

# Density-dependent selection in evolutionary genetics: a lottery model of Grime's triangle

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## Abstract

Fitness is typically represented in heavily simplified terms in evolutionary genetics, often using  
3 constant selection coefficients. This excludes fundamental ecological factors such as dynamic  
population size or density-dependence from the most genetically-realistic treatments of evolu-  
tion, a problem that inspired MacArthur’s influential but problematic  $r/K$  theory. Following  
6 in the spirit of  $r/K$ -selection as a general-purpose theory of density-dependent selection, but  
grounding ourselves empirically in “primary strategy” trait classification schemes like Grime’s  
triangle, we develop a new model of density-dependent selection which revolves around terri-  
9 torial contests. To do so, we generalize the classic lottery model of territorial acquisition, which  
has primarily been used for studying species co-existence questions, to accommodate arbitrary  
densities. We use this density-dependent lottery model to predict the direction of trait evolution  
12 under different environmental conditions and thereby provide a mathematical underpinning for  
Grime’s verbal scheme. We revisit previous concepts of density-dependent selection, including  $r$   
and  $K$  selection, and argue that our model distinguishes between different aspects of fitness in a  
15 more natural and intuitive manner.

“...the concept of fitness is probably too complex to allow of a useful mathematical development. Since it enters fundamentally into many population genetics considerations, it is remarkable how little attention has been paid to it.” — Warren J. Ewens, *Mathematical Population Genetics I*, 2004

Evolutionary models differ greatly in their treatment of fitness. In models of genetic evolution, genotypes are typically assigned constant (or frequency-dependent) selection coefficients describing the change in their relative frequencies over time. This simplified treatment of selection facilitates genetic realism, and can be justified over sufficiently short time intervals (Ewens, 2004, p. 276). The emphasis here is to infer past selection, migration and demographic change given a sample of nucleotide sequences, or to predict how allele frequencies change over time based on their fitness effects, population structure, genetic drift and linkage. The resulting picture of evolution excludes basic elements of the ecological underpinnings of selection, including density dependence, and how selection affects population size. This complicates the inference of past selection, because demographic changes can look genealogically very similar to selective frequency changes (Barton, 1998).

By contrast, models of phenotypic trait evolution use absolute fitness functions to describe how some traits of interest affect survival and reproduction in particular ecological scenarios (Diekmann et al., 2004; Metz et al., 1992). These fitness functions can be quite problem-specific and often only account for a few traits at a time. The emphasis here is on the conditions for invasion from low frequencies and co-existence, rather than frequency or abundance trajectories over time. For instance, adaptive dynamics uses “invasion fitness” to explore the consequences of eco-evolutionary feedbacks (Diekmann et al., 2004).

It is challenging to generalize beyond particular traits or ecological scenarios to model fundamentally different forms of selection. Perhaps this is not surprising given that fitness is such a complex quantity, dependent on all of a phenotype’s functional traits (Violle et al., 2007) and its environment. A detailed, trait-based, predictive model of fitness would be enormously complicated and situation-specific. It is therefore easy to doubt the feasibility of a simplified, general

mathematical treatment of fitness (Ewens, 2004, p. 276). For example, MacArthur's famous  $r/K$  scheme (MacArthur, 1962; MacArthur and Wilson, 1967) is now almost exclusively known as a framework for understanding life-history traits, and judged on its failure in that role (Boyce, 1984; Pianka, 1970; Reznick et al., 2002; Stearns, 1977). However, the  $r/K$  scheme's original purpose was to extend the existing population-genetic treatment of selection to account for population density (MacArthur, 1962). Few attempts have been made to develop it further along these lines.

Empirical trait classification studies have suggested the existence of a few "primary strategies", reflecting broadly distinct responses to selection (Winemiller et al., 2015). Grime famously considered (Grime, 1974, 1977, 1988; Westoby, 1998) two broad determinants of population density: stress (persistent hardship e.g. due to resource scarcity or unfavorable temperatures) and disturbance (intermittent destruction of vegetation e.g. due to trampling, herbivory, pathogens, extreme weather or fire). The extremes of these two factors define three primary strategies denoted by C/S/R respectively (Fig. 1): competitors "C" excel in low stress, low disturbance environments; stress tolerators "S" excel in high stress, low disturbance environments; and ruderals "R" excel in low stress, high disturbance environments. Population persistence is not possible in high-stress, high-disturbance environments. Grime showed that measures of C, S and R across a wide range of plant species are anti-correlated, so that strong C-strategists are weak S and R strategists, and so on, creating a triangular C/S/R ternary plot (Grime, 1974). Similar schemes were proposed for insects (Southwood, 1977), fishes (Winemiller and Rose, 1992), and zooplankton (Allan, 1976). More recently, modern hierarchical clustering techniques have revealed distinct trait clusters in corals analogous to Grime's primary strategies (Darling et al., 2012). These empirical findings suggest that functional traits contribute to fitness predominantly via a few key factors such as intrinsic reproductive rate or stress-tolerance.

Here we explore the interplay between some "key factors" of fitness in a simplified, territorial model of growth, dispersal and competition. This broadly follows the original spirit of MacArthur's  $r/K$  scheme. More specifically, our aim is to begin adding some ecological realism to population genetics' time-dependedent, genetically-focused view of evolution. We revisit the



Figure 1: Schematic of Grime's triangle. The two axes show increasing levels of environmental stress and disturbance, respectively. Population persistence is not possible if the combination of stress and disturbance is too large (dashed line). This creates a triangle, each corner of which corresponds to a "primary strategy".

classic lottery model of Chesson and Warner (1981), which has two features that make it well suited for this role, but one critical flaw that we rectify here.

72 The first feature is that the lottery representation of competition is particularly concise. Mature individuals ("adults") each require their own territory, whereas newborn individuals ("propagules") disperse to, and subsequently compete for, territories made available by the death  
75 of adults. Territorial contest among propagules leaves a single victorious adult per territory, the victor chosen at random from the propagules present, with probabilities weighted by a coefficient for each type representing competitive ability, akin to a lottery (Sale, 1977). By comparison,  
78 coefficients for the pairwise effects of types on each other (e.g. the  $\alpha$  coefficients in the generalized Lotka-Volterra equations and the associated concept of " $\alpha$ -selection"; Case and Gilpin 1974; Gill 1974; Joshi et al. 2001), or explicit resource consumption (Tilman, 1982), are much more  
81 complicated. The second feature is the close connection between the lottery model and one of the foundational models of population genetics, the Wright-Fisher model of genetic drift, which we discuss further below.

84 The critical flaw of the classic lottery model is that it breaks down at low densities (few propagules dispersing to each territory), precluding density-dependent behaviour. Our first task is to analytically extend the classic lottery model to correctly account for low density behavior

87 (sections “Model” and “Mean field approximation”).

