

## A Theoretical Framework for Trait-Based Eco-Evolutionary Dynamics: Population Structure, Intraspecific Variation, and Community Assembly

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A theoretical framework for trait-based eco-evolutionary dynamics: population structure, intraspecific variation, and community assembly

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#### **Abstract**

How is trait diversity in a community apportioned between and within co-evolving species? Distruptive selection may result in either a few species with large intraspecific trait variation (ITV) or many species with different mean traits but little ITV. Similar questions arise in spatially structured communities: heterogeneous environments could result in either a few species that exhibit local adaptation or many species with different mean traits but little local adaptation. To date, theory has been well-equipped to either include ITV or to dynamically determine the number of coexisting species, but not both. Here, we devise a theoretical framework that combines these facets, and apply it to the above questions of how trait variation is apportioned within and between species in unstructured and structured populations, using two simple models of Lotka-Volterra competition. For unstructured communities, we find that as the breadth of resources increases, ITV goes from being unimportant to crucial for characterizing the community. For spatially structured communities on two patches, we find that either no local adaptation, symmetric local adaptation, or asymmetric local adaptation prevails depending on how much the patches differ. Our framework provides a general approach to incorporate ITV in models of eco-evolutionary community assembly.

#### Introduction

In recent years, the need to understand intraspecific variation of functional traits has been increasingly recognized as important for understanding the functioning of ecological communities (Albert et al., 2010; Violle et al., 2012). For example, intraspecific trait variation (ITV) has been shown to be important for detecting niche differentiation and environmental filtering (Paine et al., 2011) and for quantifying how pairwise species interactions affect the total biomass in experimentally assembled communities (Kraft et al., 2014). ITV in functional traits has also been shown to often be substantial compared to variation between species (Siefert et al., 2015).

If species have heritable variation in traits that affect fitness, natural selection will act on that variation, changing the distribution of traits in the community over time. In the long run, a community with a fixed number of species will approach an attractor for the eco-evolutionary dynamics, in the simplest case an equilibrium. However, such an eco-evolutionary equilibrium could still be invasible by other species from outside the community with other trait distributions, and one of the resident species might be under selective forces that results in an 'evolutionary branching', where a species ends up at fitness minimum as a result of directional selection and consequently splits into two (Geritz et al., 1998). Thus, in the longer term, the species richness of a community at an eco-evolutionary equilibrium might not be stable. Eventually, a community that is in equilibrium and is stable to further addition of species may be reached. Such a community has been called an evolutionarily stable community (ESC); since such a community can persist over long time scales and serves as an attractor for eco-evolutionary dynamics, ESCs can serve as important model communities (Edwards et al., 2018).

If both the number of species and the trait variation within each species are driven by ecoevolutionary dynamics, this then raises questions regarding how trait variation is apportioned between and within species in ESCs. For example, what happens when selection goes from being stabilizing to being disruptive? In general, this can depend on many factors—including genetic architecture, phenotypic plasticity, and mating patterns (Rueffler et al., 2006)—but even in simplified, purely phenotypic trait-based modeling, theory gives different answers depending on the basic assumptions the theory uses. When the theory includes ITV but fixes the number of species, weaker stabilizing selection will lead to more ITV (Kimura, 1965; Bürger, 1986), whereas in theory where the number of species is dynamic, but with no ITV, weaker stabilizing selection will lead to more species coexisting (Levins, 1962; MacArthur and Levins, 1964; Dieckmann and Doebeli, 1999). If one could incorporate both facets, the actual ESC would likely be some combination of the two, but whether the ESC will comprise a few species with great ITV or many species with little ITV can not currently be determined as theoretical approaches for assembling ESCs that take ITV into account are not yet developed.

This tension between ITV and species coexistence can also play out in spatially structured communities. Given sufficient heritable trait variation, spatially varying selection can lead species' traits to vary across space, resulting in different degrees of local adaptation (Kirkpatrick and Barton, 1997; Bruggeman, 2009; Norberg et al., 2012; Le Gland et al., 2020). However, when all individuals of a species are assumed to be identical, local adaptation is not possible, but variable spatial conditions can promote species coexistence (Troost et al., 2005; Débarre and Gandon, 2010; Fortelius et al., 2015; Wickman et al., 2017, 2019). Thus, to cover trait space on the regional scale, an ESC might comprise a few species with substantial local adaptation or many species with little local adaptation.

The current state of eco-evolutionary theory is not well equipped to deal with these questions. On one hand, quantitative genetics (Lande, 1979; Lande and Arnold, 1983) and other moment-equation-based frameworks (Wirtz and Eckhardt, 1996; Norberg et al., 2001; Savage et al., 2007; Sasaki and Dieckmann, 2011; Merico et al., 2014) readily incorporate ITV into the models. However, even the versions of these models that can treat multiple species (Sasaki and Dieckmann, 2011; Débarre et al., 2014) assume that the number of species is fixed rather than a dynamic outcome of eco-evolutionary community assembly. On the other hand, using a different modeling approach called adaptive dynamics (Metz et al., 1992; Dieckmann and Law, 1996; Geritz et al., 1998; Dercole and Rinaldi, 2008; Brännström et al., 2013) one can easily determine whether

a community is closed to evolutionary branching and/or invasion by other species. Thus, using adaptive dynamics, one can assemble a community that is not only at an eco-evolutionary equilibrium, but which is also stable against further diversification into more species by invasion or evolutionary branching. However, by construction, adaptive dynamics assumes that all individuals within a species are identical, so it cannot take ITV into account. While model-specific studies in structured communities that combine species assembly with ITV have been carried out (Débarre et al., 2013), and the moment equations for a fixed number of species for a general category of class-structured communities has recently been developed (Lion et al., 2022), a framework for systematically assembling ESCs that take ITV into account does not exist.

In this paper we synthesize many recent advances in describing eco-evolutionary dynamics through moment equations taking the total density, mean traits, and trait variances into account, and adapt the community-assembly capabilities of adaptive dynamics to work with these moment equations. This yields a general framework for eco-evolutionary community assembly for class-structured communities that allows us to assemble ESCs that take ITV into account. The framework can handle complex models that include for example multiple traits and external resources, but in the main text we will focus on resolving the twin tensions described above regarding whether trait diversity will be apportioned within or between species, and within a local community or across a spatial gradient. We illustrate the framework using two simple models of Lotka-Volterra competition. First, we describe the framework in the simplest possible setting without population (spatial) structure, and use the first Lotka-Volterra model to investigate the simultaneous increase in ITV and number of species that result from weaker stabilizing selection. We then extend the framework to class-structured populations, which we illustrate with a two-patch spatially structured Lotka-Volterra model to investigate the tension between local adaptation and species coexistence as the two patches become increasingly different. These analyses show that rich patterns of intra- and interspecific trait variation emerge even in these simple models, and thus demonstrate the utility we believe this framework has for furthering our understanding of the interaction between eco-evolutionary dynamics and individual variation in traits.

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# Eco-evolutionary dynamics and community assembly in unstructured communities

In this section we will introduce the trait-space equations that underlie our approach, and describe how these equations can be approximated by moment equations that track the total densities, mean traits, and trait variances of several species. We will then explain how these equations can be used in conjunction with a community-assembly approach to determine the evolutionarily stable community (ESC). To explore the tension between intraspecific trait variation and species coexistence, we employ a simple Lotka-Volterra competition model.

## Trait-space equations for unstructured communities

We consider a single trait value x that encodes some property of an organism such as body mass or resource-uptake ability. The entire community can then be described by the trait-density distribution v(x), which tells us how many individuals there are with trait x; to be more precise,  $\int_a^b v(x) dx$  describes the total density of individuals that has a trait value in the interval  $a \le x \le b$ . We assume that the density of individuals grows due to births with per capita rate b(x,v) and declines due to mortality with per capita rate m(x,v), where both birth and death rates can depend both on the trait of an individual, x, as well as the entire trait-density distribution in which the individual exists, v. We will assume that reproduction is clonal but that parents do not give birth to exact copies of themselves, but instead produce offspring with normally distributed traits. Thus, a parent with trait y will produce offspring with trait x according to

$$\mathcal{N}(x,y,M) := \frac{1}{\sqrt{2\pi M}} \exp\left(-\frac{(x-y)^2}{2M}\right),\tag{1}$$

where M is the mutation variance. We will use the notation  $\mathcal{N}(x,\mu,V)$  throughout for the probability-density function of a normal distribution with mean  $\mu$  and variance V evaluated at

x. As in adaptive dynamics and trait-diffusion approaches (Merico et al., 2014; Le Gland et al., 2020; Nordbotten et al., 2020), we do not specify the genetic makeup that would result in these dynamics for phenotypic traits, but simply assume that new heritable variation is generated through mutations that are associated with some ecological process, such as births.

We can now write down how the trait-density distribution will change over time, which is given by the equation

$$\frac{\mathrm{d}v(x)}{\mathrm{d}t} = \int_{-\infty}^{\infty} b(y, v)v(y)\mathcal{N}(x, y, M)\mathrm{d}y - m(x, v)v(x), \qquad (2)$$

where  $\mathcal{N}(x, y, M)$  is the normal mutation kernel with variance M, describing how different offspring are from their parents on average. We will refer to these types of equations as *trait-space equations*. These models are similar to classic work in quantitative genetics (Kimura, 1965; Bürger, 1986), and models like this have been shown to be the limit of certain individual-based models in the limit of large populations (Champagnat et al., 2006).

