” to regulate philopatry and dispersal distances by a single
258 parameter in kernel NE, while NE+ allows a separate regulation of these two traits. To
259 achieve a similar dispersal probability as with kernel NE+, individuals utilizing kernel NE
260 need to increase mean dispersal distance, as otherwise too many progeny would remain

261 within the natal cell and suffer from higher kin-competition. In contrast, the skewed
262 kernel S evolves the same dispersal distances as S+. Having its peak away from the
263 source leaving the natal cell with kernel S is more likely than with NE, even if mean
264 dispersal distance is lower.

265 The dispersal kernels differ quite remarkably in their tendency to develop spatial pat-
266 terns in dispersal probability or distance. Obviously, local adaptation cannot and did
267 not evolve with global dispersal as the starting position of a dispersing individual has no
268 influence on the target position it will eventually reach. Surprisingly, we also found little
269 evidence for the evolution of local adaptation under kernel NN, even though we observed
270 some decline in parameter G_p in the very outermost ring of cells. The very low dispersal
271 distance of this kernel rather seems to promote the emergence of spatially distinct clusters
272 of individuals of common descent (cf. Figure 6), a pattern frequently detected in such
273 kinds of grid based simulations (e.g. Tilman et al. 1997; Levin and Pacala 1997; Ennos
274 2001). Travis and Dytham (1999) also implemented kernel NN in their simulation study
275 to investigate local adaptation in fractal landscapes. They found a much broader range
276 for the evolved dispersal probabilities than we and describe a clear selection for dispersal
277 inside a patch and a distinct evolution towards non-dispersal at the habitat border. This
278 is most likely caused by considering patches consisting of demes with local population
279 dynamics each rather than cells consisting of only one individual. The higher capacities
280 of surrounding cells exert less pressure against dispersal in the inner areas of a habi-
281 tat by granting a higher probability of settling for immigrants. The clear selection for
282 non-dispersal at the edge of their patches may be caused by the difficulty of gene flow
283 introduced by the “rugged” shape of fractal patches.

284 For the two exponential kernels and the skewed kernels – which are probably closest
285 to naturally occurring kernels – we observe the development of a weak spatial gradient
286 for both dispersal probability and especially dispersal distance in patches with a radius
287 of 50. From then on, the difference in mean dispersal distance between the centre of the
288 patch (A1) and the outermost ring (A4) increases rather linearly (Figure 5b). In the

289 largest patch mean dispersal distance is about one third larger in the centre than in the
290 edge of the patch while the difference is less than 1/10 in the patch with a radius of 50.
291 However, this does not imply that evolution at the edge and in the centre are completely
292 independent. Given the values for G_d which did evolve, the direct effect of losing off-
293 spring is limited to cells near the border of the patch. Nonetheless, compared to area A1
294 a reduction in dispersal distance is still noticeable in ring A2, (Figure 4), i.e. in a distance
295 which is about seven times further away from the edge than the mean value for G_d in
296 the patch's centre. Apparently, gene flow "transfers" the selective pressure on G_d near the
297 patch's edge far into the interior of the patches.

298

299 The simulation results clearly demonstrate the existence of a minimum patch area
300 necessary for the evolution of locally adapted dispersal strategies. If we assume the
301 average diameter of a tree crown to be 5 m, the minimal area of a (circular) patch in
302 which we could expect to find a gradient in dispersal strategy would be about 0.2 km²
303 (500 m diameter). In contrast, for small herbs with a average diameter of only 10 cm, a
304 spatial structure could eventually develop in a patch of only 75 m².

305 The evolution of dispersal distance and consequently the size of the values predicted
306 above would certainly be different if model parameters were altered or new ones added. For
307 example, an increase in the longevity of organisms, trade-offs between dispersal distance
308 and competitiveness (cf. Greene and Johnson 1993; Geritz 1995), or habitat disturbance
309 (cf. Comins 1982; Gandon and Michalakis 2001) would presumably all alter the evolution
310 of dispersal distance and the emergence of spatial patterns.