Using our extended lottery model, we then revisit Grime’s C/S/R scheme, and evaluate how C/S/R manifests at the level of within-population genotypic evolution (as opposed to phenotypic  
90 divergence between species; sections “Invasion of rare genotypes and coexistence” and “Primary strategies and Grime’s triangle”). This represents a “sanity check” on our density-dependent lottery model. The resulting formulation of the C/S/R scheme is mathematical, in contrast  
93 to Grime’s original verbal and descriptive approach, which is a recognized hindrance to the evaluation or broader application of the C/S/R scheme (e.g. Tilman 2007).

We then explore some time-dependent behavior of our extended lottery model. Taking an  
96 example inspired by recent studies of rapid, seasonal evolution in *Drosophila* (Bergland et al., 2014), we discuss how environmental fluctuations might stabilize polymorphisms in the presence of cyclical population density.

## 99 **Model**

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  
102  $T$ . 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 genotype is  $n_i(t)$ , the total number of adults is  $N(t) = \sum_i n_i(t)$ , and the number of unoccupied territories is  $U(t) = T - N(t)$ .

105 We assume that the  $n_i$  and  $T$  are large enough that stochastic fluctuations in the  $n_i$  (“drift”) can be ignored. We derive deterministic equations for the expected change in the  $n_i$  over time, leaving the evaluation of drift for future work. In particular, we do not evaluate the initial stochastic  
108 behaviour of adaptive mutant lineages while they are at low abundance. When considering mutations, we restrict our attention to the earliest deterministic behavior of mutant lineages while they are still at low frequency (the transition to deterministic growth occurs at an abundance of  
111 order equal to their inverse expected absolute growth rate; Uecker and Hermisson 2011).

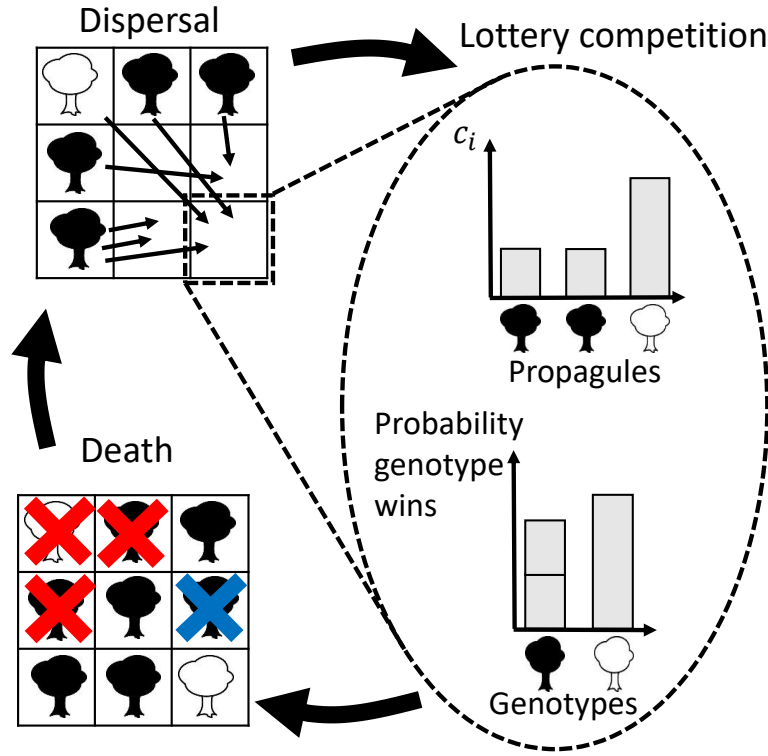


Figure 2: Each iteration of our lottery model has three main elements. First, propagules are produced by adults which are dispersed at random over the unoccupied territories (only propagules landing on unoccupied territories are shown). Lottery competition then occurs in each unoccupied territory (competition in only one territory is illustrated): each genotype has a probability proportional to  $b_i n_i c_i$  of securing the territory. Then occupied territories are freed up by adult mortality. In Eq. (3) and most of the paper, only adults can die (red crosses), but we will also consider the case where juveniles die (blue cross; section “Primary strategies and Grime’s triangle”).

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  $m_i$ .

In general,  $m_i$  will increase with  $n_i$ , and will depend on population density  $N$ . For example, if  $b_i$  is the number of successfully dispersing propagules produced per genotype  $i$  adult, then the loss of propagules due to dispersal to occupied territories implies  $m_i = b_i(1 - N/T)n_i$ , akin to Levins’ competition-colonization model (Levins and Culver, 1971; Tilman, 1994). In section “Cyclical birth and death rates” we evaluate Eq. (4) numerically using this functional form for  $m_i$ , with  $b_i$  assumed to be constant.

In the sections “Invasion of rare genotypes and coexistence” and “Primary strategies and Grime’s triangle”, we assume the simpler form  $m_i = b_i n_i$ , with constant  $b_i$ , meaning that all propagules land on unoccupied territories (a form of directed dispersal). This simplifies the mathematics without affecting the results of those sections, which only depend on the low-frequency invasion behavior of Eq. (4). 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).

The number of individuals of the  $i$ ’th genotype 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 only approximates uniform random dispersal, but is essentially exact provided that the  $n_i$  are large enough that drift can be ignored (Appendix A).

When multiple propagules land on the same territory, the victor is determined by lottery competition: genotype  $i$  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).

In the classic lottery model (Chesson and Warner, 1981), unoccupied territories are assumed



to be saturated with propagules from every genotype  $l_i \gg 1$ . 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 genotypes present), and so the probability that genotype  $i$  wins any particular unoccupied territory is approximately  $c_i l_i / \sum_j c_j l_j$ . Let  $\Delta_+ n_i$  denote the number of territories won by genotype  $i$ . Then  $\Delta_+ n_1, \Delta_+ n_2, \dots, \Delta_+ n_G$  follow a multinomial distribution with  $U$  trials and success probabilities  $\frac{c_1 l_1}{\sum_j c_j l_j}, \frac{c_2 l_2}{\sum_j c_j l_j}, \dots, \frac{c_G l_G}{\sum_j c_j l_j}$ , respectively. Genotype  $i$  is expected to win  $c_i l_i / \sum_j c_j l_j$  of the  $U$  available territories, and deviations from this expected outcome are small (since  $T$  is large by assumption), giving

$$\Delta_+ n_i(t) = \frac{c_i l_i}{\sum_j c_j l_j} U(t) = b_i n_i \frac{1}{L} \frac{c_i}{\bar{c}}, \quad (1)$$

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

There is a close connection between the classic lottery model and the Wright-Fisher model of genetic drift (Svardal et al., 2015). In the Wright-Fisher model, genotype abundances are sampled each generation from a multinomial distribution with success probabilities  $w_i n_i / \sum_j w_j n_j$ , where  $w$  is relative fitness and the  $n_i$  are genotype abundances in the preceding generation. Population size  $N$  remains constant. This is mathematically equivalent to the classic lottery model with non-overlapping generations ( $d_i = 1$  for all  $i$ ) and  $w_i = b_i c_i$ . Thus, the classic lottery model allows us to replace the abstract Wright-Fisher relative fitnesses  $w_i$  with more ecologically-grounded fecundity, competitive ability and mortality parameters  $b_i$ ,  $c_i$  and  $d_i$ , respectively. Since birth and death rates affect absolute abundances, this allows us to evaluate selection at different densities (after appropriate extensions are made), in an otherwise very similar model to the canonical Wright-Fisher. We therefore expect that drift in our extended lottery model should be similar to that in the Wright-Fisher model, but we leave this for future work.