*Trait-space equations for the unstructured Lotka-Volterra model* 

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To take a concrete example, we will consider a simple model of Lotka-Volterra competition (Lotka, 1925; Volterra, 1928). The model is similar to Lotka-Volterra models in many other recent studies using for example 'oligomorphic dynamics' (Sasaki and Dieckmann, 2011), quantitative genetics (Barabás et al., 2022), and adaptive dynamics (Ranjan and Klausmeier, 2022). For this model, we assume that individuals experience a net density-independent per capita growth r(x) in the absence of other individuals due to the environment, which we split into a birth rate b(x) and background death rate  $\mu(x)$ . Additionally, all individuals experience extra density-dependent mortality due to competition with all other individuals, at a per capita rate a(x,v), in a way such that competition is most intense between individuals with similar traits. Comparing with Eq. 2, we thus have that  $m(x,v) = \mu(x) + a(x,v)$ , and the trait-space equations are given by

$$\frac{\mathrm{d}v(x)}{\mathrm{d}t} = \int_{-\infty}^{\infty} b(y)v(y)\mathcal{N}(y, x, M)\mathrm{d}y - \mu(x)v(x) - a(x, v)v(x), \tag{3a}$$

$$b(x) = r_0$$
,  $\mu(x) = \frac{x^2}{V_r}$ ,  $r(x) = b(x) - \mu(x) = r_0 - \frac{x^2}{V_r}$ , (3b)

$$b(x) = r_0, \mu(x) = \frac{x^2}{V_r}, r(x) = b(x) - \mu(x) = r_0 - \frac{x^2}{V_r}, (3b)$$

$$a(x,v) = \int_{-\infty}^{\infty} \alpha(y,x)v(y)dy, \alpha(y,x) = \exp\left(-\frac{(y-x)^2}{2V_c}\right). (3c)$$

Here,  $V_r$  is the environmental variance and  $V_c$  is the competition variance, which is a measure of how broad competition is in trait space, with larger  $V_c$  increasing competition between individuals of different traits. For  $V_c \rightarrow 0$ , individuals will compete only with other individuals with exactly the same trait, and for  $V_c o \infty$  individuals will compete equally with individuals with any trait. Trait-matching competition of this type can be motivated by, for example, that birds with similarly-sized beaks will compete more strongly since they compete for similarly-sized seeds (MacArthur, 1972).

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In general, the generic trait-space equations (Eq. 2) will not be analytically tractable; even the equilibrium of Eq. 2 will be hard to ascertain, even for very simple examples (e.g., Kimura, 1965; Bürger, 1986). Numerically too, discretizing trait space and solving Eq. 2 often requires significant computational power. For the more complicated models we will study later in this manuscript especially, the feasibility of numerical explorations of the equations is highly limited. Instead, we will study approximations of the trait-space equations where the moments of the trait-density distribution are tracked. Such moment equations have the additional benefit that they are often more ecologically interpretable than the trait-space equations.

## Moment equations for unstructured communities

Here, we will follow the general approach of previous moment-based frameworks (Slatkin, 1980; Wirtz and Eckhardt, 1996; Norberg et al., 2001; Bruggeman, 2009; Sasaki and Dieckmann, 2011; Tirok et al., 2011; Merico et al., 2014; Débarre et al., 2014; Nordbotten et al., 2020) to derive approximate equations that track the total density, mean trait, and trait variance of populations. These approaches, and ours, all result in similar equations, but as the details differ we will here detail the precise assumptions we make to derive these equations. We will assume that the trait-density distribution v(x) can be decomposed into a set of S 'species', where each species represents a peak in the trait-density distribution so that

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$$v(x) = \sum_{i=1}^{S} v_i(x).$$
 (4)

We will then assume that each such species can be approximated with a normal distribution so that

$$v_i(x) \approx u_i \mathcal{N}(x, \bar{x}_i, V_i),$$
 (5)

where  $u_i = \int_{-\infty}^{\infty} v_i(x) dx$  is the total density of species i,  $\bar{x}_i = (1/u_i) \int_{-\infty}^{\infty} x v_i(x) dx$  is the mean trait of species i, and  $V_i = (1/u_i) \int_{-\infty}^{\infty} (x - \bar{x}_i)^2 v_i(x) dx$  is the trait variance of species i. We will use the notation

$$\tilde{v}(x) := \sum_{i=1}^{S} u_i \mathcal{N}(x, \bar{x}_i, V_i) \approx v(x)$$
(6)

for the approximate trait-density distribution. In words, the approximate community trait-density distribution  $\tilde{v}(x)$  is the sum of all approximate trait-density distributions for each species,  $u_i \mathcal{N}(x, \bar{x}_i, V_i)$ . We will assume that each species is reproductively isolated so that individuals born in species i end up as species i individuals. Finally, for the birth rate b(x, v) and mortality rate m(x, v) we will introduce notation that describes the population-level per capita rates for a normally-distributed population with mean trait  $\bar{x}$  and trait variance V in the environment set by the resident community with trait-density  $\tilde{v}$ . These population-level rates are given by the Gaussian integrals

$$\hat{b}(\bar{x}, V, \tilde{v}) := \int_{-\infty}^{\infty} b(x, \tilde{v}) \mathcal{N}(x, \bar{x}, V) dx, \qquad (7a)$$

$$\hat{m}(\bar{x}, V, \tilde{v}) := \int_{-\infty}^{\infty} m(x, \tilde{v}) \mathcal{N}(x, \bar{x}, V) dx.$$
 (7b)

Given these assumptions, without further approximation, we can derive the following equations for the total densities, mean traits, and trait variances for each species i = 1, ..., S, which are given by (see Appendix A for the derivation):

$$\frac{\mathrm{d}u_{i}}{\mathrm{d}t} = \left(\hat{b}(\bar{x}_{i}, V_{i}, \tilde{v}) - \hat{m}(\bar{x}_{i}, V_{i}, \tilde{v})\right) u_{i},$$
population-level per capita net growth

(8a)

$$\frac{\mathrm{d}\bar{x}_i}{\mathrm{d}t} = V_i \left( \frac{\partial \hat{b}}{\partial \bar{x}} (\bar{x}_i, V_i, \tilde{v}) - \frac{\partial \hat{m}}{\partial \bar{x}} (\bar{x}_i, V_i, \tilde{v}) \right), \tag{8b}$$

$$\frac{\mathrm{d}V_{i}}{\mathrm{d}t} = V_{i}^{2} \left( \underbrace{\frac{\partial^{2}\hat{b}}{\partial\bar{x}^{2}}(\bar{x}_{i}, V_{i}, \tilde{v}) - \frac{\partial^{2}\hat{m}}{\partial\bar{x}^{2}}(\bar{x}_{i}, V_{i}, \tilde{v})}_{\text{stabilizing/disruptive selection}} \right) + \underbrace{\hat{b}(\bar{x}_{i}, V_{i}, \tilde{v})M}_{\text{mutation}}.$$
(8c)

We will refer to these equations as *moment equations*. Equation 8a describes how the total density  $u_i$  of species i increases in response to its population-level birth rate  $\hat{b}(\bar{x}, V, \tilde{v})$  evaluated at its mean trait  $\bar{x}_i$  and trait variance  $V_i$ , and how it decreases in response to the population-level mortality rate  $\hat{m}(\bar{x}, V, \tilde{v})$ . Note that the birth and mortality rates may depend on the approximate trait-density distribution  $\tilde{v}$  of the entire community, not just conspecifics. Equation 8b describes how the mean trait  $\bar{x}_i$  of species i responds to directional selection. The mean trait will move along the selection gradient induced by births and deaths towards mean traits that yield higher per capita net growth, similar to the gradient dynamics of the canonical equation of adaptive dynamics (Dieckmann and Law, 1996; Champagnat, 2003) or in quantitative genetics (Lande and Arnold, 1983). The speed at which this directional selection acts depends on the selection gradient multiplied by the level of trait variance  $V_i$  in species i, but note that here the selection gradients themselves,  $\partial \hat{b}/\partial \bar{x}$  and  $\partial \hat{m}/\partial \bar{x}$ , can also depend on the trait variance (due to Eqs. 7). Equation 8c describes how the trait variance  $V_i$  of species i responds to stabilizing/disruptive selection and mutations. Selection is stabilizing—resulting in a reduction in trait variance over time—if the sign of the sum of the second derivatives is negative and selection is disruptive resulting in an increase in trait variance over time—if the sign is positive. The second term corresponds to an increase in trait variance over time due to mutations, which depends on the population-level per capita birth rate  $\hat{b}$  as well as the mutation kernel variance M.

Moment equations for the unstructured Lotka-Volterra model

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To get the moment equations for our Lotka-Volterra model, we first need to compute the populationlevel rates which can be calculated to be (see Appendix C)

$$\hat{b}(\bar{x}, V) = r_0, \tag{9a}$$

$$\hat{r}(\bar{x}, V) = \hat{b}(\bar{x}, V) - \hat{\mu}(\bar{x}, V) = r_0 - \frac{\bar{x}^2 + V}{V_r}, \tag{9b}$$

$$\hat{a}(\bar{x}, V, \tilde{v}) = \sqrt{2\pi V_c} \sum_{j=1}^{S} u_j \mathcal{N}(\bar{x}, \bar{x}_j, V + V_j + V_c). \tag{9c}$$

Having done this, we can plug these expressions into the general moment equations (Eqs. 8), which yields the equations

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$$\frac{\mathrm{d}u_i}{\mathrm{d}t} = \left[ \left( r_0 - \frac{\bar{x}_i^2 + V_i}{V_r} \right) - \sqrt{2\pi V_c} \sum_{j=1}^S u_j \mathcal{N}(\bar{x}_i, \bar{x}_j, V_i + V_j + V_c) \right] u_i, \tag{10a}$$

 $\frac{\mathrm{d}\bar{x}_{i}}{\mathrm{d}t} = V_{i} \left[ -\frac{2\bar{x}_{i}}{V_{r}} + \sqrt{2\pi V_{c}} \sum_{j=1}^{S} u_{j} \frac{\bar{x}_{i} - \bar{x}_{j}}{V_{i} + V_{j} + V_{c}} \mathcal{N}(\bar{x}_{i}, \bar{x}_{j}, V_{i} + V_{j} + V_{c}) \right], \tag{10b}$ 

$$\frac{\mathrm{d}V_{i}}{\mathrm{d}t} = V_{i}^{2} \left[ -\frac{2}{V_{r}} + \sqrt{2\pi V_{c}} \sum_{j=1}^{S} u_{j} \frac{V_{i} + V_{j} + V_{c} - (\bar{x}_{i} - \bar{x}_{j})^{2}}{(V_{i} + V_{j} + V_{c})^{2}} \mathcal{N}(\bar{x}_{i}, \bar{x}_{j}, V_{i} + V_{j} + V_{c}) \right]$$

$$+ \underbrace{r_0}_{\hat{b}(\bar{x}_i, V_i)} M. \tag{10c}$$

The growth rate of the total density  $u_i$  of species i (Eq. 10a) depends on the environmental growth rate, which is determined by the species' distance in trait mean  $\bar{x}_i$  from the optimal trait  $\bar{x}_i = 0$  and decreased due to the species' trait variance  $V_i$ . The species then suffers additional mortality from intra- and inter-specific competition, which depends on the mean traits and trait variances of both the focal species i and its competitor j. Interspecific competition is most intense between species whose mean traits  $\bar{x}_i$  and  $\bar{x}_j$  are close, and is mediated by the trait variance of both species i and i as well as the competition variance i.