311

312 From experimental work and field-observations we know that a variety of plant species
313 is able to adapt their propagation strategy to selective pressures. Michaels et al. (1988)
314 confirmed that intraspecific adaptations of dispersal strategies are generally possible.
315 More specifically, a plant can influence the dispersal capabilities of its offspring because
316 seed sizes of individual plants vary (Geritz 1995). An example for a direct adaptation to

317 landscape structure is the change of the reproductive mode from propagation via seeds
318 (long distance dispersal) to vegetative (nearest neighbour dispersal) depending on local
319 circumstances. Prati and Schmid (2000) discovered that *Ranunculus reptans* invested
320 heavily into sexual reproduction when close to water, but more into vegetative reproduc-
321 tion on land. In this case the differentiation is only an indirect adjustment to landscape
322 structure, as it results from a difference in the intensity of competition with a low chance
323 of establishment from seeds away from water. Kanno and Seiwa (2004) report that the
324 reproductive mode (sexual or vegetative) of the clonal forest understory shrub *Hydrangea*
325 *paniculata* is influenced by small scale variations in the dynamics of canopy trees. These
326 findings, as well as our simulation results, prove that adjustments of dispersal strategies
327 to local demographic situations are in principle possible and are selected for under certain
328 conditions.

329

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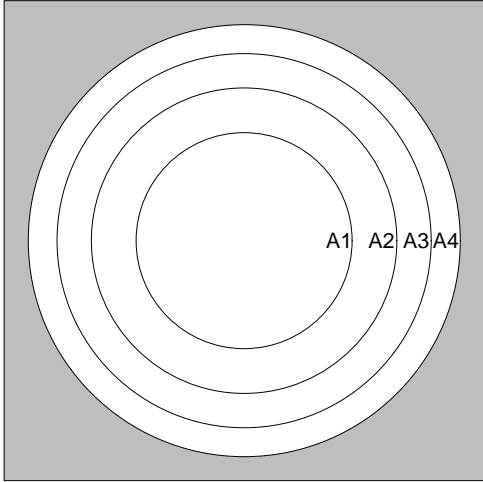


Figure 1: Simple patch-matrix landscape used in simulations. (white=habitat, gray=matrix). The indices mark the evaluation areas of approximately equal carrying capacity separately analysed for emergent dispersal strategies. Simulations were run on patches with radii varying from 25 to 150 in steps of 25.

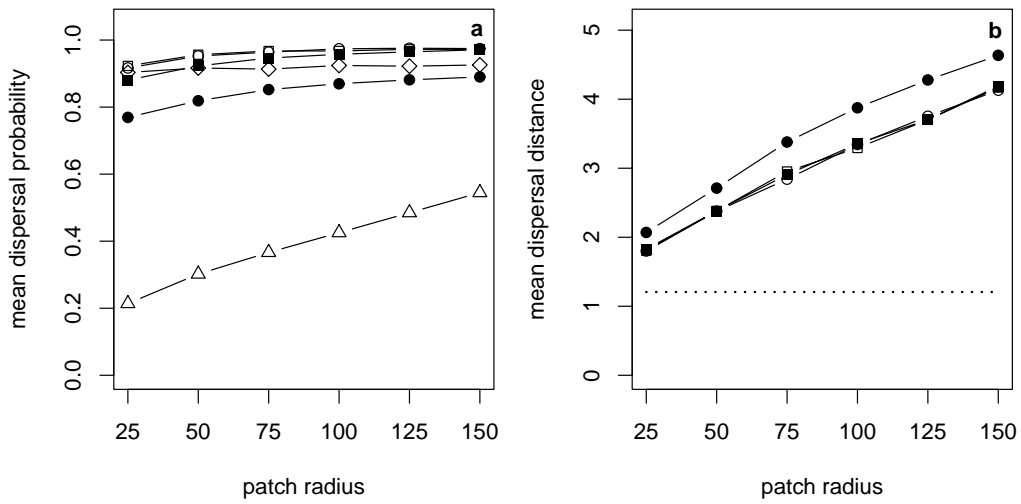


Figure 2: (a) Evolved mean dispersal probabilities (except for NE and S, parameter G_p) with either kernel NE+ (open circles), kernel NE (filled circles), S+ (open squares), S (filled squares), NN (open diamonds), or G (open triangles) in different patch sizes. For kernels NE and S the evolved mean dispersal probability is only the emergent consequence of selection on trait G_d . (b): Evolved mean dispersal distances (parameter G_d) either for kernel NE+ (open circles), NE (filled circles), S+ (open squares), or S (filled squares) in different habitat patch sizes. Dotted line indicates mean dispersal distance for nearest neighbour dispersal. The plotted trait values are averages of the traits of all individuals in a patch.

