

# Density-dependent selection and the limits of relative fitness

Jason Bertram <sup>1,\*</sup>

Joanna Masel <sup>1</sup>

1. Department of Ecology and Evolutionary Biology, University of Arizona, Tucson, AZ 85721.

\* Corresponding author; e-mail: jbertram@email.arizona.edu.

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<sup>1</sup> **Abstract**

<sup>2</sup> TBA

### 3 Introduction

There are a variety of different measures of fitness. Some widely used examples in evolutionary ecology are expected lifetime reproductive ratio  $R_0$ , intrinsic growth rate  $r$ , saturation population density (often labeled “ $K$ ”) [Benton and Grant, 2000], and invasion fitness [Metz et al., 1992]. In addition, “relative fitness” is the standard in much of evolutionary biology, particularly evolutionary genetics, where attention is generally restricted to relative genotypic proportions [Barton et al., 2007, pp. 468]. The variety of fitness measures is not problematic in itself, because different measures may be more useful in different circumstances. But it should be clear how the measure being used is connected to the processes of birth and death which govern population biology [Doebeli et al., 2017, Metcalf and Pavard, 2007]. While such a connection is fairly clear for absolute fitness measures like  $r$ , relative fitness seems largely divorced from population biology. It has even been proposed that relative fitness be justified from more abstract measure-theoretical arguments, abandoning population biology altogether [Wagner, 2010].

In uncrowded populations, relative fitness simply represents differences in intrinsic growth rate. In discrete time, the change in frequency of type  $i$  is  $\Delta p_i = \left( \frac{W_i}{\bar{W}} - 1 \right) p_i$ , where  $W_i$  is the intrinsic absolute growth factor of type  $i$ , and  $\bar{W} = \sum_i W_i p_i$  is the population mean  $W$ . Here we can rescale  $W$  however we please and replace it with “relative fitness”  $w$  without affecting the ratio  $\frac{W_i}{\bar{W}} = \frac{w_i}{\bar{w}}$ . In continuous time, the canonical selection equation is  $\frac{dp_i}{dt} = (r_i - \bar{r}) p_i$ , where  $W$  is replaced by the intrinsic exponential growth rate  $r$  [Crow et al., 1970, pp. 26]. If there are two types present, a wildtype and a mutant for instance, then the continuous time canonical selection equation can be written as

$$\frac{dp_i}{dt} = s p_i (1 - p_i), \quad (1)$$

where the constant selection coefficient  $s$  is the difference in  $r$  between types. The corresponding adaptive sweeps follow a logistic curve.

The difficulty with Eq. (1) arises in crowded populations. Since crowded and uncrowded conditions are so different,  $s$  will often depend on density. Eq. (1) is then no longer a com-

plete description of selection (we would also need to specify a model for density). Note that frequency-dependent selection does not raise similar problems; Eq. (1) is still a complete description of selection even if its behavior is more complicated compared to the constant- $s$  case. Standard population genetics evades the issue of density-dependent selection by simply assuming that total population density  $N$  has reached its equilibrium value, which is assumed to be a fixed constant. The selection coefficient  $s$  now parameterizes the rate at which selection changes relative frequencies, but no longer corresponds to differences in intrinsic growth rates  $r$ .

Counter to the assumption of constant  $N$ , MacArthur famously showed that when population growth is density-regulated, selection in crowded populations is intimately connected to the ability to keep growing at higher densities than other types can tolerate [MacArthur and Wilson, 1967]. The classic example is the logistic model, where the type with the greatest saturation population density “ $K$ ” excludes the others (Fig. 1a). Similarly, the “ $R^*$  rule”, a central tenet of resource competition theory, states that when growth is limited by a single homogeneous consumable resource, the type able to deplete the resource to the lowest equilibrium density  $R^*$  excludes the others [Grover, 1997]. Differences in  $R^*$  will often entail differences in saturation density. The Lotka-Volterra competition model also couples selection in crowded populations to changes in  $N$  except in a few special cases (we return to this in section “ $K$ -selection versus relative fitness”). In these examples, both  $N$  and  $s$  change during, and as a result of, adaptive sweeps. It would therefore seem that the ubiquitous constant- $N$ , relative fitness description of selection is incompatible with a huge class of population ecological processes driving selection (Fig. 1b).

The relative fitness description has been justified in broadly two different ways for crowded populations (we do not discuss Wagner’s [2010] measure-theoretical justification, which is explicitly independent of population biology and thus falls outside of our scope). The first is to assume that selection is independent of density but still allow density to be affected by selection [Barton et al., 2007, pp. 468] [Prout, 1980]. While this allows us to relax the assumption of constant  $N$ , it does not address the problem that  $s$  can, in reality, depend on density. In the examples from the

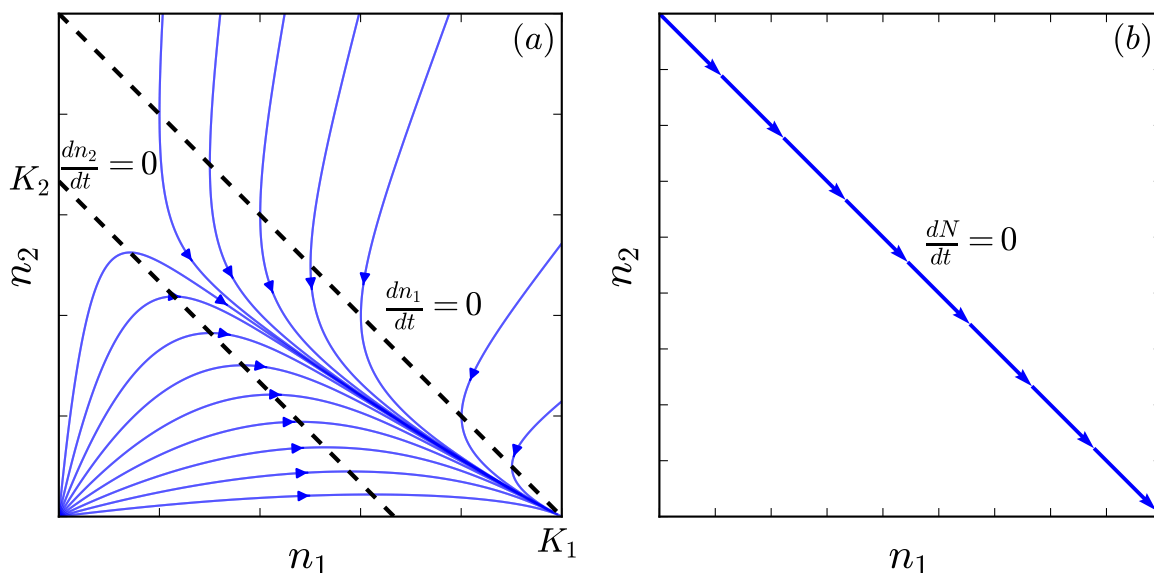


Figure 1: Selection in crowded environments shown as a phase diagram for the densities of two types  $n_1$  and  $n_2$ . (a) The logistic model  $\frac{dn_1}{dt} = r_1(1 - \frac{n_1+n_2}{K_1})n_1$  and  $\frac{dn_2}{dt} = r_2(1 - \frac{n_1+n_2}{K_2})n_2$  with  $r_1 = r_2$  and  $K_1 > K_2$ . (b) The constant- $N$ , relative fitness description of selection.

previous paragraph, selection is density-dependent; indeed, the type-specific responses to density are at the center of MacArthur’s argument and the density-dependent selection literature that grew out of it [Roughgarden, 1979].

Second, constant  $N$  and  $s$  can both be seen as a short-term linear approximation [Ewens, 2004, pp. 277]. That is, within a sufficiently short time frame,  $N$  and  $s$  can be treated as constant. Provided that selection is sufficiently weak and stable over time, this “short-term” assumption is not a major restriction. Yet it is increasingly recognized that selection is not always weak, that it can fluctuate considerably over time, and that  $N$  can vary by orders of magnitude over a few generations as a routine feature of a population’s ecology [Messer et al., 2016]. These are not rare exceptions, but occur widely in nature and the lab, including in wild *Drosophila* [Bergland et al., 2014]. Nevertheless, relative fitness models are the foundation for much of the population genetic literature, and are still widely used without considering the “short-term” restriction or the lack of integration with population ecology [Mallet, 2012]. Thus, it is important to understand the population ecological basis of relative fitness models, both to gain insight into their domain of

applicability, and as part of the broader challenge of synthesizing ecology and evolution.