In our extension of the classic lottery model, we do not restrict ourselves to high propagule densities. Eq. (1) is nonsensical at low densities ( $l_i \ll 1$ ): genotype  $i$  can win at most  $m_i$  territories,

yet Eq. (1) demands  $c_i l_i / \sum_j c_j l_j$  of the  $U$  unoccupied territories, for any value of  $U$ . Intuitively, the cause of this discrepancy is that individuals are discrete. Genotypes with few propagules  
 165 depend on the outcome of contests in territories where they have at least one propagule present, not some small fraction of a propagule as would be implied by small  $l_i$  in the classic lottery model. In other words, deviations from the mean propagule composition  $l_1, l_2, \dots, l_G$  are important at  
 168 low density.

We expect that a fraction  $p_1(x_1) \dots p_G(x_G)$  of the  $U$  unoccupied territories will have the propagule composition  $x_1, \dots, x_G$ . Genotype  $i$  is expected to win  $c_i x_i / \sum_j c_j x_j$  of these. Ignoring  
 171 fluctuations about these two expectations (due to our no-drift, large  $T$ , large  $n_i$  approximation), genotype  $i$ '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 propag-  
 174 ule present. Note that unlike the classic lottery model, not all unoccupied territories are claimed each iteration, since under Poisson dispersal a fraction  $e^{-L}$  remain unoccupied.

For the majority of this manuscript we assume that mortality only occurs in adults (setting  
 177 aside the juvenile deaths implicit in territorial contest), and at a constant, genotype-specific per-capita rate  $d_i$ , so that the overall change in genotype abundances is

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

This seems reasonable in the absence of disturbances; when we come to consider the effects of dis-  
 180 turbances (Section "Primary strategies and Grime's triangle"), we will incorporate disturbance-induced mortality in competing juveniles (Fig. 2).

## Results

### Mean Field Approximation

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 using a “mean field” approximation.

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 genotype 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 mean field 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 genotypes). We obtain (details in Appendix B)

$$\Delta_+ n_i(t) \approx b_i n_i \left[ e^{-L} + (R_i + A_i) \frac{c_i}{\bar{c}} \right], \quad (4)$$

where

$$R_i = \frac{\bar{c} e^{-l_i} (1 - e^{-(L-l_i)})}{c_i + \frac{L-1+e^{-L}}{1-(1+l_i)e^{-L}} \frac{\bar{c} L - c_i l_i}{L-l_i}}, \quad (5)$$

and

$$A_i = \frac{\bar{c}(1 - e^{-l_i})}{\frac{1-e^{-l_i}}{1-(1+l_i)e^{-L}} c_i l_i + \frac{1}{L-l_i} \left( L \frac{1-e^{-L}}{1-(1+L)e^{-L}} - l_i \frac{1-e^{-l_i}}{1-(1+l_i)e^{-L}} \right) \sum_{j \neq i} c_j l_j}. \quad (6)$$

Comparing Eq. (4) to Eq. (1), 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  $i$  genotype is a rare invader in a high density population: from Eq. (5),  $R_i \rightarrow 0$  when the  $i$  genotype is abundant ( $l_i \gg 1$ ), or other genotypes are collectively rare ( $L - l_i \ll 1$ ). The third term,  $A_i c_i/\bar{c}$ , represents competitive victories when the  $i$  genotype

is abundant:  $A_i \rightarrow 0$  if  $l_i \ll 1$ . The relative importance of these three terms varies with both the overall propagule density  $L$  and the relative propagule frequencies  $m_i/M$ . If  $l_i \gg 1$  for all  
 204 genotypes, we recover the classic lottery model (only the  $A_i c_i / \bar{c}$  term remains, and  $A_i \rightarrow 1/L$ ).

Fig. 3 shows that Eq. (4) (and its components) closely approximate direct simulations of random dispersal and lottery competition over a wide range of propagule densities. Two geno-  
 207 types are present, one of which is at low frequency. The growth of the low-frequency genotype relies crucially on the low-density competition term  $R_i c_i / \bar{c}$ , and also to a lesser extent on the high density competition term  $A_i c_i / \bar{c}$  if  $l_1$  is large enough (Fig. 3b). On the other hand,  $R_i c_i / \bar{c}$   
 210 is negligible for the high-frequency genotype, which depends instead on high density territorial victories (Fig. 3d). Fig. 3 also shows the breakdown of the classic lottery model at low propagule densities.

## 213 Primary strategies and Grime's triangle

Here we describe how Grime's "disturbed", "stressful" and "ideal" environments can be captured mathematically in our scheme. To proceed, we need to map these verbally-defined envi-  
 216 ronments to quantitative parameter regimes in our model.

The ideal environment is characterized by the near-absence of stress and disturbance:  $d \ll 1$ , whereas  $b$  is potentially much larger than 1.

219 Disturbed environments are characterized by short bursts of high extrinsic mortality  $d$  caused by physical destruction. We assume that in the disturbance extreme of Grime's triangle, many such bursts (which could each be spatially localized) will occur each iteration (i.e. over the  
 222 time from birth to reproductive maturity), and so we can approximate extreme disturbance by high constant mortality rates  $d_i$ , which are now extended to affect juveniles as well. We assume that disturbances are equally damaging to adults and juveniles, so that only  $(1 - d_i)\Delta_+ n_i$  rather  
 225 than  $\Delta_+ n_i$  territories are secured by genotype  $i$  each iteration. Heavily disturbed environments then correspond most adults and juveniles being killed every an iteration ( $d_i \approx 1$ ).

Stressful environments are more ambiguous, and have been the subject of an extensive debate