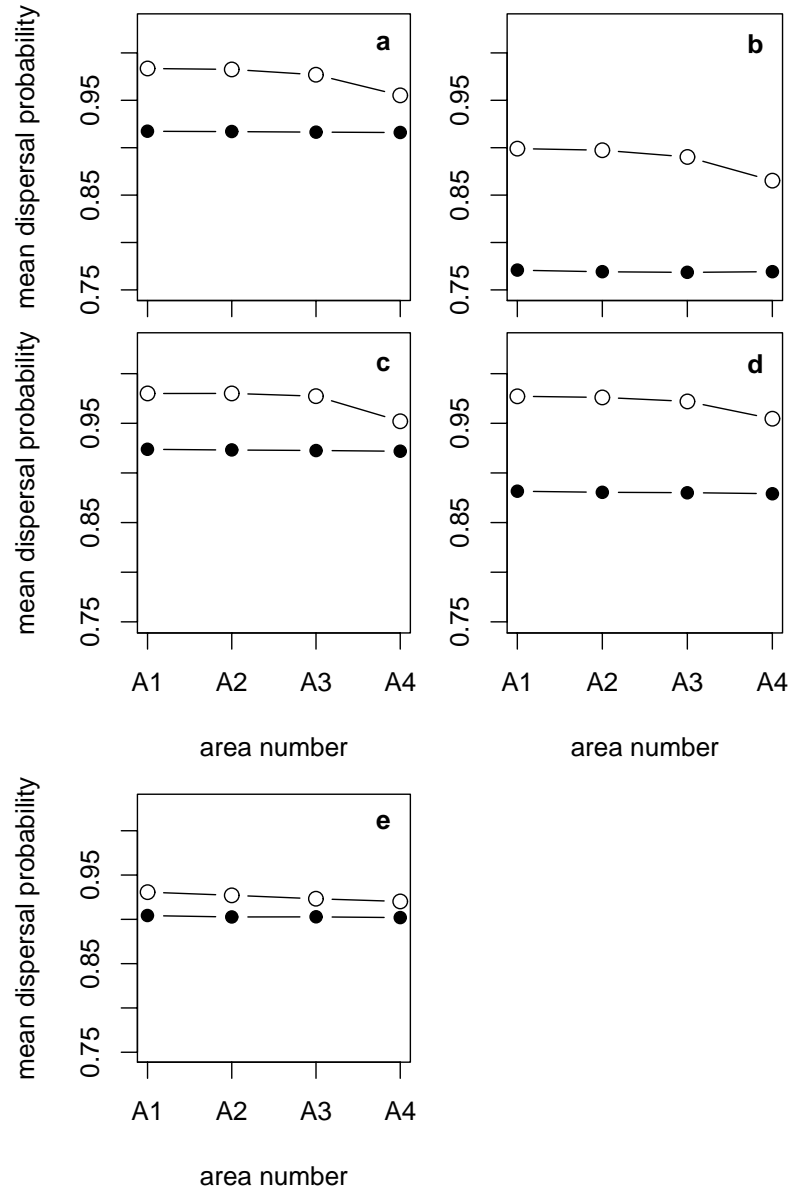


Figure 3: Distribution of mean dispersal probability (except for NE and S, parameter G_p) across the different patch zones outlined in Figure 1 either for kernel NE+ (a), kernel NE (b), kernel S+ (c), kernel S (d), or NN (e). Open circles: patch-radius 150, filled circles: 25 cells. For kernel NE and S G_p as such is not an evolving trait but rather the fraction of seeds leaving the home cell given the evolved mean dispersal distance $\overline{G_d}$. The plotted trait values result from separate averaging of individuals within the evaluation zones A1 to A4 (Figure 1).