Another issue with the constant- $N$  relative fitness description of selection is that it precludes consideration of longer-term aspects of the interplay between evolution and ecology such as population extinction. Adaptive dynamics currently provides a powerful framework for addressing the complex feedbacks between evolutionary change and population density [Diekmann et al., 2004]. However, the focus of adaptive dynamics is trait evolution rather than the underlying genetics, and in particular, selective sweeps are typically subsumed into effectively-instantaneous “trait substitutions”. We emphasize that our focus here is the description of the time-dependent process of selection itself, which is particularly critical for making sense of evolution at the genetic level for which we now have abundant data.

Here we analyze the population ecology of relative fitness using a novel model of density-dependent population growth based on territorial contests. Rather than attempting to make sense of relative fitness in the standard models of population growth mentioned above (e.g. Mallet [2012]), we instead do the reverse, and attempt to make population ecological sense of the widely-used Wright-Fisher, constant- $N$ , relative fitness model. Our starting point is the classic lottery model of territorial contest [Chesson and Warner, 1981, Sale, 1977]. Like the Wright-Fisher model, the classic lottery assumes a saturated population with constant  $N$ , and fitness involves a product of fertility and juvenile viability [Crow et al., 1970, pp. 185]. Unlike the Wright-Fisher model, generations can overlap in the lottery model. We generalize the lottery model to allow population density to vary, and show that this model can be interpreted as a density-dependent generalization of the Wright-Fisher model with overlapping generations.

We show that when this model reaches a demographic steady-state, the constant- $N$ , relative fitness picture emerges. Furthermore, we show that our model is entirely consistent with MacArthur’s analysis of selection in crowded populations. In particular, we emphasize that MacArthur’s argument does not justify the widespread intuition that selection in crowded environments is necessarily connected to achieving greater densities. This is largely an artifact of the models historically used in the density-dependent selection literature, which ignore relative

contests.

Our first task is to analytically extend the classic lottery model to correctly account for low density behavior (sections ). We then...

## Model

### Model assumptions and definitions

We assume that reproductively mature individuals (“adults”) each require their own territory to survive and reproduce (Fig. 2). All territories are identical, and the total number of territories is  $T$ . Time  $t$  advances in discrete iterations, each representing the time from birth to reproductive maturity. In iteration  $t$ , the number of adults of the  $i$ ’th type is  $n_i(t)$ , the total number of adults is  $N(t) = \sum_i n_i(t)$ , and the number of unoccupied territories is  $U(t) = T - N(t)$ .

We assume that the  $n_i$  are large enough that stochastic fluctuations in the  $n_i$  (“drift”) can be ignored. In particular, we do not evaluate the initial stochastic behaviour of mutant lineages while they are at low abundance. We derive equations for the expected change in the  $n_i$  over time, leaving the evaluation of drift for future work.

Each iteration, adults produce new offspring (“propagules”),  $m_i$  of which disperse to unoccupied territories. We assume that adults cannot be ousted from their territories, so that  $m_i$  only includes propagules landing on unoccupied territories. Propagules disperse at random over the unoccupied territories, regardless of distance from their parents, and independently of each other. There is no interaction between propagules (e.g. avoidance of territories crowded with propagules). Loss of propagules during dispersal is subsumed into  $m_i$ . We assume that each adult produces a constant number  $b_i$  of successfully dispersing propagules; the loss of propagules due to dispersal to occupied territories then implies  $m_i = b_i(1 - N/T)n_i$ . Note that due to our assumption of uniform dispersal, the parameter  $b_i$  can be thought of as a measure of “colonization ability”, which combines fecundity and dispersal ability [Bolker and Pacala, 1999, Levins and Culver, 1971, Tilman, 1994].

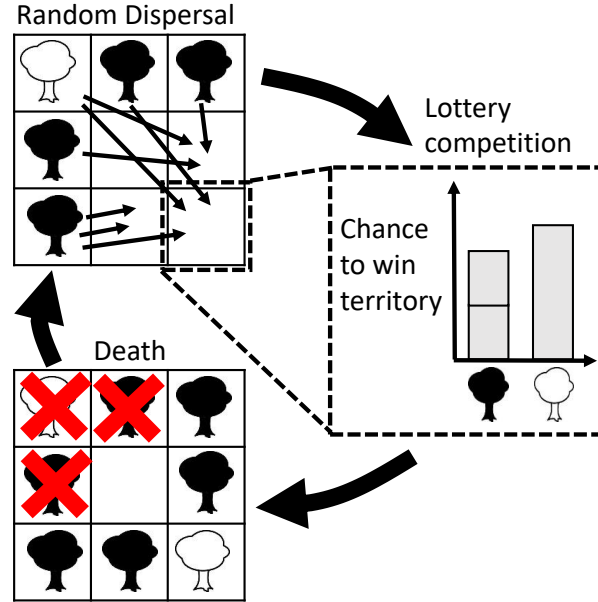


Figure 2: Each iteration of our model has three elements. First, propagules are produced by adults and dispersed at random (only propagules landing on unoccupied territories are shown). Some territories may receive zero propagules. Lottery competition then occurs in each unoccupied territory that receives a propagule (only illustrated in one territory). Each type has a probability proportional to  $c_i x_i$  of securing a given territory, where  $c_i$  measures competitive ability and  $x_i$  is the number of propagules that disperse there. In the illustrated territory, the black type disperses more propagules but is a poorer competitor. Territories are then made available by deaths among those adults present at the start of the iteration (red crosses).



The number of individuals of the  $i$ 'th type landing in any particular territory is denoted  $x_i$ . We assume that  $x_i$  follows a Poisson distribution  $p_i(x_i) = l_i^{x_i} e^{-l_i} / x_i!$ , where  $l_i = m_i / U$  is the mean territorial propagule density. This approximation becomes exact when the  $n_i$  are large enough that drift in  $n_i$  can be ignored (Appendix A).

When multiple propagules land on the same territory, the victor is determined by lottery competition: type  $i$  wins a territory with probability  $c_i x_i / \sum_j c_j x_j$ , where  $c_i$  is a constant representing relative competitive ability (Fig. 2). We expect that a fraction  $p_1(x_1) \dots p_G(x_G)$  of the  $U$  unoccupied territories will have the propagule composition  $x_1, \dots, x_G$ . type  $i$  is expected to win  $c_i x_i / \sum_j c_j x_j$  of these. Ignoring fluctuations about these two expectations (due to our no-drift, large  $T$ , large  $n_i$  approximation), type  $i$ 's territorial acquisition is given by

$$\Delta_+ n_i(t) = U(t) \sum_{x_1, \dots, x_G} \frac{c_i x_i}{\sum_j c_j x_j} p_1(x_1) \dots p_G(x_G), \quad (2)$$

in our extended lottery model, where the sum only includes territories with at least one propagule present.