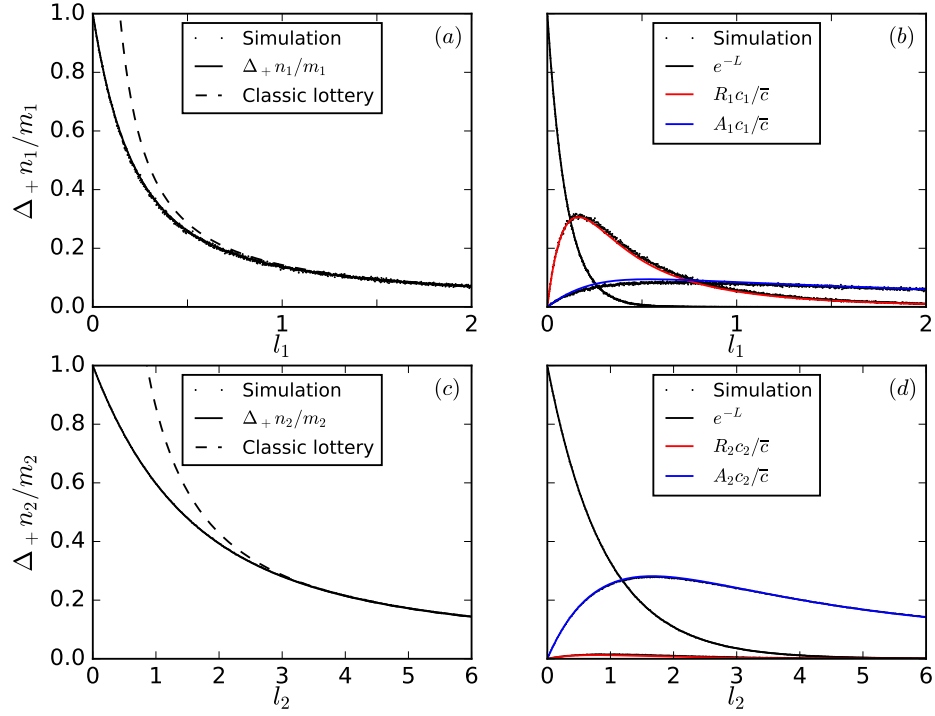


Figure 3: The change in genotype abundances in a density dependent lottery model is closely approximated by Eq. (4).  $\Delta + n_i/m_i$  from Eq. (4) (and its separate components) are shown, along with direct simulations of random dispersal and lottery competition over one iteration over a range of propagule densities ( $U$  is varied between  $5 \times 10^3$  and  $10^6$  with  $m_1 = 10^4$  and  $m_2 = 9 \times 10^4$ ). Two genotypes are present. (a) and (b) show the low-frequency genotype with  $c$ -advantage ( $c_1 = 1.5$ ), (c) and (d) show the high-frequency predominant genotype ( $c_2 = 1$ ). Simulation points are almost invisible in (c) and (d) due to near exact agreement with Eq. (4). Dashed lines in (a) and (c) show the breakdown of the classic lottery model.

in the plant ecology literature (the “Grime-Tilman” debate; Aerts 1999 and references therein). Severe stress inhibits growth and reproduction, so that  $b \ll 1$  (Grime, 1974, 1977). In Grime’s view, this means that the rate at which propagules successfully develop to adulthood cannot appreciably exceed the mortality rate  $b/d \approx 1$ . In our model, this implies low propagule density and little territorial contest.

The alternative view is that stressed environments are highly competitive. In spite of inhibited growth and reproduction, population density  $N/T$  is actually high since stressful environments also have lower environmental carrying capacity (Taylor et al., 1990). For example, if consumable resources are scarce, we expect intense resource competition (for empirical support, see Davis et al. 1998). In our model, territorial contests will then be important.

The mapping of different environments to our model parameters is summarized in the first two rows of Fig. 4. Also shown is the approximate dependence of  $\Delta n_i$  on  $b_i$  and  $c_i$  for each environment (fourth row; details in Appendix). These can be used to infer the expected direction of evolution for the traits  $b$ ,  $c$  and  $d$  (fifth row) using a standard invasion analysis.

According to Haldane’s formula, the probability that an adaptive mutant survives its initial low abundance phase and begins to grow deterministically is proportional to its expected absolute growth rate, with a proportionality factor typically of order one (Uecker and Hermisson 2011) [find Haldane reference]. The fixation of neutral mutations is exceedingly unlikely (probability of order  $1/N$ ). Consequently, the direction of evolutionary change is determined by the mutational trait changes which are available and also confer an appreciable fitness benefit, where availability is subject to constraints imposed by the environment.

For example, in Grime’s interpretation of stressful environments,  $L$  is low, so competition is not important, and only mutants with greater  $b$  or lower  $d$  will have an appreciably greater  $\Delta n_i$ . Mutations in  $c$  are effectively neutral, and will rarely fix. However,  $b$  is constrained to be small. Thus, while some rare mutations may produce small improvements in  $b$ , it is much more likely that mutations lower  $d$ , making this the expected direction of evolutionary change.

Following Grime’s original argument for a triangular scheme (Grime, 1977), Fig. 5 repre-

	Ideal	Disturbance*	Stress (G)	Stress (HD)
Constraints	$d \ll 1$	$d \approx 1$	$b \ll 1$	$b \ll 1$
Other parameters	$b \gg d$	$b \gg d$	$b \approx d$	$b > d$
Density $N/T$	High	Low	Low	High
$\Delta_+ n_i \propto$	$b_i c_i$	$b_i$	$b_i$	$b_i c_i$
Evolution for	$\uparrow b, \uparrow c$	$\uparrow b, \downarrow d$	$\downarrow d$	$\uparrow c, \downarrow d$

Figure 4: The realization of Grime’s three environmental extremes in our model, as well as the high-density variant of the stressful environment. Shown are the mapping of each environment to our parameters, the approximate dependence of  $\Delta_+ n_i$  on  $b_i$  and  $c_i$ , as well as the corresponding expected evolutionary changes in  $b_i$ ,  $c_i$  and  $d_i$ . \*Mortality affects both adults and juveniles in the disturbed environment, with  $\Delta_+ n_i$  replaced by  $(1 - d_i)\Delta_+ n_i$  in Eq. (3).

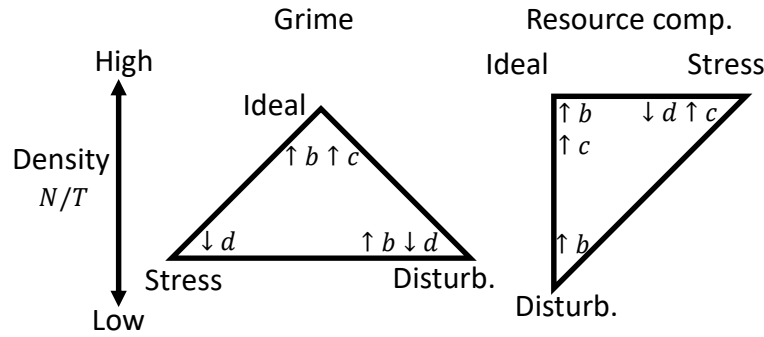


Figure 5: The realization of Grime’s triangle in our model. Schematic representation of the triangular space bounded by the low/high extremes of stress/disturbance. The low- $T$  interpretation of stress is also shown. The vertices of the triangles correspond to different environmental extremes. Selection favors different traits at each vertex, leading to different trait clusters.

255 sends each environmental extreme schematically as a vertex on a triangular space defined by  
perpendicular stress and disturbance axes. The ideal environment lies at the origin (no stress or  
disturbance), while the stressful and disturbed environments lie at the limits of survival on their  
258 respective axes. The hypotenuse connecting the stress and disturbance endpoints represents the  
limits of survival in the presence of a combination of stress and disturbance. The direction of  
evolutionary change is different at each vertex, leading to the emergence of different trait clusters  
261 or “primary strategies”.

## Coexistence in constant and cyclical environments

In the previous section we only considered the how  $b$ ,  $c$  and  $d$  should respond in Grime's environmental extremes. Here we further explore the low frequency behavior of Eq. (4) to determine which types can coexist in a constant environment, and then consider the full time-dependent behaviour of Eq. (4) in a cyclical environment.