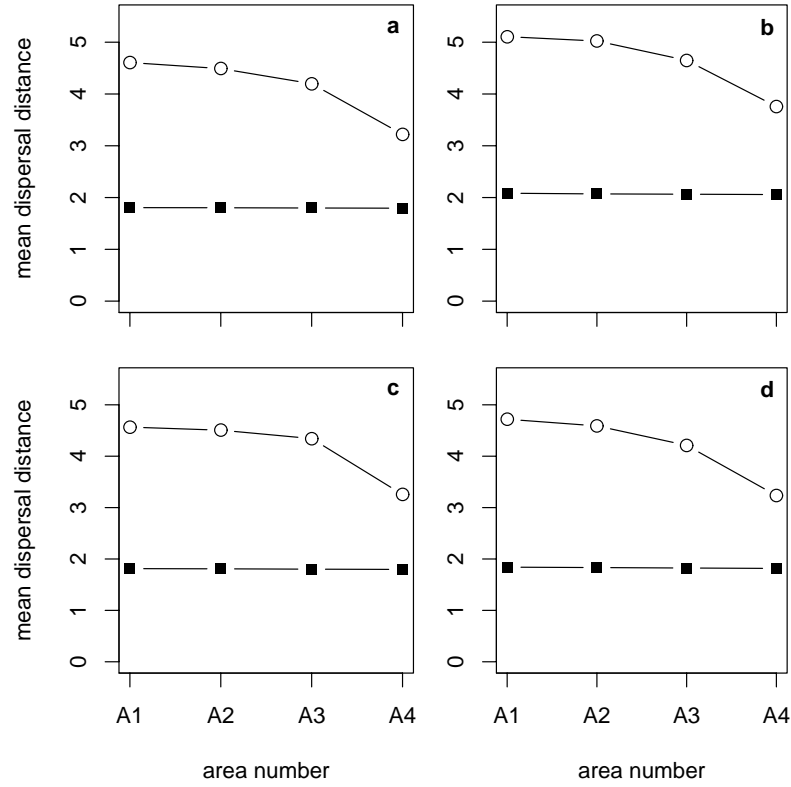


Figure 4: Distribution of mean dispersal distance with kernel NE+ (a), NE (b), S+ (c) or S (d). The panels show mean dispersal distances in evaluation areas as stated in Figures 1. Open circles: patch-radius 150, filled squares: 25 cells. The plotted trait values result from separate averaging of individuals within the evaluation zones A1 to A4 (Figure 1).