The rate of change of the mean trait  $\bar{x}_i$  of species i (Eq. 10b) depends on the directional selection induced by both the environmental growth rate and competition. The first term, which is the selection induced by the environment, always exerts selective pressure towards the optimal trait  $\bar{x}_i = 0$ . The second term, which is the selection induced by competition, always exerts selective pressure for the mean traits of any species to separate from one another.

The rate of change of the trait variance  $V_i$  of species i (Eq. 10c) depends on stabilizing/disruptive selection induced by the environment and competition. The first term, due to the environment, is always stabilizing and acts to reduce trait variance over time. This is because the quadratic environmental growth rate universally disfavors trait variance. The second term, due to competition is stabilizing if  $(\bar{x}_i - \bar{x}_j)^2 > V_i + V_j + V_c$  and disruptive if the opposite is true. For intraspecific competition (i=j) the difference between the means is zero, so intraspecific competition is always disruptive. This is because a species with more trait variance will have its individuals more spread out in trait space and consequently suffer less intraspecific competition. If two different species are far enough apart, selection will act stabilizingly on both species to reduce their overlap in trait space by reducing the trait variance of both species. The final term is the mutation term, which always acts to increase trait variance over time.

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Together, equations 10 describe the dynamics of the first three moments (zeroth: total density, first: mean trait, second: trait variance) of each species in a community of *S* species. As we have made a normal approximation for the trait-density distribution for each species, no higher moments have to be tracked. We further discuss our choice of normal approximation in the discussion section.

## Eco-evolutionary community assembly for unstructured communities

So far we have derived how to treat a fixed number of species, S, and their eco-evolutionary dynamics, including the effects on the intraspecific trait variance of the species, but this then raises the question: how many species can coexist? For our Lotka-Volterra model (Eqs. 10) we can see an example of how there exists an intrinsic tension between large intraspecific variance and the number of species: Intraspecific competition will increase trait variance and interspecific competition can reduce it, thus, under weak stabilizing selection (e.g., small  $V_c$  or large  $V_r$ ) will we get many species with small trait variance or a few—or even just one—species with large trait variance? Likely the answer is some combination of the two, but without some method for being able to ascertain whether a community where intraspecific variation is taken into account is open

to the addition of more species, it is not possible to determine the relative importance of these two effects.

To be able to answer these questions we need to adapt the eco-evolutionary community-assembly methods available in adaptive dynamics. Specifically, we devise a method for determining whether a species in a community can undergo evolutionary branching when in equilibrium and a method for determining whether a community is invasible by any other rare species.

#### Evolutionary branchings

In adaptive dynamics, evolutionary branching occurs when a species has evolved a trait in accordance with directional selection until directional selection ceases and the species finds itself at a fitness minimum causing the species to split in two (Geritz et al., 1998). This procedure cannot be directly translated to our moment-equation framework due to the fact that we include trait variance. Instead, after Eqs. 8 have reached an equilibrium for S species we virtually split each species into two identical copies and examine the linear stability of the resulting S+1 species equilibrium. If such a split-species equilibrium is unstable, we say that the system has undergone an evolutionary branching and keep the split-species pair. The details of the procedure are available in Appendix B. Figure 1 depicts an example of a branching in the Lotka-Volterra model.

#### 279 Invasion analysis

Even if no evolutionary branchings are possible, the community might not be closed to invasion by types that are farther away in trait space. We will here employ a scheme for carrying out a global invasion analysis inspired by Kremer and Klausmeier (2013). To determine whether a community is closed to invasion, we introduce a rare invading population with mean trait  $\bar{x}^{inv}$  and trait variance  $V^{inv}$  into a resident community whose species are all in equilibrium. Let  $\tilde{v}^{res}$  denote the sum-of-normals trait-density distribution of the residents. As we assume that the invader will initially remain rare, we do not need to track its total density, and the equations for

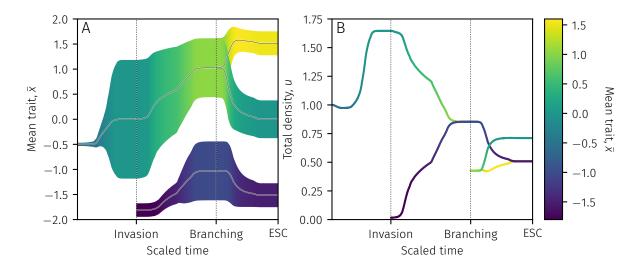


Figure 1: Community assembly through invasion and branching in the unstructured Lotka-Volterra model. The panels depict how mean traits  $\bar{x}_i$  and trait variances  $V_i$  (Panel A, one standard deviation is depicted as a filled area) and the total densities  $u_i$  (Panel B) evolve over time during a community-assembly procedure. To start with, a single species with initial moments u=1,  $\bar{x}=-0.5$ , and V=0.001 is introduced. Selection from the environment and competition leads to changes in the density, mean trait ('ecological character displacement'; Slatkin, 1980), and variance according to Eqs. 10, until it reaches an eco-evolutionary equilibrium (first dotted line). Then, the system is checked for whether any branchings or invasions are possible. In this case, no branching is possible, but an invader with positive invasion fitness is found and introduced. After that, Eqs. 10 are once again run for the two-species community until it reaches an eco-evolutionary equilibrium (second dotted line). Here, a branching is detected and the top species is split into two new species with slightly different mean traits. We then once again solve Eqs. 10 until equilibrium, during which the branching species diverge. At the final time point the system is once again at an eco-evolutionary equilibrium, and no branchings or invasions are possible meaning that we have reached a three-species eco-evolutionarily stable community (ESC). To show all pertinent events, time has been rescaled nonuniformly. **Parameter values**:  $V_r = 9.0$ ,  $M = 10^{-4}$ , and other parameters are as in Table 1.

its mean trait and trait variance are given by

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$$\frac{\mathrm{d}\bar{x}^{\mathrm{inv}}}{\mathrm{d}t} = V^{\mathrm{inv}} \left( \frac{\partial \hat{b}}{\partial \bar{x}} (\bar{x}^{\mathrm{inv}}, V^{\mathrm{inv}}, \tilde{v}^{\mathrm{res}}) - \frac{\partial \hat{m}}{\partial \bar{x}} (\bar{x}^{\mathrm{inv}}, V^{\mathrm{inv}}, \tilde{v}^{\mathrm{res}}) \right), \tag{11a}$$

$$\frac{\mathrm{d}V^{\mathrm{inv}}}{\mathrm{d}t} = (V^{\mathrm{inv}})^2 \left( \frac{\partial^2 \hat{b}}{\partial \bar{x}^2} (\bar{x}^{\mathrm{inv}}, V^{\mathrm{inv}}, \tilde{v}^{\mathrm{res}}) - \frac{\partial^2 \hat{m}}{\partial \bar{x}^2} (\bar{x}^{\mathrm{inv}}, V^{\mathrm{inv}}, \tilde{v}^{\mathrm{res}}) \right) + \hat{b}(\bar{x}^{\mathrm{inv}}, V^{\mathrm{inv}}, \tilde{v}^{\mathrm{res}}) M, \quad (11b)$$

where we note that the invader rates depend only on the resident densities, because we assume it to be so rare that its effect on itself is negligible.

As long as the invader starts out sufficiently rare, we can assume that its mean trait and trait variance will settle onto an attractor, in the simplest case an equilibrium, where its exponential growth rate can be determined (c.f., Lin et al., 2020). Since the invader equations are nonlinear, several attractors may possibly exist. We will here assume equilibrium dynamics, and we can thus assume that a rare invader will eventually settle onto one of several equilibria. Assume that there are N such equilibria and denote invaders' means and variances by  $\bar{x}^{\text{inv},n}$  and  $V^{\text{inv},n}$  respectively for equilibrium n=1,...,N. Once an invader's trait distribution has reached an equilibrium mean and variance, we can calculate its per capita growth  $\lambda_n$  as

$$\lambda_n = \hat{b}(\bar{x}^{\text{inv},n}, V^{\text{inv},n}, \tilde{v}^{\text{res}}) - \hat{m}(\bar{x}^{\text{inv},n}, V^{\text{inv},n}, \tilde{v}^{\text{res}}).$$
(12)

If  $\lambda_n > 0$ , the per capita growth rate of the invader will be positive in the environment set by the residents and the invader can successfully invade, and if  $\lambda_n \leq 0$ , the invader will not be able to invade. Note that all resident species will show up as neutrally stable ( $\lambda_n = 0$ ) equilibria for the invader, though not necessarily attractors.