In a population with a single genotype  $i$  which is in equilibrium,  $R_i = 0$ ,  $\bar{c} = c_i$  and  $\Delta n_i = 0$ , and Eq. (4) gives

$$b_i \left( e^{-L} + A_i \right) - d_i = 0, \quad (7)$$

where  $A_i = (1 - (1 + L)e^{-L})/L$ . Now suppose that a new genotype  $j$ , which is initially rare, appears in the population. Then  $A_j \ll R_j$ ,  $l_j \approx 0$  and  $\bar{c} \approx c_i$ , and so, from Eq. (4),  $n_j$  will increase if

$$b_j \left( e^{-L} + R_j \frac{c_j}{c_i} \right) - d_j > 0, \quad (8)$$

where  $R_j \approx (1 - e^{-L}) / \left( \frac{c_j}{c_i} + \frac{L-1-e^{-L}}{1-(1+L)e^{-L}} \right)$ .

Stable coexistence is possible between genotypes that are superior in different traits. Suppose that  $j$  is better at securing territories ( $c_j > c_i$ ), that  $i$  is better at producing propagules ( $b_i > b_j$ ), and that  $d_i = d_j$ . Coexistence occurs if  $j$  will invade an  $i$ -dominated population, but  $i$  will also invade a  $j$ -dominated population ("mutual invasion"). If  $b_i$  is so large that  $L \gg 1$  when  $i$  is dominant, and  $b_j$  is so small that  $L \ll 1$  when  $j$  is dominant, then, combining Eqs. (7) and (8), we find that  $i$  invades  $j$  because  $b_i > b_j$ , while  $j$  invades  $i$  provided that

$$b_j c_j R_j - b_i c_i A_i > 0. \quad (9)$$

Thus, coexistence occurs if  $c_j/c_i$  is large enough. This is a version of the classic competition-colonization trade-off (Levins and Culver, 1971; Tilman, 1994): the competitor ( $c$ -specialist) leaves many territories unoccupied (low  $L$ ) due to its poor colonization ability (low  $b$ ), which the colonizer ( $b$ -specialist) can then exploit. A similar argument applies for coexistence between high- $c$



and low- $d$  specialists; a “competition-longevity” trade-off (Tilman, 1994). These forms of co-existence require density dependence, and are not present in the classic lottery model. Mutual  
285 invasibility is not possible between  $b$ - and  $d$ -specialists.

Now suppose that birth and death rates vary periodically with amplitude sufficient to cause large changes in population density. This example is inspired by natural *Drosophila* populations,  
288 which expand rapidly in the warmer months when fruit is abundant, but largely die off in the colder months. Within this seasonal population density cycle, hundreds of polymorphisms also cycle in frequency (Bergland et al., 2014). Some of these polymorphisms may be adaptive and  
291 potentially millions of years old, suggesting stable coexistence (Bergland et al., 2014; Messer et al., 2016). Selection on allele frequencies thus occurs on the same time scale as population demography, a situation vastly more complicated than classical sweeps in demographically stable  
294 populations (Messer et al., 2016).

The classical population genetic treatment of fluctuating selection suggests that environmental fluctuations do not promote coexistence. Allele frequencies are successively multiplied by  
297 relative fitness values for each environmental iteration, and so two alleles favored in different environments can only stably coexist if the product of fitnesses for one type exactly equals the product for the other (Dempster, 1955). Thus, stable coexistence still requires frequency-dependent  
300 selection or heterozygote advantage (as is required in a constant environment).

This classical argument overlooks two effects that are present in our extended lottery model. The first is the storage effect, which requires part of the population to be protected from selection  
303 each iteration (as occurs when generations are non-overlapping) (Chesson and Warner, 1981), and which is also present in the classic lottery model. The second is the bounded population size effect of Yi and Dean (2013), which requires fluctuations in population density and density-  
306 dependent regulation of population growth.

Figure 6 shows the behavior of Eq. (4) for an example where  $b$  and  $d$  cycle between zero and positive values (“summers” with rapid growth and no mortality, and “winters” with mortality  
309 and no growth). Both the storage effect (adults are sheltered from selection during the summer

growth phase) and the bounded density effect (expansion to high density occurs every cycle) are operating. Two types are present, a  $b$  specialist, which is better at rapidly growing in the summer (higher  $b$ ), and a  $d$  specialist which is better at surviving the winter (lower  $d$ ).

Neither type has an advantage over a full environmental cycle, and they stably coexist. This is due to some combination of the storage and bounded population size effects (stable coexistence between  $b$  and  $d$  specialists was not possible in a constant environment). The classic lottery model gives dramatically different co-existence predictions in this scenario (keeping all other parameters the same, the birth rate of the winter survivor must be about 5 times smaller). This occurs because density returns immediately to capacity  $N = T$  in the first summer iteration, after which type frequencies remain constant until the winter. The  $d$  specialist thus effectively has infinitely many propagules to secure its winter frequency gains, an enormous advantage compared to the finite propagule density dynamics in Fig. 6. Similar difficulties arise in previous models of how the storage effect promotes genetic variation (Ellner and Hairston Jr, 1994), which assume that the total number of offspring per iteration is constant. Beyond this observation, disentangling the storage and bounded population size effects is not straightforward, and requires a more detailed discussion of each effect than we have space for here. Our model is well suited for such a disentangling since it extends the canonical example of the storage effect to allow for density dependent effects.

## Discussion

In the introduction we mentioned the recurring difficulties with confounding selection and demography in population genetic inference. While we have not directly attempted to perform inference with our model, and Eq. (4) may not be appropriate for particular inference problems, it seems that something similar (and hopefully more analytically tractable) to our extension of the lottery model is unavoidable because, fundamentally, selective births and deaths affect both abundances and frequencies, not one or the other in isolation. Moreover, some aspects of al-