Finally, we assume that mortality only occurs in adults (Fig. 2; setting aside the juvenile deaths implicit in territorial contest), and at a constant, type-specific per-capita rate  $0 \leq d_i \leq 1$ , so that the overall change in type abundances is

$$\Delta n_i(t) = \Delta_+ n_i(t) - d_i n_i(t). \quad (3)$$

## Connection to the Wright-Fisher and classic lottery models

In the classic lottery model [Chesson and Warner, 1981], unoccupied territories are assumed to be saturated with propagules from every type  $l_i \gg 1$ . From the law of large numbers, the composition of propagules in each territory will then not deviate appreciably from the mean composition  $l_1, l_2, \dots, l_G$  ( $G$  is the number of types present), and so the probability that type  $i$  wins any particular unoccupied territory is approximately  $c_i l_i / \sum_j c_j l_j$ . Then the numbers of territories

142 won by each type  $\Delta_+n_1, \Delta_+n_2, \dots, \Delta_+n_G$  follow a multinomial distribution with  $U$  trials and  
 143 success probabilities  $\frac{c_1l_1}{\sum_j c_jl_j}, \frac{c_2l_2}{\sum_j c_jl_j}, \dots, \frac{c_Gl_G}{\sum_j c_jl_j}$ , respectively. Type  $i$  is expected to win  $c_il_i / \sum_j c_jl_j$  of  
 144 the  $U$  available territories, and deviations from this expected outcome are small (since  $T$  is large  
 145 by assumption), giving

$$\Delta_+n_i(t) = \frac{c_il_i}{\sum_j c_jl_j}U(t) = \frac{c_il_i}{\bar{c}L}U(t), \quad (4)$$

146 where  $\bar{c} = \sum_j c_jm_j / M$  is the mean propagule competitive ability for a randomly selected propag-  
 147 ule,  $L = M/U$  is the total propagule density and  $M = \sum_j m_j$  is the total number of propagules.

148 Eq. (4) breaks down for types with low propagule density ( $l_i \ll 1$ ) because territorial acqui-  
 149 sition is then not correctly represented by a lottery in each territory with the mean propagule  
 150 density. Instead, a rare type's propagules only make it to a few territories where at least one of  
 151 its propagule present. In our extension of the classic lottery model, we correct (Eq. 3) to account  
 152 for this.

153 There is a close connection between the classic lottery model and the Wright-Fisher model  
 154 of genetic drift [Svardal et al., 2015]. In the Wright-Fisher model, type abundances are sampled  
 155 each generation from a multinomial distribution with success probabilities  $w_in_i / \sum_j w_jn_j$ , where  
 156  $w$  is relative fitness and the  $n_i$  are type abundances in the preceding generation. Population  
 157 size  $N$  remains constant. This is equivalent to the classic lottery model with non-overlapping  
 158 generations ( $d_i = 1$  for all  $i$ ) and relative fitness given by  $w_i = b_ic_i$  i.e. a product of fecundity and  
 159 viability [Crow et al., 1970, pp. 185]. Thus, the classic lottery model is essentially the Wright-  
 160 Fisher model extended to allow overlapping generations, but ignoring drift. This means that  
 161 our extension of the classic lottery model to arbitrary densities represents a density-dependent  
 162 generalization of the Wright-Fisher model.

## Results

### Analytical approximation of the density-dependent lottery

Eq. (2) involves an expectation over the time-dependent dispersal distributions  $p_i$ , and is thus too complicated to give intuition about the dynamics of density-dependent lottery competition. We now evaluate this expectation.

Similarly to the high- $l_i$  approximation of classic lottery model, we replace the  $x_i$  with appropriate mean values, although we cannot simply replace  $x_i$  with  $l_i$ . For a type with low propagule density  $l_i \ll 1$ , we have  $x_i = 1$  in the territories where its propagules land, and so its growth comes entirely from territories which deviate appreciably from  $l_i$ . To account for this, we separate Eq. (2) into  $x_i = 1$  and  $x_i > 1$  parts. Our more general approximation only requires that there are no large discrepancies in competitive ability (i.e. we do not have  $c_i/c_j \gg 1$  for any two types). We obtain (details in Appendix B)

$$\Delta_+ n_i(t) \approx \left[ e^{-L} + (R_i + A_i) \frac{c_i}{\bar{c}} \right] l_i U(t), \quad (5)$$

where

$$R_i = \frac{\bar{c} e^{-l_i} (1 - e^{-(L-l_i)})}{c_i + \frac{\bar{c} L - c_i l_i}{L - l_i} \frac{L - 1 + e^{-L}}{1 - (1+L)e^{-L}}},$$

and

$$A_i = \frac{\bar{c} (1 - e^{-l_i})}{\frac{1 - e^{-l_i}}{1 - (1+l_i)e^{-l_i}} c_i l_i + \frac{\bar{c} L - c_i l_i}{L - l_i} \left( L \frac{1 - e^{-L}}{1 - (1+L)e^{-L}} - l_i \frac{1 - e^{-l_i}}{1 - (1+l_i)e^{-l_i}} \right)}.$$

Comparing Eq. (5) to Eq. (4), the classic lottery per-propagule success rate  $c_i/\bar{c}L$  has been replaced by three separate terms. The first,  $e^{-L}$ , accounts for propagules which land alone on unoccupied territories; these territories are won without contest. The second,  $R_i c_i/\bar{c}$  represents competitive victories when the  $i$  type is a rare invader in a high density population, determining its invasion fitness [Metz et al., 1992]. The third term,  $A_i c_i/\bar{c}$ , represents competitive victories when the  $i$  type is abundant. The relative importance of these three terms varies with both the

183 overall propagule density  $L$  and the relative propagule frequencies  $m_i/M$ . If  $l_i \gg 1$  for all types,  
 184 we recover the classic lottery model (only the  $A_i c_i / \bar{c}$  term remains, and  $A_i \rightarrow 1/L$ ). Note that  
 185 not all unoccupied territories are claimed each iteration, since under Poisson dispersal a fraction  
 186  $e^{-L}$  remain unoccupied; total population density thus obeys

$$\Delta N = (1 - e^{-L})U - \sum_i d_i n_i \quad (6)$$

187 Fig. 3 shows that Eq. (5) and its components closely approximate simulations of the density-  
 188 dependent lottery model over a wide range of propagule densities. Two types are present, one  
 189 of which is at low frequency. The growth of the low-frequency type relies crucially on the low-  
 190 density competition term  $R_i c_i / \bar{c}$ . On the other hand,  $R_i c_i / \bar{c}$  is negligible for the high-frequency  
 191 type, which depends instead on high density territorial victories. Fig. 3 also shows the break-  
 192 down of the classic lottery model at low propagule densities.

### 193 **K-selection versus relative fitness**

194 We now compare the density-dependent lottery model from the previous section with MacArthur's  
 195 analysis of selection in crowded environments [MacArthur and Wilson, 1967]. MacArthur con-  
 196 siders a population with two types that have densities  $n_1$  and  $n_2$  subject to density-dependent  
 197 growth described by

$$\frac{dn_1}{dt} = f_1(n_1, n_2) \quad \frac{dn_2}{dt} = f_2(n_1, n_2). \quad (7)$$

198 The environment is assumed to remain constant apart from the type densities. The functions  $f_1$   
 199 and  $f_2$  must decline to zero if  $n_1$  or  $n_2$  are sufficiently large, because no population has unlimited  
 200 resources. This defines the nullclines  $f_1(n_1, n_2) = 0$  and  $f_2(n_1, n_2) = 0$  in  $(n_1, n_2)$  space. The  
 201 outcome of selection is then determined by the relationship between these nullclines. Specifically,  
 202 a type will be excluded if its nullcline is completely contained in the region bounded by the other  
 203 type's nullcline. In other words, for a type to have the possibility of persisting, it must be able to  
 204 keep growing to higher densities than the other type can tolerate in some region of  $(n_1, n_2)$  space