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In Fig. 1 we depict an invasion event in the Lotka-Volterra model. For the single resident species depicted at equilibrium at the dotted line marked "invasion" we can find two invader equilibria given by

$$\bar{x}^{\text{inv,1}} \approx -1.81$$
,  $V^{\text{inv,1}} \approx 0.0182$ ,  $\lambda_1 \approx 0.0962$ , (13a)

$$\bar{x}^{\text{inv,2}} \approx 1.81$$
,  $V^{\text{inv,2}} \approx 0.0182$ ,  $\lambda_2 \approx 0.0962$ . (13b)

The Lotka-Volterra model is symmetric in trait space, and thus, with a single resident with  $\bar{x} = 0$ , we find two invaders equidistant from the middle, both with positive invasion fitness. As in adaptive dynamics, we assume that only one invasion event is allowed to happen at once, and so for this example, invader one was chosen at random to invade the community.

In principle, this procedure gives us an invasion criterion for a community. If there exists any invader equilibrium with  $\lambda_n > 0$  we can add a species to the community at a low density with mean trait  $\bar{x}^{\text{inv},n}$  and trait variance  $V^{\text{inv},n}$ . However, in practice, exhaustively proving that all such equilibria have been found is in general not feasible, so we will use a heuristic. For a given resident community we compute the invasion fitness for all invaders across a range of

mean traits and with zero trait variance. This is equivalent to computing the invasion-fitness landscape in adaptive dynamics. We then find all the local maxima of this adaptive-dynamics fitness landscape and use those as the initial conditions for the invader equations (Eqs. 11), and solve the equations until they reach equilibrium. We can then compute the invasion fitness for all these equilibria to determine whether the community is closed to invasion. While theoretically not exhaustive, we have found this heuristic to work very well in practice, as the zero-variance invaders serve as good first approximations to where positive invasion fitness might be available.

#### Assembly protocol

- We can now use the moment equations, the branching condition, and the invasion process to assemble an eco-evolutionarily stable community. To assemble a globally eco-evolutionarily stable community we start with an arbitrarily specified community of S species with total densities  $u_i^0$ , mean traits  $\bar{x}_i^0$  and trait variances  $V_i^0$ . We then proceed along the following steps.
  - 1. We let the community evolve according to Eqs. 8 until it reaches equilibrium.
  - 2. We check each species for evolutionary branching. In case of a branching we split the species undergoing branching into two new species and then return to step 1, letting the new community of S + 1 species evolve according to Eqs. 8.
  - 3. In case the moment equations for the resident community reach equilibrium and there are no branchings, we use our invasion scheme to see if any invader with positive invasion fitness exists. If an invader with positive invasion fitness is found, it is added to the community with a small density, and we return to step 1, and let the new community evolve once again according to Eqs. 8.

We continue going through these steps until we have reached a community where Eqs. 8 are in equilibrium and no more invaders with positive invasion fitness can be found. This community is thus eco-evolutionarily stable. In Fig. 1 we depict an example of this process for the Lotka-Volterra model. Note that at the first dotted line in Fig. 1, we first calculate the branching criterion, but a branching is not possible for that configuration, and we thus move on to step 3.

to check for invasions.

The purpose of our algorithm is to find the final evolutionarily stable community (ESC). Our assembly process cannot accurately capture the temporal dynamics of the trait-space equations or other assembly processes, as we integrate the moment equations to equilibrium between each branching or invasion event. Moreover, we have necessarily made some choices regarding the order in which we carry out our assembly steps. We have chosen to check for evolutionary branchings before invasions, as the existence of a branching implies a successful invasion but not vice versa. When a single final ESC exists, the order will not matter much as the assembly process will converge on this ESC. Our Lotka-Volterra example models in this paper are of this type. However, for more complicated eco-evolutionary dynamics, multiple alternate ESCs may exist, and under such conditions choices made regarding assembly order may yield different final communities. This situation is, however, no different compared to community assembly in adaptive dynamics, and similarly to the situation there, care must be taken when multiple ESCs are present, using tools from, for example, bifurcation theory to capture all the possible ESCs.

We now have all the tools necessary for assembling ESCs, so we will now turn to applying them to our unstructured Lotka-Volterra model (Eqs. 10). As we stated, the Lotka-Volterra model exhibits an inherent tension between the tendency towards multiple species and larger intraspecific trait variation (ITV) in each species under disruptive or weak stabilizing selection. Using adaptive dynamics, where no species has any ITV, Ranjan and Klausmeier (2022) studied a similar Lotka-Volterra model and found that as the environmental width became wider, an increasingly large number of species could co-exist in the assembled eco-evolutionarily stable community. Conversely, in another similar Lotka-Volterra model Barabás et al. (2022) found that ITV decreased when more species were included in a quantitative genetics models for a given environmental width, but had no way of systematically determine whether any of their communities were stable

Eco-evolutionarily stable communities in the unstructured Lotka-Volterra model

to invasions or evolutionary branchings. Here, we will use our moment equations together with

our assembly procedure to determine how community trait variation is partitioned into interand intraspecific terms in our Lotka-Volterra model.

To see how this tension manifests, we assemble eco-evolutionarily stable communities for a range of different environments. Specifically, we vary the environment variance  $V_r$  from 1 to 36, although for ease of interpretation we will here present results using  $w_r = \sqrt{r_0 V_r}$  as the independent variable, which describes the half-width of where the net growth function r(x) is positive (the *fundamental community* sensu Klausmeier et al. 2020). We depict the results in Fig. 2A. To further examine the role of ITV in eco-evolutionary community assembly, we also compare the results from our model with ITV to a model that does not incorporate ITV (adaptive dynamics, see Appendix C), depicted in Fig. 2B.

When  $w_r = 1$ , selection is strongly stabilizing, and only mutations prevent the trait variance of the single species from collapsing to zero. As  $w_r$  becomes wider, stabilizing selection weakens, and the disruptive selection from intraspecific competition initially increases trait variance, but eventually the one-species community becomes invasible and the community transitions into a two-species community. As we increase  $w_r$  the ESCs with ITV initially follows the ESCs without ITV closely (Fig. 2D). However, as  $w_r$  becomes increasingly large, the role of ITV becomes increasingly important, and the bifurcations into more species desynchronize between our model and the one without ITV (Fig. 2A–B). In particular, the species more centrally located in trait space show large differences for when ITV is included compared to when it is not.

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Figure 2E–F show two communities where our model with ITV exhibits large discrepancies compared to when ITV is not taken into account, both in terms of the number of species present in the community as well as the values of the mean traits. One primary reason for this discrepancy is the fact that species close to the center of the environment develop large trait variances. This is in contrast to the species closer to the edges of the environment, which have less trait variance. These differences come about through intra- and interspecific competition. As can be seen in Eq. 10c, intraspecific competition always generates disruptive selection, and inter-specific competition can engender either stabilizing or disruptive selection, depending on how far apart

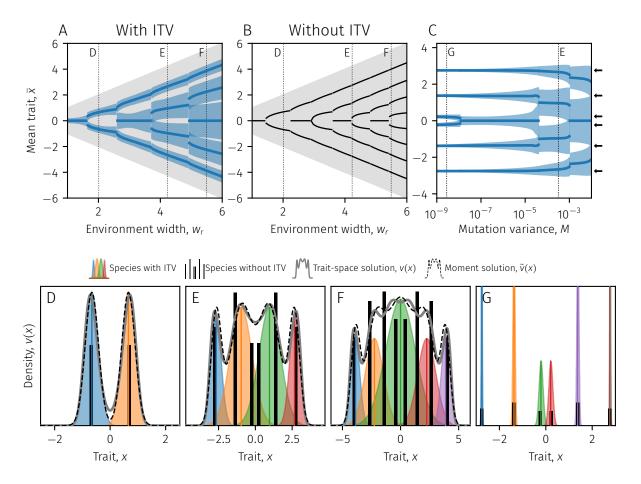


Figure 2: Eco-evolutionarily stable communities for different environmental widths and mutation variances in the unstructured Lotka-Volterra model. (A) For each value of environmental half-widths  $w_r = \sqrt{r_0 V_r}$  we depict the mean traits (solid blue lines) and one standard deviation (filled blue areas) for each species in the eco-evolutionarily stable community (ESC) computed assuming species with intraspecific variation (ITV) for that environmental width. The gray area depicts where the environment yields positive growth rate, i.e.,  $r(x) \ge 0$ . The mutation variance is  $M = 10^{-3.5}$ . (B) Same as panel A, but black lines here depict the mean traits in ESCs computed assuming species without ITV. (C) For each value of mutation variance M we depict the mean traits (solid blue lines) and one standard deviation (filled blue areas) for each species in the eco-evolutionarily stable community (ESC) for that mutation variance. Arrows on the right indicate the mean traits of the ESCs without ITV. The environmental width is  $w_r \approx 4.2$ . (D-G) ESCs computed assuming species with and without ITV for the values of  $w_r$  and M indicated by dotted lines in panels A, B, and C. The gray line depicts the numerical solution of the trait-space equations (Eqs. 3), v(x), and the black broken line depicts the numerical solution of the moment equations (Eqs. 10),  $\tilde{v}(x) = \sum_{i=1}^{S} u_i \mathcal{N}(x, \tilde{x}_i, V_i)$ , where the number of species S was determined through our assembly procedure. The colored areas depict the trait-densities of each species i = 1, ..., S when ITV is included, and the black bars depict the densities and traits of species when ITV is not included. Parameter values other than  $w_r$  and M are as in Table 1.

the species' mean traits are. Additionally, all species are not equally prevalent since the environmental conditions are better towards the center of trait space, and the species there have larger total densities u compared to species close to the edge. This means that species close to the center will experience more intraspecific competition and less interspecific competition resulting in stronger disruptive selection, which in turn translates to more standing variation in the ESC for these species. This model is thus an example of when being able to keep track of both ITV and dynamically assembling a community with a variable number of species is required for understanding how trait variation is partitioned over the long term. We also note that the substantial differences in trait variances between species in the ESCs for larger environmental widths means that models that incorporate ITV, but fixes the trait variances, would also have been insufficient for a good characterization of the distribution of traits.