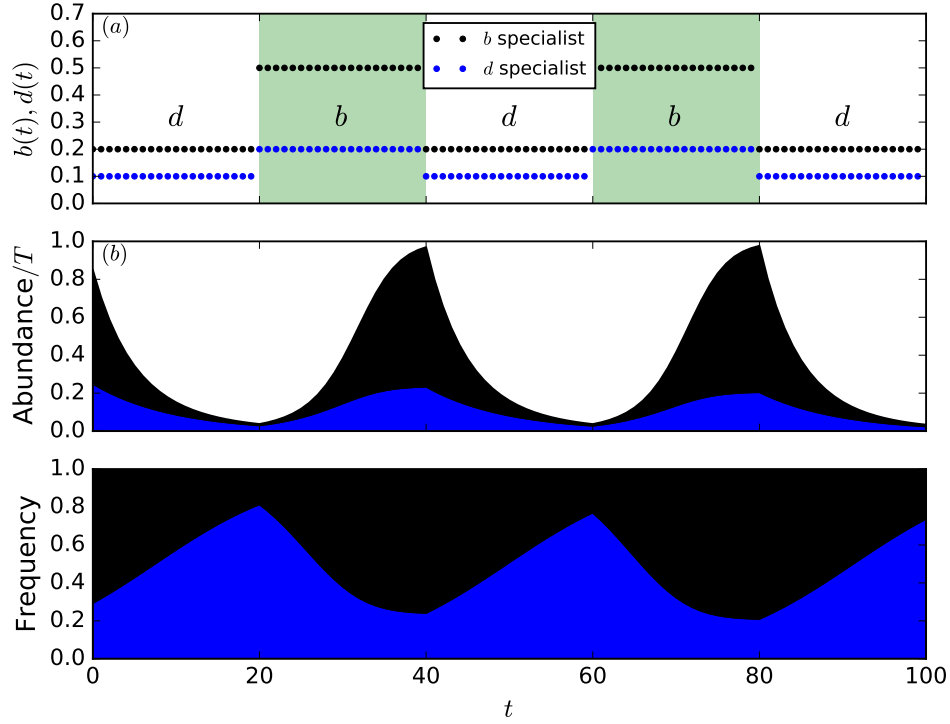


Figure 6: Stable coexistence between  $b$  and  $d$  specialists in a fluctuating environment. (a) Birth and death rates seasonally alternate being nonzero (white for winter, green for summer). The  $b$  specialist (black) has higher  $b$  and  $d$  ( $b = 0.5, d = 0.2$ ) than the  $d$  specialist ( $b = 0.2, d = 0.1$ ) (blue). (b) Both types grow during the positive  $b$  phase, and decline during the positive  $d$  phase, but the  $d$  specialist does so at a lower rate. Total height (blue+black) is population density  $N/T$ . (c) Summer favors the  $b$  specialist, winter the  $d$  specialist, and they stably coexist. For illustration, the propagule abundances are assumed to have the form  $m_i = b_i(1 - N/T)n_i$ , reflecting non-directed dispersal.

allele frequency change are intrinsically density dependent. In the classic lottery model, which as we have seen is essentially the Wright-Fisher model with overlapping generations,  $b_i$  and  $c_i$  are equivalent in the sense that the number of territorial victories only depends on the product  $b_i c_i$  (see “Model”). This is no longer the case in our extension, where  $b$  and  $c$  specialists can co-exist. This “colonization-competition trade-off” is well known in the co-existence literature (Tilman, 1994). It and similar forms of “spatial co-existence” in stable environments have previously been modeled either with Levin’s qualitative representation of competition (Levins and Culver, 1971; Tilman, 1994), as opposed to the quantitative  $c$  of lottery competition, or with a more sophisticated treatment of space (non-uniform dispersal; Bolker and Pacala 1999; Shmida and Ellner 1984). In cyclical environments, polymorphisms can be stabilized by the bounded density effect which is completely lost if there is an exclusive focus on allele frequencies (Yi and Dean, 2013). We leave the details of how our model might be applied in inference, including the crucial issue of its genetic drift predictions, for future work.

It is interesting to compare the predictions of the extended lottery model with earlier approaches, such as the  $r/K$  scheme. While adaptive evolution in the direction predicted by our model does produce traits broadly consistent with Grime’s scheme, trait data on selection for higher  $b$  at high density was ambiguous. This prediction is also counter to the expectations of MacArthur’s  $r/K$  dichotomy (MacArthur and Wilson, 1967), since  $b$  is closely related to the maximal, low-density growth rate  $r = b - d$  (Pianka, 1972), yet in the  $r/K$  scheme, high density populations should be subject to  $K$ , not  $r$ , selection. Yet it is not surprising that  $b$  can matter at high densities. In our model (or any lottery model of competition),  $b$  matters at high densities because territorial contests among juveniles are intrinsically unpredictable. This is a realistic feature of the model. Even if one genotype is guaranteed to win a territory in a “fair” contest (e.g. it is the most efficient exploiter of a limiting consumable resource; Tilman 1982), inferior competitors can win by chance. For example, an inferior competitor’s propagules may happen to arrive first, gaining a decisive developmental advantage. First arrivals are more likely to occur for genotypes with a fecundity and/or dispersal advantage, as represented by higher  $b$  in lottery

models. The analogous intuition in the Wright-Fisher model is that fecundity confers a relative fitness advantage, even though population size is not changing. The logistic model for which  $r$  and  $K$  are named, does not capture this intuition.

Confusingly, the term “ $K$ -selection” sometimes refers generally to selection at high density (Pianka, 1972), encompassing both selection for higher saturation density (MacArthur and Wilson, 1967) and competitive ability (Gill, 1974). Contrary to an  $r/K$  dichotomy, empirical studies have shown that maximal growth rate and saturation density (measured by abundance) are positively correlated, both between species/strains (Fitzsimmons et al., 2010; Hendriks et al., 2005; Kuno, 1991; Luckinbill, 1979), and as a result of experimental evolution (Luckinbill, 1978, 1979). From the perspective of our model, this correlation is not surprising since the saturation density, which is determined by a balance between births and deaths, increases with  $b$ .

There is support for a negative relationship between competitive success at high density and maximal growth rate (Luckinbill, 1979), consistent with an  $r/K$  dichotomy. This could be driven by a tradeoff between individual size and reproductive rate. To avoid confusion with other forms of “ $K$ -selection”, selection for competitive ability has been called “ $\alpha$ -selection” after the competition coefficients in the Lotka-Volterra equation (Case and Gilpin, 1974; Gill, 1974; Joshi et al., 2001). However, competitive success as measured by  $\alpha$  (i.e. the per-capita effect of one genotype on another genotype’s growth rate) is only partly determined by individual competitive ability — in the presence of age-structured competition and territoriality, it also includes the ability of each genotype to produce contestants i.e.  $b$  in our model. Our  $c$  is strictly competitive ability only — as such, changes in  $c$  do not directly affect population density (the total number of territories occupied in an iteration is  $\Delta_+ N = U(1 - e^{-L})$ , which does not depend directly on the  $c_i$ ). The clean separation of a strictly-relative  $c$  parameter is particularly useful from an evolutionary genetics perspective, essentially embedding a zero-sum relative fitness trait within a non-zero-sum fitness model. This could have interesting applications for modeling the impacts of intra-specific competition on species extinction, for example due to clonal interference (Desai and Fisher, 2007; Gerrish and Lenski, 1998) between  $c$ -strategists on the one hand, and  $b$ -

and  $d$ - strategists on the other.

390  $K$ -selection in the narrow logistic sense of selection for a greater environmental carrying capacity for given birth and death rates, sometimes referred to as “efficiency” (MacArthur and Wilson, 1967), could be represented in our model by smaller individual territorial requirements.

393 To a first approximation, two co-occurring genotypes which differ by a small amount in their territorial requirements only should have the same fitness since the costs or benefits of a change in the amount of unoccupied territory is shared equally among genotypes via the propagule density

396 per territory  $L$ . The situation is more complicated when the differences in territorial requirements become large enough that territorial contests can occur on different scales for different genotypes. We leave these complications for future work.