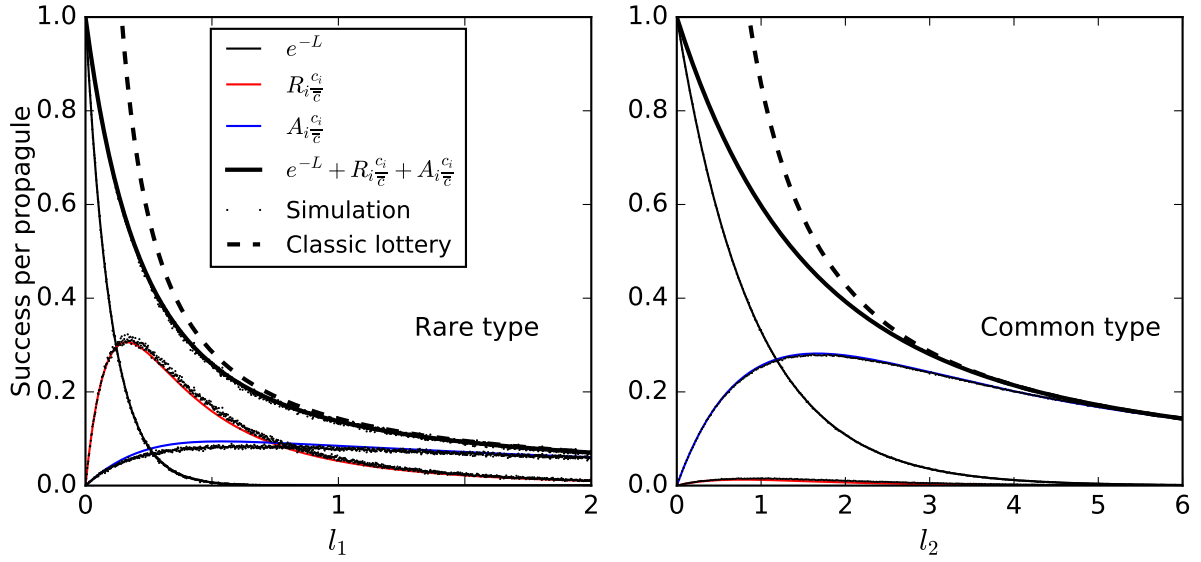


Figure 3: Comparison of the analytical approximation Eq. (5) with simulations. Per-propagule success probability  $\Delta_+ n_i / l_i U$  from the classic lottery model, individual-based simulations of random dispersal and lottery competition, and Eq. (5) and its three components. Two types are present, a rare type with  $c_1 = 1.5$ , and a common type with  $c_2 = 1$ . Simulation points are almost invisible in for the common type due to near exact agreement with Eq. (5). Dashed lines in show the breakdown of the classic lottery model. Parameters:  $m_1 = 10^4$  and  $m_2 = 9 \times 10^4$  and  $U$  varies between  $5 \times 10^3$  and  $10^6$ .

205 (Fig. 1a).

To formalize the relationship between nullclines, MacArthur used the symbol “ $K$ ” to label the four intersection points of the nullclines with the  $n_1$  and  $n_2$  axes, specifically  $f_1(K_{11}, 0) = 0$ ,  $f_1(0, K_{12}) = 0$ ,  $f_2(0, K_{22}) = 0$  and  $f_2(K_{21}, 0) = 0$ . These  $K$  values determine whether a region of higher-density growth exists for each type, provided that the nullclines are close to being straight lines. Note that only  $K_{11}$  and  $K_{22}$  are saturation densities akin to the  $K$  parameter in the logistic model; following widespread convention, we will refer to selection on these saturation densities as “ $K$ -selection” (Fig. 1a). The other intersection points,  $K_{12}$  and  $K_{21}$ , are related to competition between types. For instance, in the Lotka-Volterra competition model we have

$$\begin{aligned} f_1(n_1, n_2) &= r_1(1 - \alpha_{11}n_1 - \alpha_{12}n_2)n_1 \\ f_2(n_1, n_2) &= r_2(1 - \alpha_{22}n_1 - \alpha_{21}n_2)n_2 \end{aligned} \quad (8)$$

206 where  $\alpha_{11} = 1/K_{11}$  and  $\alpha_{22} = 1/K_{22}$  measure competitive effects within types, while  $\alpha_{12} = 1/K_{12}$   
207 and  $\alpha_{21} = 1/K_{21}$  measure competitive effects between types (Fig. 4a).

208 Thus, when MacArthur concludes that “fitness is  $K$ ” in crowded populations [MacArthur and  
209 Wilson, 1967, pp. 149], the meaning is that selection either favors the ability to keep growing at  
210 ever higher densities (moving a type’s own nullcline outwards), or the ability to suppress the  
211 growth of competitors at lower densities (moving the nullcline of competitors inwards) [Gill,  
212 1974]. This general idea applies even if the nullclines are nonlinear to such an extent that the “ $K$ ”  
213 values themselves do not give much information about the regions of high-density growth.

214 It is obvious from Eq. (8) that selection can favor a superior competitor in a crowded popu-  
215 lation even if its saturation density is the same as, or lower than that of the other types present.  
216 However, note that the Lotka-Volterra model still closely couples selection to population density  
217 [Smouse, 1976]. Fig. 4a shows Lotka-Volterra selection between two types with the same satura-  
218 tion density ( $\alpha_{11} = \alpha_{22}$ ,  $\alpha_{21} > \alpha_{12}$ ). Even though the initial and final densities of a sweep are the  
219 same, density is not constant during a sweep. Only a highly restricted subset of  $r$  and  $\alpha$  values

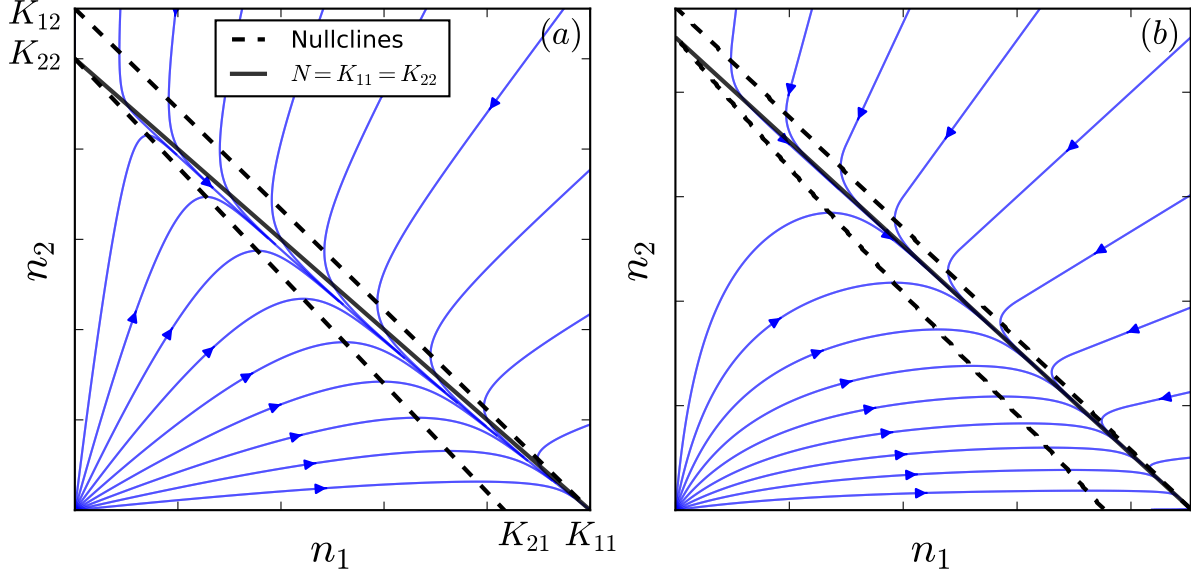


Figure 4: Selection between types with identical saturation density but different inter-type competitive ability. (a) Lotka-Volterra competition (Eq. 8) with  $r_1 = r_2 = 1$ ,  $\alpha_{11} = \alpha_{22} = 1$ ,  $\alpha_{12} = 0.9$  and  $\alpha_{21} = 1.2$ . Trajectories do not follow the line  $N = K_{11} = K_{22}$ . (b) Lottery competition (Eq. 5) with  $b_1 = b_2 = 5$ ,  $d_1 = d_2 = 0.1$  and  $c_1/c_2 = 5$ . Trajectories converge on the line  $N = K_{11} = K_{22}$ .

will keep  $N$  constant over a selective sweep (further details in Appendix C). Intuitively, for one type to exclude another with the same saturation density, inter-type competitive effects must be stronger than intra-type competitive effects, causing a dip in  $N$  over the sweep.