Figure 2D–E show good agreement between the trait-space solution (in gray) and the moment-equation approximation (in black). Although qualitative agreement is usually good between the moment solution and trait-space solution for the ESC (e.g., Fig. 2F), the moment approximation becomes less accurate near transitions in species richness for the moment equation ESC. This is due to the fact that while the moment equations by construction always has a well-defined number of species, the trait-space equations have no such constraints and around the transition points in species richness for the moment equations, the trait-space ESCs tend to exhibit non-normal shapes that are ambiguous with regards to the number of species. We provide examples of this in Supplementary S1 where assembled communities can be seen for all different levels of environmental widths  $w_r$ .

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The amount of standing variation in an ESC also depends on how much variation is generated through mutation (Fig. 2C). For exceedingly low mutation variances M, the ESCs with ITV closely resemble those without ITV (Fig. 2G). However, for the species located in the middle of trait space, even very low levels of mutation variance can result in qualitative differences, with the two central species merging around  $M \approx 10^{-8}$ . To better understand why this merging happens, we note as trait variances get larger due to increased mutation widths, both the directional

selection repulsing the two species (Eq. 10b) and the stabilizing selection generated by interspecific competition with other species (Eq. 10c) will get weaker. This will ultimately lead to the two species collapsing into one as the mutation variance gets bigger. As the mutation variance is further increased, other species will merge for the same reasons, but as stated above, more centrally located species are more sensitive to this pattern as they experience more intraspecific competition.

**Table 1:** Parameters for the two Lotka-Volterra models.

		Value/Range	
Symbol	Description	Unstructured	Two-patch
$r_0$	Maximal growth rate	1	1
$V_r$	Environment variance	[1,36]	4
$V_c$	Competition variance	1	1
M	Mutation variance	$10^{-3.5}$	$10^{-4}$
$x_1^{\text{opt}}$	Optimal trait, patch 1	-	[-2,0]
$x_2^{\text{opt}}$	Optimal trait, patch 2	-	[0,2]
d	Dispersal rate	-	$10^{-3}$

# Eco-evolutionary dynamics and community assembly in structured populations

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For communities of unstructured populations we saw how weakened stabilizing selection could increase both the number of species and intraspecific trait variation (ITV), and that there was an inherent tension between these two forces. In spatially structured communities a related phenomenon spread over space can take place. In heterogeneous environments, spatially varying selection can lead to local adaptation within a species (Kirkpatrick and Barton, 1997; Bruggeman, 2009; Norberg et al., 2012; Le Gland et al., 2020), resulting in greater ITV across the landscape (essentially, increased beta trait diversity within a species). On the other hand, under the novariance conditions of adaptive dynamics, variable local conditions can lead to coexistence of multiple species (Troost et al., 2005; Débarre and Gandon, 2010; Fortelius et al., 2015; Wickman

et al., 2017). Additionally, using models with fixed trait variance, large fixed variances have been shown to lead to communities with fewer surviving species but with more local adaptation, and smaller fixed variances to more surviving species but with less local adaptation (Norberg et al., 2012; Edwards et al., 2018). Thus, we here have a similar but distinct tension between ITV and diversification into multiple types, but now playing out over space in the form of local adaptation. To be able to model such scenarios, we need to generalize Eq. 2 to take population structure (including spatial structure) into account.

## Trait-space equations for class-structured communities

Since populations can be structured in ways other than spatial, for generality we will here assume that the community is class-structured, meaning that the community can be sorted into K discrete bins such as spatial patches, age classes, or size classes. The trait-density distribution in each class k is given by  $v_k(x)$ ,  $k=1,2,\ldots,K$ , which describes how abundant individuals with a given trait x in class k are. We also write  $\mathbf{v}:=(v_1,...,v_K)$  for the vector of all trait-density distributions. For unstructured communities it was sufficient to consider a birth rate and a mortality rate, but in general structured communities other demographic processes can cause the trait-density  $v_k(x)$  in each class to change over time. We can consider separately the contribution of each process with per-capita rate  $f(x,\mathbf{v})$  from a source class s to a destination class s. Within-class processes s is s to a may include local birth and mortality rates on a spatial patch, whereas between-class processes s to juvenile class s in a stage-structured model. Each such process can have a mutation kernel s s to juvenile class s in a stage-structured model. Each such process can have a mutation kernel s s to the trait-space equations is given by

$$\frac{\mathrm{d}v_d(x)}{\mathrm{d}t} \stackrel{+}{=} \int_{-\infty}^{\infty} f(y, \mathbf{v}) v_s(y) \mathcal{N}(y, x, M) \mathrm{d}y, \qquad (14)$$

where the  $\stackrel{+}{=}$  operator means addition to the left-hand side, so that we sum up the rates of all processes to get the rate of change of  $v_d(x)$ . For (most) processes where M=0, we will interpret

integration of the process rate against the mutation kernel in the delta-Dirac sense so that simply

$$\int_{-\infty}^{\infty} f(y, \mathbf{v}) v_s(y) \mathcal{N}(y, x, 0) dy = f(x, \mathbf{v}) v_s(x).$$
(15)

Trait-space equations for the two-patch Lotka-Volterra model

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To take a concrete example, we generalize our Lotka-Volterra competition model to take place on two patches, so that K = 2, with local births  $b_1$  and  $b_2$ , deaths  $\mu_1$  and  $\mu_2$ , competition a on each patch, and a constant symmetric rate of dispersal d between the patches. The trait-space equations are given by

$$\frac{\mathrm{d}v_1(x)}{\mathrm{d}t} = \int_{-\infty}^{\infty} b_1(y)v_1(y)\mathcal{N}(y,x,M)\mathrm{d}y - \mu_1(x)v_1(x) - a(x,v_1)v_1(x) - dv_1(x) + dv_2(x), \quad (16a)$$

$$\frac{dv_2(x)}{dt} = \int_{-\infty}^{\infty} b_2(y)v_2(y)\mathcal{N}(y,x,M)dy - \mu_2(x)v_2(x) - a(x,v_2)v_2(x) + dv_1(x) - dv_2(x), \quad (16b)$$

$$b_k(x) = r_0$$
,  $\mu_k(x) = \frac{(x - x_k^{\text{opt}})^2}{V_r}$ ,  $r_k(x) = b_k(x) - \mu_k(x) = r_0 - \frac{(x - x_k^{\text{opt}})^2}{V_r}$ . (16c)

This model is locally the same as the unstructured Lotka-Volterra model (Eqs. 3) on each patch apart from the optimal traits  $x_1^{\text{opt}}$  and  $x_2^{\text{opt}}$  now potentially being different. Comparing with the generic trait-space equations (Eq. 14), when patch one is the destination patch (Eq. 16a), we thus have five demographic processes, four for which patch one is the source patch, namely  $b_1$ ,  $-\mu_1$ , -a, and -d, and one for which patch two is the source patch, d. Of these, only  $b_1$  has a non-zero mutation variance M associated with it.

## Moment equations for class-structured communities

As for the unstructured community, we will assume that we can approximate each trait-density distribution  $v_k(x)$  in each class with a sum of S normal distributions with total density  $u_{ik}$ , mean trait  $\bar{x}_{ik}$  and trait variance  $V_{ik}$  for species i = 1, ..., S in class k = 1, ..., K, so that

$$v_k(x) \approx \tilde{v}_k(x) = \sum_{i=1}^{S} u_{ik} \mathcal{N}(x, \bar{x}_{ik}, V_{ik}). \tag{17}$$

Note that a species will exist across all classes (even if its density could be very close to zero in some) so that the species richness in each class, as well as globally, is equal to S. We define  $\tilde{\mathbf{v}} = \mathbf{v}$ 

 $(\tilde{v}_1,...,\tilde{v}_K)$  to be the vector of approximate densities. Also as for the unstructured communities we define the population-level per capita rate for a population with mean  $\bar{x}$  and trait variance V to be

$$\hat{f}(\bar{x}, V, \tilde{\mathbf{v}}) = \int_{-\infty}^{\infty} f(x, \tilde{\mathbf{v}}) \mathcal{N}(x, \bar{x}, V) dx.$$
(18)

We can now derive the moment equations for our class-structured system (see Appendix A),
which, when summing over all demographic processes, are given by

(i) population-level per capita rate

$$\frac{\mathrm{d}u_{id}}{\mathrm{d}t} \stackrel{+}{=} \widehat{f}(\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}}) u_{is}, \tag{19a}$$

(ii) relative-density weight

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$$\frac{\mathrm{d}\bar{x}_{id}}{\mathrm{d}t} \stackrel{+}{=} \underbrace{u_{is}}_{u_{id}} \left[ \underbrace{V_{is} \frac{\partial \hat{f}}{\partial \bar{x}} (\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}})}_{(iii) \text{ directional selection}} + \underbrace{\hat{f}(\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}}) (\bar{x}_{is} - \bar{x}_{id})}_{(iv) \text{ mean-trait flow}} \right], \tag{19b}$$

$$\frac{\mathrm{d}V_{id}}{\mathrm{d}t} \stackrel{+}{=} \frac{u_{is}}{u_{id}} \left[ \underbrace{V_{is}^2 \frac{\partial^2 \hat{f}}{\partial \bar{x}^2} (\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}})}_{(v) \text{ stabilizing/disruptive selection}} + \underbrace{\hat{f}(\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}})(V_{is} - V_{id})}_{(vi) \text{ trait-variance flow}} \right]$$

$$+\underbrace{\hat{f}(\bar{x}_{is},V_{is},\tilde{\mathbf{v}})(\bar{x}_{is}-\bar{x}_{id})^2}_{(viia) \text{ between-to-within class variation}} + \underbrace{2V_{is}\frac{\partial \hat{f}}{\partial \bar{x}}(\bar{x}_{is},V_{is},\tilde{\mathbf{v}})(\bar{x}_{is}-\bar{x}_{id})}_{(viib) \text{ class-local adaptation}}$$

 $+\underbrace{\hat{f}(\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}})M}_{\text{19c}}$ 

Interpreting the moment equations for class-structured communities

As noted for other moment-based frameworks (e.g., Norberg et al., 2001), in addition to being more tractable, moment equations can also be more interpretable than the trait-space equations from which they are derived. We now go through the various terms and factors in the moment equations (Eqs. 19) and their interpretations. Table 2 contains a list of symbols and descriptions of the various quantities related to the class-structured trait-space and moment equations.