399 Our realization of Grime’s triangle (Fig. 4) differs from approaches which identify primary strategies as trait combinations which can co-exist (Bolker and Pacala, 1999), referring instead to the direction of adaptive trait evolution under different regimes of stress and disturbance, which

402 is closer in spirit to Grime’s arguments (Grime, 1974, 1977). In addition, we have not assumed any kind of trade-offs or pleiotropy between  $b$ ,  $c$  and  $d$ , only constraints imposed by the environment on the order of magnitude of  $b$  and  $d$ . As an example of a trade-off, corals which rapidly out-

405 shade neighbors have a tall, branched morphology which is vulnerable to disturbances, and so, all else being equal, ideal environment  $c$ -strategists will suffer higher mortality from disturbances (Darling et al., 2012). Fig. 5 gives the same conclusion without invoking trade-offs; mutations

408 which reduce disturbance vulnerability are essentially neutral under ideal conditions, leading to no improvements in mortality from disturbances, whereas  $c$  will tend to increase over time. Thus, while trade-offs may amplify specialization, and are sometimes invoked to explain primary

411 strategy schemes (Aerts, 1999; MacArthur and Wilson, 1967; Winemiller and Rose, 1992), they are not necessary for it.

One limitation of our model as a general-purpose model of density-dependent selection is

414 the restriction of competition to interference competition between juveniles for durable resources (lottery recruitment to adulthood), analogous to the ubiquitous assumption of viability selection

in population genetics (Ewens, 2004, p. 45). In some respects this is the complement of resource  
417 competition models, which restrict their attention to exploitation competition, typically without  
age structure (Tilman, 1982). In the particular case that resources are spatially localized (e.g. due  
to restricted movement through soils), resource competition and territorial acquisition effectively  
420 coincide, and in principle resource competition could be represented by a competitive ability  $c$  (or  
conversely,  $c$  should be derivable from resource competition). The situation is more complicated  
if the resources are well-mixed, since, in general, resource levels then need to be explicitly tracked.  
423 It seems plausible that explicit resource tracking may not be necessary when the focus is on the  
evolution of similar genotypes rather than the stable co-existence of widely differing species  
(Ram et al., 2016). We are not aware of any attempts to delineate conditions under which explicit  
426 resource tracking is unnecessary even if it is assumed that community structure is ultimately  
determined by competition for consumable resources. More work is needed connecting resource  
competition models to the density-dependent selection literature, since most of the former has  
429 to date been focused on narrower issues of the role of competition at low resource availability  
(Aerts, 1999; Davis et al., 1998; Tilman, 2007).

While our model can be applied to species rather than genotypes (e.g. ecological invasions),  
432 our focus is genotype evolution. Our assumption that there are no large  $c$  discrepancies (section  
“Mean field approximation”) amounts to a restriction on the amount of genetic variation in  $c$  in  
the population. Since beneficial mutation effect sizes will typically not be much larger than a few  
435 percent, large  $c$  discrepancies can only arise if the mutation rate is extremely large, and so the  
assumption will not be violated in most cases. However, this restriction could become important  
when looking at species interactions rather than genotype evolution.

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## Appendix A: Poisson approximation

546 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  
549  $m_i$ , 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  
552 in each territory.

In the exact model of random dispersal, the counts of a genotype's propagules across unoccupied territories follows a multinomial distribution with dimension  $U$ , total number of trials

555 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  
558 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  
561 if there is vanishing population turnover, and then the dispersal distribution is irrelevant any-  
way. 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  $1/\sqrt{m_i}$ ;  
564 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  
567 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.

### 570 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  
573 occurs is  $l_i e^{-L}$ , and so

$$\Delta_u n_i = U l_i e^{-L} = m_i e^{-L}. \quad (10)$$

### Competition when rare

The second component,  $\Delta_r n_i$ , accounts for territories where a single focal propagule is present  
576 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  $Up_i(1)P(X_i \geq 1) = b_i n_i e^{-l_i}(1 - e^{-(L-l_i)})$ . Thus

$$\Delta_r n_i = m_i e^{-l_i}(1 - e^{-(L-l_i)}) \left\langle \frac{c_i}{c_i + \sum_{j \neq i} c_j x_j} \right\rangle_{\tilde{p}}, \quad (11)$$

579 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.

582 Our “mean field” approximation is to replace  $x_j$  with its mean in the last term in Eq. (11),

$$\left\langle \frac{c_i}{c_i + \sum_{j \neq i} c_j x_j} \right\rangle_{\tilde{p}} \approx \frac{c_i}{c_i + \sum_{j \neq i} c_j \langle x_j \rangle_{\tilde{p}}}. \quad (12)$$

Below we justify this replacement by arguing that the standard deviation  $\sigma_{\tilde{p}}(\sum_{j \neq i} c_j x_j)$  (with 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

$$\begin{aligned} \tilde{p}(\mathbf{x}_i) &= p(\mathbf{x}_i | X \geq 2, x_i = 1) \\ &= \frac{P(\mathbf{x}_i, X \geq 2 | x_i = 1)}{P(X \geq 2)} \\ &= \frac{1}{1 - (1 + L)e^{-L}} \sum_{X=2}^{\infty} P(X) p(\mathbf{x}_i | X_i = X - 1), \end{aligned} \quad (13)$$

and so

$$\begin{aligned} \langle x_j \rangle_{\tilde{p}} &= \sum_{\mathbf{x}_i} \tilde{p}(\mathbf{x}_i) x_j \\ &= \frac{1}{1 - (1 + L)e^{-L}} \sum_{X=2}^{\infty} P(X) \sum_{\mathbf{x}_i} p(\mathbf{x}_i | X_i = X - 1) x_j. \end{aligned} \quad (14)$$

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,

$$\begin{aligned}\langle x_j \rangle_{\tilde{p}} &= \frac{l_j}{1 - (1+L)e^{-L}} \frac{1}{L-l_i} \sum_{k=2}^{\infty} P(X)(X-1) \\ &= \frac{l_j}{1 - (1+L)e^{-L}} \frac{L-1+e^{-L}}{L-l_i},\end{aligned}\tag{15}$$

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

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  $\mathbf{x}_i$  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  $\langle x_j \rangle_{\tilde{q}} = \langle x_j \rangle_p / C = l_j / C$ ,

$$\begin{aligned}\sigma_{\tilde{q}}^2(x_j) &= \langle x_j^2 \rangle_{\tilde{q}} - \langle x_j \rangle_{\tilde{q}}^2 \\ &= \frac{1}{C} \langle x_j^2 \rangle_p - \frac{l_j^2}{C^2} \\ &= \frac{1}{C} (l_j^2 + l_j) - \frac{l_j^2}{C^2} \\ &= \frac{l_j^2}{C} \left(1 - \frac{1}{C}\right) + \frac{l_j}{C},\end{aligned}\tag{16}$$

and

$$\begin{aligned}
\sigma_{\tilde{q}}(x_j, x_k) &= \langle x_j x_k \rangle_{\tilde{q}} - \langle x_j \rangle_{\tilde{q}} \langle x_k \rangle_{\tilde{q}} \\
&= \frac{1}{C} \langle x_j x_k \rangle_p - \frac{l_j l_k}{C^2} \\
&= \frac{l_j l_k}{C} \left( 1 - \frac{1}{C} \right),
\end{aligned} \tag{17}$$

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

588 The exact distribution  $\tilde{p}$  assumes that exactly one of the propagules present in a given site after dispersal belongs to the focal type, whereas  $\tilde{q}$  assumes that there is a focal propagule present before non-focal dispersal commences. As a result,  $\tilde{q}$  predicts that the mean propagule  
591 density is greater than  $L$  (in sites with only one focal propagule is present) when the focal 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  
594 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. (15) correctly predicts that there are on average  $\sum_{j \neq i} \langle x_j \rangle_{\tilde{p}} \approx L - 1$   
597 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  
600 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 propagaule density.