By contrast, if one type in our density-dependent lottery model has a  $c$  advantage but birth and death rates are identical (and hence so is saturation density), the density trajectories converge on the line of constant density equal to the saturation density (Fig. 4b). Selection then occurs purely along this line, uncoupled from the regulation of density. In other words, once the population reaches demographic equilibrium, it behaves indistinguishably from a constant- $N$  relative fitness model. More generally, the competitive ability trait  $c$  does not directly affect population density (this can be seen formally in Eq. (6)), since  $c$  only affects which type wins a territory, not whether a territory is won at all. While quite different from classical growth models like the Lotka-Volterra, this is all perfectly consistent with MacArthur’s general argument.

## Density-dependence and the strength of selection

We are now in a position to analyze the validity of Eq. (1) more explicitly. In the previous section we showed that selection and the regulation of population density can be completely independent of each other even if population growth is density-regulated, and moreover that MacArthur's general argument [MacArthur and Wilson, 1967] for the  $r/K$  scheme never precluded this possibility. Nevertheless, selection and density regulation *are* intimately connected in widely used models of population growth. To understand why this poses a problem for Eq. (1), consider the simple birth-death model [Kostitzin, 1939, pp. 20]

$$\frac{dn_i}{dt} = (b_i - \delta_i N)n_i \quad (9)$$

where  $\delta_i$  is the per-capita increase in type  $i$ 's mortality rate due to crowding (for simplicity, there are no deaths when uncrowded). Then, starting from a monomorphic population, the frequency of an adaptive  $\delta$ -variant  $\delta_i \rightarrow \delta_i(1 - \epsilon)$  obeys

$$\frac{dp_i}{dt} = \epsilon \delta_i N p_i (1 - p_i). \quad (10)$$

The selection coefficient  $s = \epsilon \delta_i N$  thus depends on density (compare [Crow et al., 1970, pp. 29]). On the other hand, the frequency of an adaptive  $b$ -variant  $b_i \rightarrow b_i(1 + \epsilon)$  will exactly obey Eq. (1) with  $s = \epsilon b_i$ , independent of density.

In practice the density dependence in Eq. (10) only matters if  $N$  changes substantially during a sweep. This can easily occur if a population is far from demographic equilibrium (we return to this scenario in the Discussion). A more serious objection to Eq. (1) is that it is internally inconsistent even when  $N$  has reached equilibrium. To quantify how serious this objection is, we need to account for how much  $N$  changes as a result of a sweep involving a density-regulating trait. In Eq. (9), the saturation density is  $N_{\text{initial}} = b_i / \delta_i$ , which increases to  $N_{\text{final}} = b_i / \delta_i(1 - \epsilon) = N_{\text{initial}} / (1 - \epsilon)$  over a  $\delta$  sweep. Thus, the selection coefficient increases from  $s_{\text{initial}} = \epsilon b_i$  to



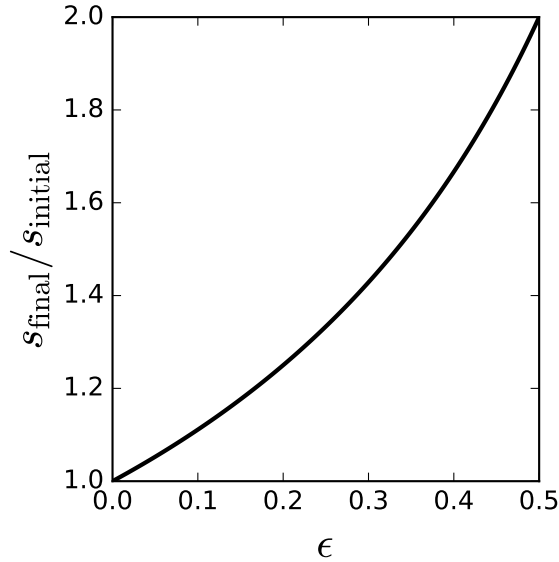


Figure 5: Proportional change in the selection coefficient over a “K-selection”-type sweep for a type that experiences proportionally  $1 - \epsilon$  fewer deaths induced by crowding. The population is in demographic equilibrium at the start of the sweep.

$s_{\text{final}} = s_{\text{initial}} / (1 - \epsilon)$  over a  $\delta$  sweep (Fig. 5). Consequently, Eq. (1) breaks down if selection is sufficiently strong on  $\delta_i$ , with proportional effects of  $\epsilon > 0.2$  inducing substantial deviations from constant selection. The cause of this effect is that the mortality rate  $\delta_i N$  is both density-regulating and subject to density-dependent selection; thus selection on  $\delta$  induces a change in  $N$  but also changes in strength in response to  $N$ .

Let us now contrast the simple linearly density-dependent model Eq. (9) with our density-dependent lottery. As we have seen in our lottery model, the importance of  $c$  depends on density, yet since  $c$  has no effect on density,  $s$  is exactly constant for  $c$  sweeps. For  $b$  and  $d$  sweeps,  $s$  is also exactly constant, because the overall regulation of population density applies equally to all types [Prout, 1980]. To see this formally, we set  $c_i$  to be the same for all types in Eq. (5) which yields

$$\Delta n_i = \frac{m_i}{M}(1 - e^{-L})U - d_i n_i = \left( b_i \frac{1 - e^{-L}}{L} - d_i \right) n_i. \quad (11)$$

Thus, the density-regulation of population size occurs via the juvenile recruitment fraction ( $1 -$

$e^L)/L$ . This applies uniformly to all types and therefore does not induce density-dependence in selective advantages related to  $b$  or  $d$ . Note that our lottery model accounts for two key aspects of the interaction between selection and demography: selection is density-dependent, and density will change as a result of selection on absolute fitness traits. And yet pure  $b$ ,  $c$  and  $d$  sweeps all obey Eq. (1) exactly. [Need to flesh this out a little more and address some subtleties with discrete vs. continuous time]

## Discussion

It is widely recognized that the relative fitness description of selection widely used by evolutionists is poorly integrated with the ecological literature on population growth [Mallet, 2012]. This is not simply a lack of ecological realism on the part of relative fitness models. In many population growth models, only one life-history stage is represented, and the competitive effects resulting from crowding appear as a reduction in absolute fitness that only depends on the type densities at this life-history stage (e.g. the  $n_i^2$  and  $n_i n_j$  terms in the Lotka Volterra equation). However, many species have a “reproductive excess” of juveniles that are considerably more fragile than their adult counterparts [Chesson, 1983]. As a result, competition and the selection it induces can be concentrated at the juvenile phase, where a large reproductive excess allows for for most juveniles to be competitively eliminated. In our lottery model, this excess appears when the number of propagules is greater than the number of available territories. Then only  $\approx 1/L$  of the juveniles contesting available territories survive to adulthood. Note that unlike the role of adult density  $n_i$  in single-life-stage models, it is the propagule densities  $l_i$  that represent the crowding drives competition. In general, reproductive excesses will tend to produce strictly-relative lottery-type contests in which fitter types can grow at the expense of others by preferentially filling the available adult “slots”. The number of slots can remain fixed or change independently of selection at the juvenile stage. By ignoring reproductive excesses, single life-stage models are biased to have total population density be sensitive to ongoing selection, unfairly invalidating Eq. (1). In

290 this respect, the Wright-Fisher model and similar “viability selection” models actually capture an  
291 important ecological process.

292 Nevertheless, relative fitness does indeed break down if strong selection occurs in a way  
293 that changes (adult) population density and is also density-dependent (Fig. 5). In our lottery  
294 model, the this can only occur if types differ in  $c$  as well as  $b$  or  $d$ . The reason for this is  
295 that density-dependent ( $c$ ) and density-determining traits ( $b$  and  $d$ ) are completely separate. This  
296 may seem odd given the behavior of most models in the density-dependent literature, so it worth  
297 investigating this point further.

298 The essential distinction between selection in uncrowded and crowded conditions is the ab-  
299 sence or presence of interactions between types (these interactions may be indirect, as in the case  
300 of consumable resource competition). That is, selective shifts in frequency are a result of differ-  
301 ences in absolute growth rates, but these differences can arise in two logically distinct ways: (i)  
302 some types expand more rapidly in the absence of interactions between types or (ii) some types  
303 are superior in their interactions with other types. This distinction captures a key property of  
304 crowding, namely that you must displace others to grow.