Equation 19a describes the rate of change of the total density  $u_{id}$  of species i in destination class d. Term (i), population per capita growth, describes the per capita rate of process  $\hat{f}$  between

 Table 2: Quantities involved in the trait-space and moment equations for class-structured communities.

Symbol	Description	Definition	Label in Eqs. 19
x	Trait value		
K	Number of classes		
$v_k(x)$	Trait-density distribution in class $k =$		
	1,,K		
v	Vector of trait-density distributions	$\mathbf{v}=(v_1,,v_K)$	
$f(x, \mathbf{v})$	Per capita rate of a demographic process		
М	Mutation variance associated with pro-		
	cess f		
$\hat{f}(\bar{x}, V, \mathbf{v})$	Population-level rate for mean trait $\bar{x}$	$\hat{f}(\bar{x}, V, \mathbf{v}) = \int_{-\infty}^{\infty} f(x, \mathbf{v}) \mathcal{N}(x, \bar{x}, V) dx$	
	and trait variance $V$ for rate $f$		
S	Number of species		
$v_{ik}(x)$	Trait-density distribution of species $i$ in		
	class k		
$u_{ik}$	Total density of species $i$ in class $k$	$u_{ik} = \int_{-\infty}^{\infty} v_{ik}(x) \mathrm{d}x$	
$ar{x}_{ik}$	Mean trait of species $i$ in class $k$	$\bar{x}_{ik} = (1/u_{ik}) \int_{-\infty}^{\infty} x v_{ik}(x) dx$	
$V_{ik}$	Trait variance of species $i$ in class $k$	$V_{ik} = (1/u_{ik}) \int_{-\infty}^{\infty} (x - \bar{x}_{ik})^2 v_{ik}(x) dx$	
$\tilde{v}_k(x)$	Approximate trait-density distribution	$\tilde{v}_k(x) = \sum_{i=1}^{S} u_i \mathcal{N}(x, \bar{x}_{ik}, V_{ik})$	
	in class k		
$\mathbf{ ilde{v}}$	Vector of approximate trait-density dis-	$\mathbf{\tilde{v}}=(\tilde{v}_1,,\tilde{v}_K)$	
	tributions		
d	Index of the destination class		
s	Index of the source class		
$\hat{f}(ar{x}_{is}, V_{is}, \mathbf{ ilde{v}})$	Population-level per capita growth		(i)
$u_{is}/u_{id}$	Relative-density weight		(ii)
$V_{is}rac{\partial \hat{f}}{\partial ar{x}}(ar{x}_{is},V_{is},ar{f v})$	Directional selection		(iii)
$\hat{f}(\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}})(\bar{x}_{is} - \bar{x}_{id})$	Mean-trait flow		(iv)
$V_{is}^2 rac{\partial^2 f}{\partial ar{x}^2}(ar{x}_{is}, V_{is}, oldsymbol{ ilde{v}})$	Stabilizing/disruptive selection		(v)
$\hat{f}(\bar{x}_{is}, V_{is}, \mathbf{\tilde{v}})(V_{is} - V_{id})$	Trait-variance flow		(vi)
$\hat{f}(\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}})(\bar{x}_{is} - \bar{x}_{id})^2$	Between-to-within class variation		(viia)
$2V_{is}\frac{\partial \hat{f}}{\partial \bar{x}}(\bar{x}_{is},V_{is},\tilde{\mathbf{v}})(\bar{x}_{is}-\bar{x}_{id})$	Class-local adaptation and directional		(viib)
	selection interaction		
(viia) + (viib)	Effects of class-local adaptation on vari-	(vii) = (viia) + (viib)	(vii)
	ance		
$\hat{f}(ar{x}_{is}, V_{is}, \mathbf{ ilde{v}})M$	Mutation		(viii)

source class s and destination class d evaluated at the mean trait  $\bar{x}_{is}$  and trait variance  $V_{is}$  of species i in the source class s. The equations capture how the total population densities of species change both due to within-class processes (s = d) such as local birth and death, and between-class processes ( $s \neq d$ ) such as dispersal between patches.

Equation 19b describes the rate of change of the mean trait  $\bar{x}_{id}$  of species i in destination class 513 d. Term (ii), relative-density weight, weighs contributions by the relative total densities of classes d and s, so that if the density in the destination class d is much greater than that in the source class s, the ecological processes going from s to d will only have a marginal impact on the mean trait in class d. Conversely, if the total density in the source class s is much greater than in the destination class d, the ecological process will have a large impact on the mean trait in class d. The change of the mean trait is then governed by two terms, (iii) and (iv). The first term, (iii), directional selection, describes the effect of directional selection in the process  $\hat{f}$  in class s, pushing  $\bar{x}_{id}$  in the direction of maximum increase of  $\hat{f}$ , at a rate proportional to the trait variance of species i in class s,  $V_{is}$ . This effect comes about since the process in the source class will produce more trait-density on the side of the mean in which the slope is pointing, and less on the other side. The second term, (iv), mean-trait flow, describes how mean traits are homogenized by betweenclass transitions, where the rate of homogenization is governed by the per capita rate function f, so that the mean trait of the destination class,  $\bar{x}_{id}$ , will change in the direction of the mean trait in the source class,  $\bar{x}_{is}$ . For within-class processes (s = d) we note that the relative-density weight (ii) = 1 and the mean-trait flow (iv) = 0, meaning that for within-class processes only directional 528 selection (iii) is relevant. If the process under consideration is trait-independent, such as for a constant dispersal rate between patches, directional selection (iii) would be equal to zero, but mean-trait flow (iv) could still contribute towards changing the mean trait in class d if the mean traits in s and d differ.

Equation 19c describes the rate of change of the trait variance  $V_{id}$  of species i in destination class d. As for the mean traits, the changes are weighted by the relative densities between class d and s, term (ii). The dynamics of the trait variance then depends on five terms. The first

term, (v), describes stabilizing/disruptive selection resulting from the process with rate  $\hat{f}$ . Roughly speaking, if individuals close to the mean trait  $\bar{x}_{is}$  of species i in class s contribute more than individuals away from this optimum to process  $\hat{f}$  then the curvature as measured by  $\partial^2 \hat{f}/\partial \bar{x}^2$ will be negative, which will contribute to a decrease in trait variances. Conversely, if individuals close to the mean contribute less, the curvature will be positive and this will contribute towards increases in trait variances. The second term, (vi), trait-variance flow, homogenizes trait variance between classes, so that having trait-density flow from class s to d drive the variance  $V_{id}$  of species i in class d closer to the trait variance  $V_{is}$  in class s. Terms (vii), effects of classlocal adaptation on variance, describe the effects of variability in mean traits between classes on the trait variance within each class. In the case where the classes are spatial patches, a species having different mean traits for different patches would simply be referred to as 'local adaptation', and we adapt this moniker here to the broader context of any class-structured community. Term (viia), between-to-within class variation, describes how trait variances are increased by the differences in mean traits between classes, converting between-class variance into within-class variance. Term (viib), class-local adaptation and directional selection interaction, describes the interaction between directional selection and between-class differences in mean traits. Roughly speaking, trait variances will decrease when the mean trait difference and the selection gradient point in opposite directions, and increase if they are aligned. Finally, term (viii), mutation, is the contribution to trait variance from mutations in process  $\hat{f}$ , which will contribute towards increasing trait variances. Note that typically for most processes under consideration M would be zero, as in our Lotka-Volterra example (Eqs. 16), where only birth processes are assumed to have mutations associated with them. How much mutations contribute towards trait variance increase also depends on the rate  $\hat{f}$ . Thus, for example, in a system with high birth and death rates with mutations associated with births the mutations would have a stronger impact on trait variance than in a system with low birth and death rates even if net per capita growth were the same in both systems. For within-class processes (s = d), the relative density weight (ii) will be equal to one, and only stabilizing/disruptive selection (v) and mutations (viii) will be nonzero, making these the only contributing factors. If the process  $\hat{f}$  under consideration is trait independent, stabilizing/disruptive selection (v) and class-local adaptation and directional selection interaction (viib) will be zero, but mutations (viii), variance flow (vi), and between-to-within class variation (viia) may still contribute to changes in the trait variances.