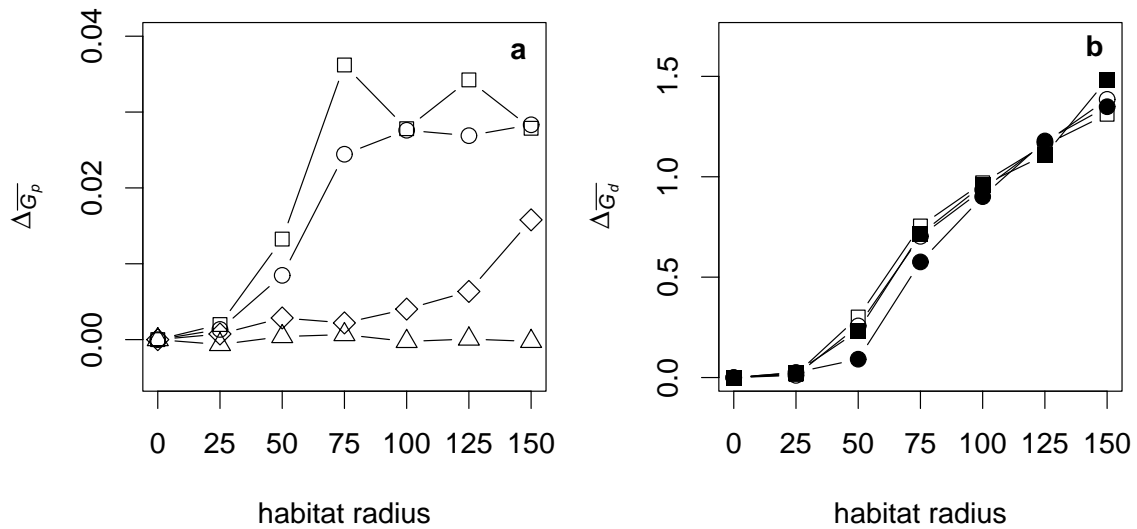


Figure 5: Difference of evolved mean dispersal probability ($\overline{G_p}$) and mean dispersal distance ($\overline{G_d}$) between area A1 and A4 in relation to habitat radius. (a) Mean dispersal probability ($\overline{G_p}$) and (b) mean $1/\alpha$ in kernels NE and NE+ and mean $2/\alpha$ in kernels S and S+ ($\overline{G_d}$). Open circles: kernel NE+, filled circles: kernel NE, open squares: kernel S+, filled squares: kernel S, open diamonds: kernel NN, open triangles: kernel G.

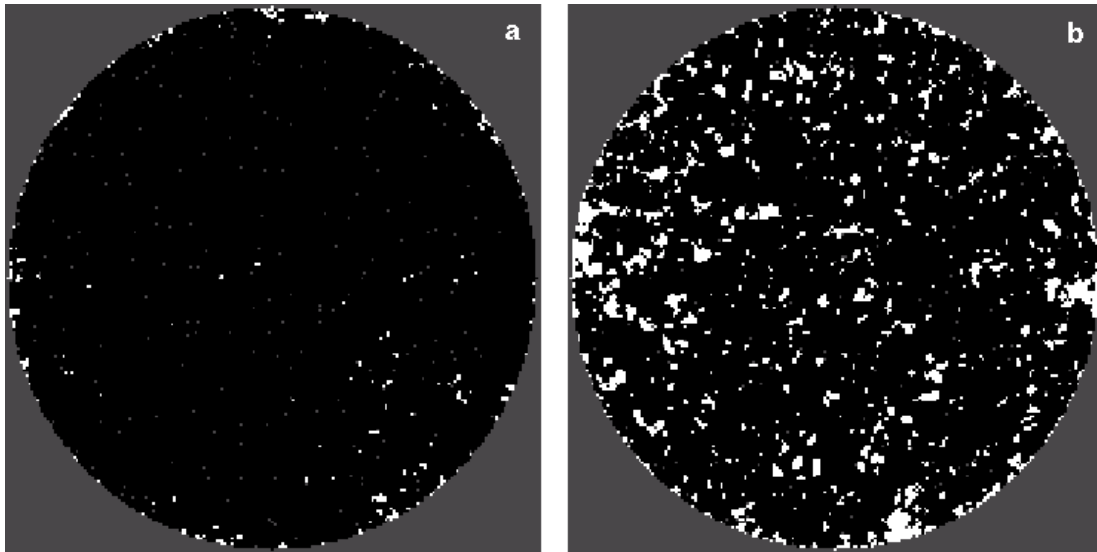


Figure 6: Similarity of G_p -values in patches of radius 100 with either kernel NE+ (a) or kernel NN (b) at the end of a simulation run. Occupied habitat cells are coloured either black or white. A cell is coloured white, if it is surrounded by at least seven cells with same trait values or matrix cells. Dark gray areas outside patch boundary indicate matrix, inside the patch currently empty cells. In contrast to our other findings here we find different pictures with different mutation rates.

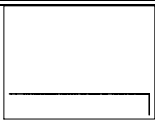
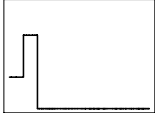
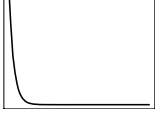
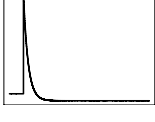
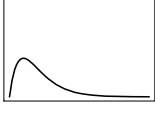
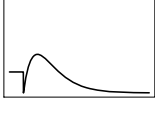
kernel	distance probability density	evolving traits
Global (G)		G_p
Nearest Neighbour (NN)		G_p
Negative Exponential (NE)		G_d
Negative Exponential plus disp. probability (NE+)		G_d, G_p
Skewed (S)		G_d
Skewed plus disp. probability (S+)		G_d, G_p

Table 1: Pictographic presentation of the different dispersal kernels implemented in simulation models (for more details see text). The term “plus disp. probability” means that these kernels make use of both genetic characters, dispersal distance and dispersal probability.