305 By contrast, the separation of traits in the  $r/K$  scheme is presented as a dichotomy between  
306  $r$ -selection (uncrowded) and  $K$ -selection (crowded), with the latter taken to mean selection for  
307 greater saturation density (e.g. [Gill, 1974]). As we have seen, MacArthur’s general argument  
308 [MacArthur and Wilson, 1967] does not justify this dichotomy, because selection in crowded pop-  
309 ulations also involves inter-type competition represented by the Lotka-Volterra  $\alpha_{ij}$  coefficients;  
310 selection on the latter has been termed “ $\alpha$ -selection” [Gill, 1974, Joshi et al., 2001]. In the Lotka-  
311 Volterra model,  $r_i$  belongs to (i) and the inter-type coefficients  $\alpha_{ij}$  ( $i \neq j$ ) belong to (ii). But  $\alpha_{ii}$ , the  
312 inverse of type  $i$ ’s carrying capacity  $K_{ii}$ , straddles both (i) and (ii). For this reason,  $K$ -selection —  
313 selection for greater carrying capacity — is a particularly confusing way to characterize selection  
314 in crowded populations.

315 In our lottery model,  $b$  and  $d$  are interaction-independent traits, whereas  $c$  is entirely about  
316 interactions between types.

(factors which cause density trajectories to move “outwards” in Fig. 1a)

(factors which cause density trajectories to move diagonally in Fig. 1b).

[Chesson, 2000]

Another common feature of density-regulated growth models is the presence of traits which both regulate density and are subject to density-dependent selection, such as the  $\delta$  trait in the simple birth-death model Eq. (9). The  $b/\delta$  parameterization in Eq. (9) emphasizes the obvious point that traits which control density need not be subject to density-dependent selection. The  $K$  parameter in the standard  $r/K$  parameterization of the logistic model has been particularly misleading in this respect, because it is solely responsible for the regulation of density and is subject to density-dependent selection. Nevertheless,  $\delta$ -like traits arise automatically in the simplest linear models of density-regulated growth, including the logistic and Lotka-Volterra models, regardless of how they are parameterized, and are thus deeply ingrained in the literature on density-dependent selection [Christiansen, 2004, Mallet, 2012, Roughgarden, 1979]. In our lottery model,  $b$  and  $d$  control density, but do not exhibit density-dependent selection, and thus do not pose the same threat to Eq. (1) as a  $\delta$ -like trait.

It is not obvious that we should expect this as a general rule. Much of our intuition about type-specific regulation of density (and density-dependent selection in general) Consumable resource models are a better guide, because they explicitly model the processes underlying an important form of competition. Density regulation is type-specific in well-mixed resource competition models, but for many populations consumable resources are not well-mixed. Spatial localization of consumable resources (e.g. due to restricted movement of nutrients through soils) will tend to create a territorial situation similar to the lottery model, where resource competition only occurs locally and is subsumed into the competitive ability  $c$ . Density regulation will then apply at the population level similarly to the lottery model, allowing  $N$  to change via  $b$  or  $d$  without affecting Eq. (1).

Relative fitness models truly breaks down if  $N$  is far from equilibrium and selection is density-dependent. For example, wild *Drosophila* experience huge seasonal boom-bust cycles in popu-

lation density coupled to strong selection that drives large swings in allele frequency [Bergland et al., 2014]. In this case there is no choice but to abandon relative fitness. Our density-dependent lottery model may not be a particularly good description of *Drosophila* ecology, but the close connection between our model and Wright-Fisher is particularly useful, because drift in our model should behave broadly similarly. Thus, our model it should provide a useful starting point for analyzing evolution in this and other from-from-equilibrium situations.

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## Appendix A: Poisson approximation

For simplicity of presentation, we have assumed a Poisson distribution for the  $x_i$  as our model of dispersal. Strictly speaking, the total number of  $i$  propagules  $\sum x_i$  (summed over unoccupied territories) is then no longer a constant  $m_i$ , but fluctuates between generations for a given mean  $m_i$ , which is more biologically realistic. Nevertheless, since we do not consider the random fluctuations in type abundances here, and for ease of comparison with the classic lottery model, we ignore the fluctuations in  $m_i$ . Instead we focus, on Poisson fluctuations in propagule composition in each territory.

In the exact model of random dispersal, the counts of a type’s propagules across unoccupied territories follows a multinomial distribution with dimension  $U$ , total number of trials equal to  $m_i$ , and equal probabilities  $1/U$  for a propagule to land in a given territory. Thus, the  $x_i$  in different territories are not independent random variables. However, for sufficiently large  $U$  and  $m_i$ , this multinomial distribution for the  $x_i$  across territories is closely approximated by a product of independent Poisson distributions for each territory, each with rate parameter  $l_i$  [Arenbaev, 1977, Theorem 1]. Since we are ignoring finite population size effects, we effectively have  $T \rightarrow \infty$ , in which case  $U$  can be only be small enough to violate the Poisson approximation if there is vanishing population turnover, and then the dispersal distribution is irrelevant anyway. Likewise, in ignoring stochastic finite population size for the  $n_i$ , we have effectively already



assumed that  $m_i$  is large enough to justify the Poisson approximation (the error scales as  $1/\sqrt{m_i}$ ; Arenbaev 1977).

## Appendix B: Derivation of growth equation

We separate the right hand side of Eq. (2) into three components  $\Delta_+ n_i = \Delta_u n_i + \Delta_r n_i + \Delta_a n_i$  which vary in relative magnitude depending on the propagule densities  $l_i$ . Following the notation in the main text, the Poisson distributions for the  $x_i$  (or some subset of the  $x_i$ ) will be denoted  $p$ , and we use  $P$  as a general shorthand for the probability of particular outcomes.

### Growth without competition

The first component,  $\Delta_u n_i$ , accounts for territories where only one focal propagule is present  $x_i = 1$  and  $x_j = 0$  for  $j \neq i$  ( $u$  stands for “uncontested”). The proportion of territories where this occurs is  $l_i e^{-L}$ , and so

$$\Delta_u n_i = U l_i e^{-L} = m_i e^{-L}. \quad (12)$$

### Competition when rare

The second component,  $\Delta_r n_i$ , accounts for territories where a single focal propagule is present along with at least one non-focal propagule ( $r$  stands for “rare”) i.e.  $x_i = 1$  and  $X_i \geq 1$  where  $X_i = \sum_{j \neq i} x_j$  is the number of nonfocal propagules. The number of territories where this occurs is  $U p_i(1)P(X_i \geq 1) = b_i n_i e^{-l_i}(1 - e^{-(L-l_i)})$ . Thus

$$\Delta_r n_i = m_i e^{-l_i}(1 - e^{-(L-l_i)}) \left\langle \frac{c_i}{c_i + \sum_{j \neq i} c_j x_j} \right\rangle_{\tilde{p}}, \quad (13)$$

where  $\langle \rangle_{\tilde{p}}$  denotes the expectation with respect to  $\tilde{p}$ , and  $\tilde{p}$  is the probability distribution of nonfocal propagule abundances  $x_j$  after dispersal, in those territories where exactly one focal propagule, and at least one non-focal propagule, landed.

455 Our “mean field” approximation is to replace  $x_j$  with its mean in the last term in Eq. (13),

$$\left\langle \frac{c_i}{c_i + \sum_{j \neq i} c_j x_j} \right\rangle_{\tilde{p}} \approx \frac{c_i}{c_i + \sum_{j \neq i} c_j \langle x_j \rangle_{\tilde{p}}}. \quad (14)$$

456 Below we justify this replacement by arguing that the standard deviation  $\sigma_{\tilde{p}}(\sum_{j \neq i} c_j x_j)$  (with  
457 respect to  $\tilde{p}$ ), is much smaller than  $\langle \sum_{j \neq i} c_j x_j \rangle_{\tilde{p}}$ .