567 Moment equations for the two-patch Lotka-Volterra model

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For a specific example, we take our two-patch Lotka-Volterra model with trait-space equations given by Eqs. 16. We can, after identifying the various rates now plug these into the generic class-structured moment equations (Eqs. 19) to yield the moment equations for the two-patch Lotka-Volterra system. Below we display the moment equations for the dynamics on patch one; the dynamics on patch two are nearly identical with patch index one swapped for patch index two as necessary:

$$\frac{du_{i1}}{dt} = \left[ \underbrace{\left( r_0 - \frac{(\bar{x}_{i1} - x_1^{\text{opt}})^2 + V_{i1}}{V_r} \right)}_{V_r} - \underbrace{\sqrt{2\pi V_c}}_{\sum_{j=1}^{S}} u_{j1} \mathcal{N}(\bar{x}_{i1}, \bar{x}_{j1}, V_{i1} + V_{j1} + V_c) \right] u_{i1}}_{(i), \ \hat{r}_1(\bar{x}_{i1}, V_{i1}) = \hat{b}_1(\bar{x}_{i1}, V_{i1}) - \hat{\mu}_1(\bar{x}_{i1}, V_{i1})} - \underbrace{\sqrt{2\pi V_c}}_{\sum_{j=1}^{S}} u_{j1} \underbrace{\frac{\bar{x}_{i1} - \bar{x}_{j1}}{V_{i1} + V_{j1} + V_c}}_{(ii), \ \hat{a}(\bar{x}_{i1}, V_{i1}, \bar{v}_{i1})} - \underbrace{\frac{d\bar{x}_{i1}}{dt}}_{(i)} = V_{i1} \left[ \underbrace{-\frac{2(\bar{x}_{i1} - x_1^{\text{opt}})}{V_r}}_{(iii), \ \frac{\partial \bar{v}_1}{\partial \bar{x}^2}(\bar{x}_{i1}, V_{i1})} + \underbrace{\sqrt{2\pi V_c}}_{j=1} \underbrace{\sum_{j=1}^{S}}_{ij1} \frac{\bar{x}_{i1} - \bar{x}_{j1}}{V_{i1} + V_{j1} + V_c} \mathcal{N}(\bar{x}_{i1}, \bar{x}_{j1}, V_{i1} + V_{j1} + V_c) \right] + \underbrace{\frac{u_{i2}}{u_{i1}}}_{(iii)} \underbrace{\frac{d(\bar{x}_{i2} - \bar{x}_{i1})}{(iii)}}_{(iii)} + \underbrace{\frac{\partial \bar{v}_1}{\partial \bar{x}^2}(\bar{x}_{i1}, V_{i1})^2}_{(iv)} + \underbrace{\frac{\partial \bar{v}_1}{\partial \bar{x}^2}(\bar{x}_{i1}, V_{i1})^2}_{(v), -\frac{\partial^2 \bar{v}_1}{\partial \bar{x}^2}(\bar{x}_{i1}, V_{i1}, \bar{v}_{i1})} + \underbrace{\frac{u_{i2}}{u_{i1}}}_{(iii)} \underbrace{\frac{d(\bar{v}_{i2} - \bar{v}_{i1})^2}{(v_{i1}} + \underbrace{\frac{u_{i2}}{v_{i1}}}_{(viia)} + \underbrace{\frac{u_{i2}}{v_{i1}}}_{(viia)}}_{(viia)} + \underbrace{\frac{u_{i2}}{v_{i1}}}_{(viii)} \underbrace{\frac{d(\bar{v}_{i2} - \bar{v}_{i1})^2}{(v_{i1}} + \underbrace{\frac{v_{i1}}{v_{i1}}}_{(viii)} + \underbrace{\frac{u_{i2}}{v_{i1}}}_{(viii)}}_{(viii)} + \underbrace{\frac{u_{i2}}{v_{i1}}}_{(viii)} + \underbrace{\frac{u_{i2}}{v_{i1}}}_{(viia)} + \underbrace{\frac{u_{i2}}{v_{i1}}}_{(viii)} + \underbrace{\frac{u_{i2}}{v_{i1}}}_{($$

Here, we have marked the various terms with their corresponding terms in the generic equations Eqs. 19. The total-density dynamics (Eq. 20a) describe the local net growth on patch one due to the environmental birth and death rates, the mortality from local competition, and dispersal to and from patch two. The mean-trait dynamics (Eq. 20b) describe local selection on patch one, where the selection due to the environmental growth rate drives the mean trait towards the patch one optimum  $x_1^{\mathrm{opt}}$ , and the selection due to local competition drives each species mean trait apart from the mean traits of other species. The second term describes mean-trait flow from patch two driving the mean trait on patch one to become more similar on patch two, eroding local adaptation over time. The first term of the trait-variance dynamics (Eq. 20c) describes local stabilizing/disruptive selection, where selection due the environmental growth rate is universally stabilizing, and selection from local competition can be both stabilizing or disruptive in the same way as for the unstructured model. The next term describes trait-variance flow which drives the trait variance on patch one to become closer to the variance on patch two. The final term describes how between-patch variation, i.e., the difference between mean traits on the patches, is converted to within-patch variation by driving an increase in variance. Note that since the only between-patch process, with rate d, is trait independent, term (viib) in the generic equations (Eq. 19c) does not arise in this two-patch model.

## Eco-evolutionary community assembly for class-structured communities

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Our general approach for community assembly in class-structured communities closely resembles that for unstructured communities, albeit with more involved mathematical machinery. For evolutionary branchings, we perform the same kind of splitting and stability analysis as for the unstructured communities. The invasion analysis too proceeds along similar lines, but since the community is now structured we need to keep track of the frequency distribution of invaders across classes. As for the unstructured model, we can use these branching and invasion criteria to build up a community one species at a time until no more invasions or branchings are possible and we have an eco-evolutionarily stable community. The details of how the branching and

invasion analysis are carried out for structured communities are available in Appendix B.

### Eco-evolutionarily stable communities in the two-patch Lotka-Volterra model

When the optimal traits on the patches  $x_1^{\text{opt}}$  and  $x_2^{\text{opt}}$  differ between the patches there will be local selection towards different traits on the two patches (Eq. 20b). Under sufficiently low dispersal a single species can thus be expected to exhibit local adaptation, with its mean trait differing between patches. However, based on insights derived from adaptive dynamics, we expect to instead see multiple species as a response to heterogeneous local conditions. This then raises the question when these two possibilities are combined: with heterogeneous local conditions and weak dispersal, will we end up with fewer locally adapted species or more species with less local adaptation but differing in their mean traits?

In the two-patch Lotka-Volterra model (Eqs. 20) as well as the general class-structured moment equations (Eqs. 19), we can see that directional selection (term (iii)) is multiplied by the within-patch trait variance of the species to determine the effect of directional selection on changes in the mean trait. We can also see that that there is a term that converts between-patch variation into within-patch variation (term (viia)). This means that if the trait optima on the two different patches are different, there will be selective pressure for the mean traits in a species to separate, and as they separate, term (viia) will increase within-class variation strengthening local directional selection, further increasing the selective pressure on trait separation. This, then, creates a positive feedback between local adaptation (between-class variation) and within-class variation. However, the potential of local adaptation as a strategy for covering more of trait space on the regional scale has two limitations potentially opening up a locally adapted species to invasion. First, the mean-trait-flow term (iv) acts as a barrier to local adaptation by exerting a force towards mean-trait homogenization and may prevent sufficient local adaptation from developing, leaving unused trait space available for invasion. Conversely, if local adaptation, and hence within-patch trait variance, becomes too large this might make the species relatively maladapted by covering too much unfavorable trait space, again opening up the species to invasion. None of these scenarios are universally favored above another, and local adaptation, multiple species, or neither will be model- and parameter-dependent.

To explore a specific instance of this tension between local adaptation and divergence into multiple species we use our Lotka-Volterra model (Eqs. 20) and assemble eco-evolutionarily stable communities under conditions of weak dispersal and for a range of differences in the trait optima between the two patches. Specifically, we let  $V_r = 4$  on each patch, which is enough environmental breadth for two species to coexist in the unstructured model, and then make the patches more dissimilar by varying  $x_2^{\text{opt}} = -x_1^{\text{opt}}$  from 0 to 2. The results are depicted in Fig. 3, and parameter values are listed in Table 1.

Generally, the outcomes when we vary the patch dissimilarity fall into three categories with regards to local adaptation. The first is no local adaptation (for example, Fig. 3E–F). The second is symmetric local adaptation, meaning that a species is split roughly equally between the two patches, and the mean traits between the patches differ (for example, Fig. 3C). The third is asymmetric local adaptation, where species are significantly more prevalent on one patch, and their mean trait on the sink patch differs from that of the main patch (for example, Fig. 3D). To better illustrate the effects of the inclusion of intraspecific trait variation (ITV), we also depict ESCs for a model which does not incorporate ITV (adaptive dynamics, see Appendix C). Note that without ITV, all individuals in a species are identical, meaning that a species necessarily has the same mean trait on both patches. Below we describe in detail how the ESCs change as the patch optima become further separated.

When the optima are both equal to zero, the patches are identical and the two-patch system is functionally equivalent to an unstructured model. Conversely, when the optima are equal to  $\pm 2$  there is no overlap in trait space of positive growth rates between the two patches, and for any species having a positive environmental net growth rate on one patch, the other patch will be a pure sink. To the very left in Fig. 3A–B the communities with and without ITV agree in terms of mean traits, and since the patches are identical, two species exist across the region. However, after the patch optima separate only slightly, the community without ITV diverges into a four-species

system, with two species roughly corresponding to the community that would have evolved on patch one in isolation and one community corresponding to the one that would have evolved on patch two in isolation. In contrast, the communities with ITV remain as a two-species system all the way up to roughly  $x_k^{\rm opt} = \pm 0.25$ , but with both species exhibiting symmetric local adaptation between the patches (Fig. 3C).

The community with ITV does split into four species around  $x_k^{\rm opt}=\pm 0.25$ , but the resulting four-species community is still characterized by significant asymmetric local adaptation in at least two species for the interval between approximately  $0.25 \le \pm x_k^{\rm opt} \le 0.5$  (Fig. 3D). The two species depicted in blue and orange are here primarily patch-one specialists and the species depicted in green and red are primarily patch-two specialists. The asymmetry in local adaptation can come about through the weighted effect of densities on mean-trait flow between the patches, terms (ii) and (iii) in Eqs. 20, where the species density on the off-patch exerts relatively little pressure on the mean trait on the main patch to diverge from its local optimum.