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

$$\sigma_{\tilde{q}}^2(\sum_{j \neq i} c_j x_j) = \sum_{j \neq i} \left[ c_j^2 \sigma_{\tilde{q}}^2(x_j) + 2 \sum_{k > j, k \neq i} c_j c_k \sigma_{\tilde{q}}(x_j, x_k) \right], \tag{18}$$

603 and using the fact that  $\sigma_{\tilde{q}}(x_j, x_k)$  and the first term in Eq. (16) are negative because  $C < 1$ , we



obtain an upper bound on the relative fluctuations in  $\sum_{j \neq i} c_j x_j$ ,

$$\frac{\sigma(\sum_{j \neq i} c_j x_j)}{\langle \sum_{j \neq i} c_j x_j \rangle} = C^{1/2} \frac{\left( \sum_{j \neq i} c_j^2 l_j + (1 - 1/C) \left( \sum_{j \neq i} c_j l_j \right)^2 \right)^{1/2}}{\sum_{j \neq i} c_j l_j} < C^{1/2} \frac{\left( \sum_{j \neq i} c_j^2 l_j \right)^{1/2}}{\sum_{j \neq i} c_j l_j}. \quad (19)$$

Suppose that the  $c_j$  are all of similar magnitude (their ratios are of order one). Then Eq. (19) 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. (19) 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 ( $c_j l_j \gg c_{j'} l_{j'}$  for all other nonfocal genotypes  $j'$ , and  $l_j \ll 1$ ), then the RHS of Eq. (19) can be large and we cannot make the replacement Eq. (12).

Substituting Eqs. (12) and (15) into Eq. (11), we obtain

$$\Delta_r n_i \approx m_i R_i \frac{c_i}{\bar{c}}, \quad (20)$$

where  $R_i$  is defined in Eq. (5).

## 618 Competition when abundant

The final contribution,  $\Delta_a n_i$ , accounts for territories where two or more focal propagules are present ( $a$  stands for “abundant”). Similarly to Eq. (11), we have

$$\Delta_a n_i = U(1 - (1 + l_i)e^{l_i}) \left\langle \frac{c_i x_i}{\sum_j c_j x_j} \right\rangle_{\hat{p}} \quad (21)$$

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

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

$$\left\langle \frac{c_i x_i}{\sum_j c_j x_j} \right\rangle_{\hat{p}} \approx \frac{c_i \langle x_i \rangle_{\hat{p}}}{\sum_j c_j \langle x_j \rangle_{\hat{p}}}. \quad (22)$$

Following a similar procedure as for  $\Delta_r n_i$ , where the vector of propagaule abundances is denoted  $\mathbf{x}$ , the mean focal genotype abundance is,

$$\begin{aligned} \langle x_i \rangle_{\hat{p}} &= \sum_{\mathbf{x}} x_i p(\mathbf{x} | x_i \geq 2) \\ &= \sum_{x_i} x_i p(x_i | x_i \geq 2) \\ &= \frac{1}{1 - (1 + l_i)e^{-l_i}} \sum_{x_i \geq 2} p(x_i) x_i \\ &= l_i \frac{1 - e^{-l_i}}{1 - (1 + l_i)e^{-l_i}}. \end{aligned} \quad (23)$$

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

$$\begin{aligned} \langle x_j \rangle_{\hat{p}} &= \sum_{\mathbf{x}} x_j p(\mathbf{x} | x_i \geq 2) \\ &= \sum_X P(X | x_i \geq 2) \sum_{\mathbf{x}} x_j p(\mathbf{x} | x_i \geq 2, X) \\ &= \sum_X P(X | x_i \geq 2) \sum_{x_i} p(x_i | x_i \geq 2, X) \sum_{\mathbf{x}_i} x_j p(\mathbf{x}_i | X_i = X - x_i) \\ &= \sum_X P(X | x_i \geq 2) \sum_{x_i} p(x_i | x_i \geq 2, X) \frac{l_j (X - x_i)}{L - l_i} \\ &= \frac{l_j}{L - l_i} \left[ \sum_X P(X | x_i \geq 2) X - \sum_{x_i} p(x_i | x_i \geq 2) x_i \right] \\ &= \frac{l_j}{L - l_i} \left( L \frac{1 - e^{-L}}{1 - (1 + L)e^{-L}} - l_i \frac{1 - e^{-l_i}}{1 - (1 + l_i)e^{-l_i}} \right). \end{aligned} \quad (24)$$

To calculate the relative fluctuations in  $\sum_{j \neq i} c_j x_j$ , we use a similar approximation as for  $\Delta_r n_i$ :  $\hat{p}$

is approximated by  $\hat{q}$ , defined as the  $\mathbf{x}$  dispersal probabilities in a territory conditional on  $x_i > 2$   
 627 (that is, treating the  $x_j$  as independent). All covariances between nonfocal genotypes are now zero,  
 so 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

$$\sigma_{\hat{q}}^2(x_i) = \frac{l_i}{D} \left( l_i + 1 - e^{-l_i} - \frac{l_i}{D} (1 - e^{-l_i})^2 \right), \quad (25)$$

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

$$\frac{\sigma_{\hat{q}}(\sum c_j x_j)}{\langle \sum c_j x_j \rangle} = \frac{\left( \sum_{j \neq i} c_j^2 l_j + c_i^2 \sigma_{\hat{q}}^2(x_i) \right)^{1/2}}{\sum_{j \neq i} c_j l_j + c_i l_i (1 - e^{-l_i}) / D}. \quad (26)$$

630 Similarly to Eq. (19), the RHS of Eq. (26) is  $\ll 1$  for the case that  $L \ll 1$  (due to a factor of  
 $D^{1/2}$ ), and also for the case when at least some of the propagule densities (focal or nonfocal) are  
 large — provided that  $c_i$  and the  $c_j$  are all of similar magnitude. Again, the worst case scenario  
 633 occurs when  $l_i$  and  $L - l_i$  are of order 1, in which case Eq. (26) is around 35%, which is again  
 where the  $\hat{q}$  approximation produces the biggest overestimate of the fluctuations in  $\mathbf{x}$ . Similarly  
 to Eq. (19), the RHS of (26) will not be  $\ll 1$  in the presence of a rare, extremely strong competitor.

636 Combining Eqs. (21) and (22), we obtain

$$\Delta_a n_i = m_i A_i \frac{c_i}{\bar{c}}, \quad (27)$$

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