We first calculate  $\langle x_j \rangle_{\tilde{p}}$ . Let  $X = \sum_j x_j$  denote the total number of propagules in a territory and  $\mathbf{x}_i = (x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_G)$  denote the vector of non-focal abundances, so that  $p(\mathbf{x}_i) = p_1(x_1) \dots p_{i-1}(x_{i-1}) p_{i+1}(x_{i+1}) \dots p_G(x_G)$ . Then,  $\tilde{p}$  can be written as

$$\begin{aligned} \tilde{p}(\mathbf{x}_i) &= p(\mathbf{x}_i | X \geq 2, x_i = 1) \\ &= \frac{P(\mathbf{x}_i, X \geq 2 | x_i = 1)}{P(X \geq 2)} \\ &= \frac{1}{1 - (1 + L)e^{-L}} \sum_{X=2}^{\infty} P(X) p(\mathbf{x}_i | X_i = X - 1), \end{aligned} \quad (15)$$

and so

$$\begin{aligned} \langle x_j \rangle_{\tilde{p}} &= \sum_{\mathbf{x}_i} \tilde{p}(\mathbf{x}_i) x_j \\ &= \frac{1}{1 - (1 + L)e^{-L}} \sum_{X=2}^{\infty} P(X) \sum_{\mathbf{x}_i} p(\mathbf{x}_i | X_i = X - 1) x_j. \end{aligned} \quad (16)$$

The inner sum over  $\mathbf{x}_i$  is the mean number of propagules of a given nonfocal type  $j$  that will be found in a territory which received  $X - 1$  nonfocal propagules in total, which is equal to  $\frac{l_j}{L - l_i}(X - 1)$ . Thus,

$$\begin{aligned} \langle x_j \rangle_{\tilde{p}} &= \frac{l_j}{1 - (1 + L)e^{-L}} \frac{1}{L - l_i} \sum_{k=2}^{\infty} P(X)(X - 1) \\ &= \frac{l_j}{1 - (1 + L)e^{-L}} \frac{L - 1 + e^{-L}}{L - l_i}, \end{aligned} \quad (17)$$

458 where the last line follows from  $\sum_{X=2}^{\infty} P(X)(X - 1) = \sum_{X=1}^{\infty} P(X)(X - 1) = \sum_{X=1}^{\infty} P(X)X -$

459  $\sum_{X=1}^{\infty} P(X)$ .

The exact analysis of the fluctuations in  $\sum_{j \neq i} c_j x_j$  is complicated because the  $x_j$  are not independent with respect to  $\tilde{p}$ . These fluctuations are part of the “drift” in type abundances which we leave for future work. Here we use the following approximation to give some insight into the magnitude of these fluctuations and also the nature of the correlations between the  $x_j$ . We replace  $\tilde{p}$  with  $\tilde{q}$ , defined as the  $x_i$  Poisson dispersal probabilities conditional on  $X_i \geq 1$  (which are independent). The distinction between  $\tilde{p}$  with  $\tilde{q}$  will be discussed further below. The  $\tilde{q}$  approximation gives  $\langle x_j \rangle_{\tilde{q}} = \langle x_j \rangle_p / C = l_j / C$ ,

$$\begin{aligned} \sigma_{\tilde{q}}^2(x_j) &= \langle x_j^2 \rangle_{\tilde{q}} - \langle x_j \rangle_{\tilde{q}}^2 \\ &= \frac{1}{C} \langle x_j^2 \rangle_p - \frac{l_j^2}{C^2} \\ &= \frac{1}{C} (l_j^2 + l_j) - \frac{l_j^2}{C^2} \\ &= \frac{l_j^2}{C} \left( 1 - \frac{1}{C} \right) + \frac{l_j}{C}, \end{aligned} \tag{18}$$

and

$$\begin{aligned} \sigma_{\tilde{q}}(x_j, x_k) &= \langle x_j x_k \rangle_{\tilde{q}} - \langle x_j \rangle_{\tilde{q}} \langle x_k \rangle_{\tilde{q}} \\ &= \frac{1}{C} \langle x_j x_k \rangle_p - \frac{l_j l_k}{C^2} \\ &= \frac{l_j l_k}{C} \left( 1 - \frac{1}{C} \right), \end{aligned} \tag{19}$$

460 where  $C = 1 - e^{-(L-l_i)}$  and  $j \neq k$ .

461 The exact distribution  $\tilde{p}$  assumes that exactly one of the propagules present in a given site  
 462 after dispersal belongs to the focal type, whereas  $\tilde{q}$  assumes that there is a focal propagule  
 463 present before non-focal dispersal commences. As a result,  $\tilde{q}$  predicts that the mean propagule  
 464 density is greater than  $L$  (in sites with only one focal propagule is present) when the focal  
 465 type is rare and the propagule density is high. This is erroneous, because the mean number

of propagules in every site is  $L$  by definition. Specifically, if  $L - l_i \approx L \gg 1$ , then the mean propagule density predicted by  $\tilde{q}$  is approximately  $L + 1$ . The discrepancy causes rare invaders to have an intrinsic rarity disadvantage (territorial contests under  $\tilde{q}$  are more intense than they should be). In contrast, Eq. (17) correctly predicts that there are on average  $\sum_{j \neq i} \langle x_j \rangle_{\tilde{p}} \approx L - 1$  nonfocal propagules because  $\tilde{p}$  accounts for potentially large negative covariances between the  $x_j$  “after dispersal”. By neglecting the latter covariances,  $\tilde{q}$  overestimates the fluctuations in  $\sum_{j \neq i} c_j x_j$ ; thus  $\tilde{q}$  gives an upper bound on the fluctuations. The discrepancy between  $\tilde{q}$  and  $\tilde{p}$  will be largest when  $L$  is of order 1 or smaller, because then the propagule assumed to already be present under  $\tilde{q}$  is comparable to, or greater than, the entire propgaule density.

Decomposing the variance in  $\sum_{j \neq i} c_j x_j$ ,

$$\sigma_{\tilde{q}}^2(\sum_{j \neq i} c_j x_j) = \sum_{j \neq i} \left[ c_j^2 \sigma_{\tilde{q}}^2(x_j) + 2 \sum_{k > j, k \neq i} c_j c_k \sigma_{\tilde{q}}(x_j, x_k) \right], \quad (20)$$

and using the fact that  $\sigma_{\tilde{q}}(x_j, x_k)$  and the first term in Eq. (18) are negative because  $C < 1$ , we obtain an upper bound on the relative fluctuations in  $\sum_{j \neq i} c_j x_j$ ,

$$\frac{\sigma(\sum_{j \neq i} c_j x_j)}{\langle \sum_{j \neq i} c_j x_j \rangle} = C^{1/2} \frac{\left( \sum_{j \neq i} c_j^2 l_j + (1 - 1/C) \left( \sum_{j \neq i} c_j l_j \right)^2 \right)^{1/2}}{\sum_{j \neq i} c_j l_j} < C^{1/2} \frac{\left( \sum_{j \neq i} c_j^2 l_j \right)^{1/2}}{\sum_{j \neq i} c_j l_j}. \quad (21)$$

Suppose that the  $c_j$  are all of similar magnitude (their ratios are of order one). Then Eq. (21) is  $\ll 1$  for the case when  $L - l_i \ll 1$  (due to the factor of  $C^{1/2}$ ), and also for the case when at least some of the nonfocal propagule densities are large  $l_j \gg 1$  (since it is then of order  $1/\sqrt{L - l_i}$ ). The worst case scenario occurs when  $L - l_i$  is of order one. Then Eq. (21) gives a relative error of approximately 50%, which from our earlier discussion we know to be a substantial overestimate when  $L$  is of order 1. Our numerical results (Fig. 3) confirm that the relative errors are indeed small.

However, the relative fluctuations in  $\sum_{j \neq i} c_j x_j$  can be large if some of the  $c_j$  are much larger than the others. Specifically, in the presence of a rare, extremely strong competitor ( $c_j l_j \gg c_{j'} l_{j'}$

487 for all other nonfocal types  $j'$ , and  $l_j \ll 1$ ), then the RHS of Eq. (21) can be large and we cannot  
 488 make the replacement Eq. (14).

489 Substituting Eqs. (14) and (17) into Eq. (13), we obtain

$$\Delta_r n_i \approx m_i R_i \frac{c_i}{\bar{c}}, \quad (22)$$

490 where  $R_i$  is defined in Eq. (6).

### 491 **Competition when abundant**

492 The final contribution,  $\Delta_a n_i$ , accounts for territories where two or more focal propagules are  
 493 present ( $a$  stands for “abundant”). Similarly to Eq. (13), we have

$$\Delta_a n_i = U(1 - (1 + l_i)e^{l_i}) \left\langle \frac{c_i x_i}{\sum_j c_j x_j} \right\rangle_{\hat{p}} \quad (23)$$

494 where  $\hat{p}$  is the probability distribution of both focal and nonfocal propagaule abundances *after*  
 495 dispersal in those territories where at least two focal propagules landed.

496 Again, we argue that the relative fluctuations in  $\sum c_j x_j$  are much smaller than 1 (with respect  
 497 to  $\hat{p}$ ), so that,

$$\left\langle \frac{c_i x_i}{\sum_j c_j x_j} \right\rangle_{\hat{p}} \approx \frac{c_i \langle x_i \rangle_{\hat{p}}}{\sum_j c_j \langle x_j \rangle_{\hat{p}}}. \quad (24)$$

Following a similar procedure as for  $\Delta_r n_i$ , where the vector of propagule abundances is denoted

$\mathbf{x}$ , the mean focal type abundance is,

$$\begin{aligned}
\langle x_i \rangle_{\hat{p}} &= \sum_{\mathbf{x}} x_i p(\mathbf{x} | x_i \geq 2) \\
&= \sum_{x_i} x_i p(x_i | x_i \geq 2) \\
&= \frac{1}{1 - (1 + l_i)e^{-l_i}} \sum_{x_i \geq 2} p(x_i) x_i \\
&= l_i \frac{1 - e^{-l_i}}{1 - (1 + l_i)e^{-l_i}}.
\end{aligned} \tag{25}$$

For nonfocal types  $j \neq i$ , we have

$$\begin{aligned}
\langle x_j \rangle_{\hat{p}} &= \sum_{\mathbf{x}} x_j p(\mathbf{x} | x_i \geq 2) \\
&= \sum_X P(X | x_i \geq 2) \sum_{\mathbf{x}} x_j p(\mathbf{x} | x_i \geq 2, X) \\
&= \sum_X P(X | x_i \geq 2) \sum_{x_i} p(x_i | x_i \geq 2, X) \sum_{\mathbf{x}_i} x_j p(\mathbf{x}_i | X_i = X - x_i) \\
&= \sum_X P(X | x_i \geq 2) \sum_{x_i} p(x_i | x_i \geq 2, X) \frac{l_j(X - x_i)}{L - l_i} \\
&= \frac{l_j}{L - l_i} \left[ \sum_X P(X | x_i \geq 2) X - \sum_{x_i} p(x_i | x_i \geq 2) x_i \right] \\
&= \frac{l_j}{L - l_i} \left( L \frac{1 - e^{-L}}{1 - (1 + L)e^{-L}} - l_i \frac{1 - e^{-l_i}}{1 - (1 + l_i)e^{-l_i}} \right).
\end{aligned} \tag{26}$$

498 To calculate the relative fluctuations in  $\sum_{j \neq i} c_j x_j$ , we use a similar approximation as for  $\Delta_r n_i$ :  $\hat{p}$   
499 is approximated by  $\hat{q}$ , defined as the  $\mathbf{x}$  dispersal probabilities in a territory conditional on  $x_i > 2$   
500 (that is, treating the  $x_j$  as independent). All covariances between nonfocal types are now zero, so  
501 that  $\sigma_{\hat{q}}^2(\sum c_j x_j) = \sum c_j^2 \sigma_{\hat{q}}^2(x_j)$ , where  $\sigma_{\hat{q}}^2(x_j) = l_j$  for  $j \neq i$ , and

$$\sigma_{\hat{q}}^2(x_i) = \frac{l_i}{D} \left( l_i + 1 - e^{-l_i} - \frac{l_i}{D} (1 - e^{-l_i})^2 \right), \tag{27}$$

502 where  $D = 1 - (1 + l_i)e^{-l_i}$ , and

$$\frac{\sigma_{\hat{q}}(\sum c_j x_j)}{\langle \sum c_j x_j \rangle} = \frac{\left( \sum_{j \neq i} c_j^2 l_j + c_i^2 \sigma_{\hat{q}}^2(x_i) \right)^{1/2}}{\sum_{j \neq i} c_j l_j + c_i l_i (1 - e^{-l_i}) / D}. \quad (28)$$

503 Similarly to Eq. (21), the RHS of Eq. (28) is  $\ll 1$  for the case that  $L \ll 1$  (due to a factor of  
 504  $D^{1/2}$ ), and also for the case when at least some of the propagule densities (focal or nonfocal) are  
 505 large — provided that  $c_i$  and the  $c_j$  are all of similar magnitude. Again, the worst case scenario  
 506 occurs when  $l_i$  and  $L - l_i$  are of order 1, in which case Eq. (28) is around 35%, which is again  
 507 where the  $\hat{q}$  approximation produces the biggest overestimate of the fluctuations in  $\mathbf{x}$ . Similarly  
 508 to Eq. (21), the RHS of (28) will not be  $\ll 1$  in the presence of a rare, extremely strong competitor.

509 Combining Eqs. (23) and (24), we obtain

$$\Delta_a n_i = m_i A_i \frac{c_i}{\bar{c}}, \quad (29)$$

510 where  $A_i$  is defined in Eq. (6).

## 511 **Appendix C: Total density in the Lotka-Volterra competition model**

512 Here we show that under the Lotka-Volterra model of competition, total density  $N$  does not in  
 513 general remain constant over a selective sweep in a crowded population even if the types have  
 514 the same saturation density (for a related discussion on the density- and frequency-dependence  
 515 of selection in the Lotka-Volterra mode, see [Mallet, 2012, Smouse, 1976]).

We assume equal effects of crowding within types  $\alpha_{11} = \alpha_{22} = \alpha_{\text{intra}}$  and  $N = 1/\alpha_{\text{intra}}$  and  
 check whether it is then possible for  $\frac{dN}{dt}$  to be zero in the sweep ( $n_1, n_2 \neq 0$ ). Substituting these

conditions into Eq. (8), we obtain

$$\begin{aligned}\frac{dn_1}{dt} &= r_1(\alpha_{11} - \alpha_{12})n_1n_2 \\ \frac{dn_2}{dt} &= r_2(\alpha_{22} - \alpha_{21})n_1n_2\end{aligned}\tag{30}$$

516 Adding these together,  $\frac{dN}{dt}$  can only be zero if

$$r_1(\alpha_{\text{intra}} - \alpha_{12}) + r_2(\alpha_{\text{intra}} - \alpha_{21}) = 0.\tag{31}$$

517 To get some intuition for Eq. (31), suppose that a mutant arises with improved competitive  
518 ability but identical intrinsic growth rate and saturation density ( $r_1 = r_2$  and  $\alpha_{11} = \alpha_{22}$ ). This  
519 could represent a mutation to an interference competition trait, for example [Gill, 1974]. Then,  
520 according the above condition, for  $N$  to remain constant over the sweep, the mutant must find  
521 the wildtype more tolerable than itself by exactly the same amount that the wildtype finds the  
522 mutant less tolerable than itself.

523 Even if we persuaded ourselves that this balance of inter-type interactions is plausible in some  
524 circumstances, when multiple types are present the requirement for constant  $N$  becomes

$$\sum_{ij} r_i(\alpha_{\text{intra}} - \alpha_{ij})p_i p_j = 0,\tag{32}$$

525 which depends on frequency and thus cannot be satisfied in general for constant inter-type  
526 coefficients  $\alpha_{ij}$ . We conclude that selection in the Lotka-Volterra competition model will generally  
527 involve non-constant  $N$ .