Around  $x_k^{\text{opt}} = \pm 0.7$  the two sets of lines describing the community without ITV on each patch cross, and there is a small interval where the community without ITV will have only three species before the lines separate after the cross into four species again. For the community with ITV, the interval with three species is significantly larger, spanning roughly  $0.5 \le \pm x_k^{\text{opt}} \le 0.9$ . For this interval, the community is characterized by two outer species (blue and red) with little local adaptation and a central species (olive) that exhibits significant and symmetrical local adaptation, except in the middle of the interval, where there is no significant local adaptation in any of the three species (Fig. 3E).

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After  $x^{\mathrm{opt}} = \pm 0.9$  the community with ITV once again splits into four species, where the central two species (orange and green) are initially characterized by asymmetrical local adaptation. As the environmental optima separate further the means converge onto those for the community without ITV, and for large separations  $|x_k^{\mathrm{opt}}| > 1.1$  the system for both the communities with and without ITV are characterized by two species (blue and orange) being present almost entirely on patch one, and two species (green and red) being present almost entirely on patch two (Fig. 3F).

Due to the huge asymmetry in densities across the two patches, the mean-trait flow from the main patch to the sink patch becomes so strong that local adaptation can effectively not occur on the sink patch.

Across the range of patch dissimilarities, this model then showcased a range of behaviors with regards to local adaptation and diversification into multiple species. The fact that we could roughly sort these outcomes into three qualitatively different regimes is particularly interesting, and we could not have come across this behavior without the use of our framework.

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As for the unstructured model, the two-patch moment equation ESCs mostly have good agreement with the trait-space equations, with some issues around the transition points in the number of species (see Supplementary S1). One issue that did not arise in the unstructured model is that very close to the transition from two to four species ( $x_k^{\rm opt} \approx \pm 0.25$ ), the two-species community depicted is invasible, but after the invasion, one of the original species is depressed to extinction, after which the invader assumes the total density, mean, and variance of the extinct resident, yielding a never-ending cycle of invasions and extinctions. Similarly, the species are also branchable, but after an initial divergence in trait space, one of the branching species goes extinct and the remaining species assumes the distribution of the original branched resident, yielding a never-ending branching–extinction cycle. For these kind of cycles, we define the ESC to be the community to which the cycle returns between branchings or invasions that is in equilibrium with respect to Eqs. 19, which is the community we depict in Fig. 3A–B for  $x_k^{\rm opt} \approx \pm 0.25$ . This cycling phenomenon only occurs in a very small sliver of parameter space.

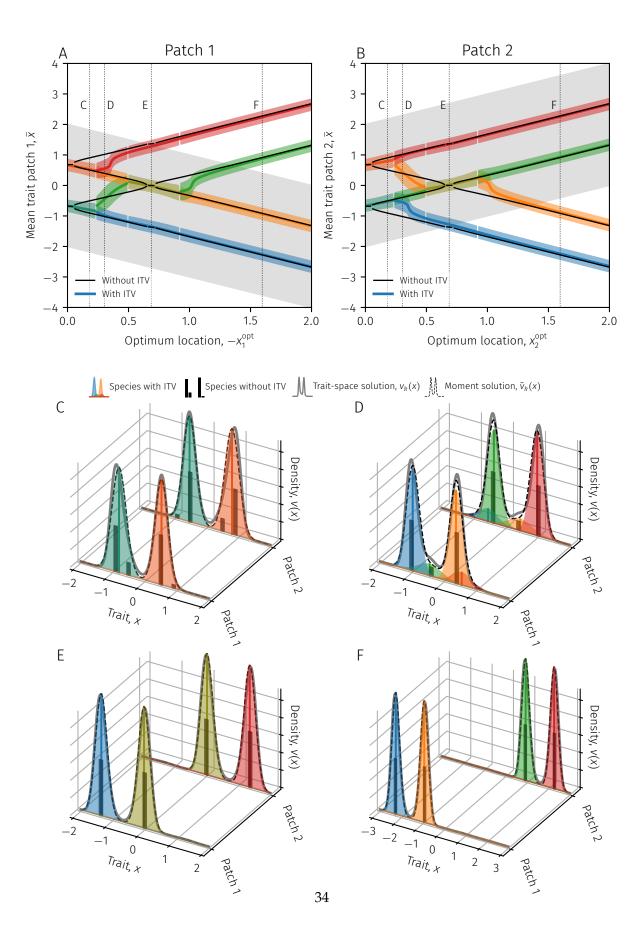


Figure 3: Eco-evolutionarily stable communities for different environmental optima in the two-patch Lotka-Volterra model. (A-B) For each value of environmental optima  $x_1^{\text{opt}}$  and  $x_2^{\text{opt}}$  we depict the mean traits (solid colored lines) and one standard deviation (filled colored areas) for each species in the eco-evolutionarily stable community (ESC) computed assuming species with intraspecific trait variation (ITV) for that pair of optima. Depicted as black lines are the ESCs for communities computed assuming species without ITV. Note that without ITV, local adaptation is precluded, and these black lines are the same in panels A and B. The gray area depicts where the environment yields positive growth rate, i.e.,  $r_k(x) \geq 0$ , on patch one (panel A), and patch two (panel B). The species in the communities with ITV are color coded so that the same species is depicted in the same color for both patches for any given value of  $x_k^{\text{opt}}$ . (C-F) ESCs for the values of  $x_k^{\text{opt}}$  indicated by the dotted lines in panels A and B. The gray line depicts the numerical solution of the trait-space equations (Eqs. 16),  $v_k(x)$ , and the black broken line depicts the numerical solution of the moment equations (Eqs. 20),  $\bar{v}_k(x) = \sum_{i=1}^S u_{ik} \mathcal{N}(x, \bar{x}_{ik}, V_{ik})$ , where the number of species S was determined through our assembly procedure. The colored areas depict the trait-density of each species i=1,...,S for the moment equations, and the black bars depict the traits and densities of the ESC without ITV. Parameter values are as in Table 1.

### Generalizing the framework

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For the purposes of exposition and to focus on our main questions regarding the tension between intraspecific trait variation, local adaptation, and diversification into multiple species we have kept our example models simple. However, several more complications can be handled by generalizing the framework. First, more than one trait may affect performance, so tracking a single scalar trait may not always be sufficient, and in such cases we would need some way of deriving the dynamics for a mean-trait vector and a trait variance-covariance matrix. In Appendix A and Appendix B we show how the framework can be expanded to include multiple traits in this way. Second, in our Lotka-Volterra models the rate functions were simple enough that we could calculate the population-level rates necessary for the moment equations using Gaussian integration analytically. This will in general not be possible, and in Appendix A, section Series solutions and Taylor approximations, we show how to derive Taylor-approximations of arbitrary order to accommodate such situations. Third, our Lotka-Volterra models do not include any dependence on any external variables such as abiotic resources, and in Appendix A, section Environmental variables, we show how external variables can be included in the framework. To provide an example that includes all these complications we have in Appendix D briefly explored a stage-structured model with one juvenile and one adult stage in two traits that compete for two abiotic resources.

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We have here focused on fully heritable trait variation, but our framework can be extended to include non-heritable environmental variation. While we have not worked this case out to the same level of generality as we have for fully heritable traits, in Appendix A, section *Environmental*, non-heritable trait variation, we provide a sketch for the simplest case of one trait in unstructured populations. While it is relatively straight-forward to incorporate the generation of non-heritable variation into the model, it requires additional moment equations, and the derivation of the moment equations from the trait-space equations becomes more involved.

#### Discussion

In this paper we have presented a general framework for eco-evolutionary community assembly for class-structured communities that incorporates intraspecific trait variation. We have done so by deriving moment equations for the total density, mean trait, and trait variance for each species in a community, combined with a procedure for determining whether additional species need to be added to a community in order for it to be closed to further invasion. Through examples, we demonstrated the application of the framework in an unstructured and a two-patch-structured Lotka-Volterra competition model, where we saw how less stabilizing conditions could result in different combinations of more intraspecific variation, local adaptation, and the addition of more species to the assembled eco-evolutionarily stable community (ESC).

## Intra- and interspecific trait variation

In recent years, the role of intraspecific vs. interspecific variation in traits has received increasing attention in functional and community ecology, with two broad questions at the center. First, how much of trait variation is intraspecific and how much is interspecific (Albert et al., 2011; Siefert et al., 2015; Griffiths et al., 2016; Gaudard et al., 2019; Xavier Jordani et al., 2019)? And second, how important is intraspecific trait variation (ITV) for higher-level outcomes such as

species coexistence and ecosystem functioning (Bolnick et al., 2011; Violle et al., 2012; Turcotte and Levine, 2016; Raffard et al., 2019)?

Regarding the first question, ITV has in general been found to account for substantial portions of trait variation, especially in plants (Siefert et al., 2015; Westerband et al., 2021). However, in some study systems of ants (Gaudard et al., 2019) and beetles (Griffiths et al., 2016) ITV was found to be negligible, and even among plant studies the preponderance of ITV is highly variable (Westerband et al., 2021), and patterns of intra- and interspecific variation can be highly idiosyncratic (Costa-Pereira et al., 2018; Umaña and Swenson, 2019). For the insect-plant discrepancy, Gaudard et al. (2019) suggested that one explanation could be related to the higher plasticity in plants that arises as a consequence of plants being sessile. In the context of individual niche specialization, several factors have been proposed as important for accounting for the level of ITV including intra- and interspecific competition, ecological opportunity (the diversity of resources), and predation (Araújo et al., 2011). While these factors can no doubt play a role in shaping ITV, they can also, in turn be shaped by ITV. In our unstructured Lotka-Volterra model (Eqs. 10, Fig. 2) ecological opportunity can roughly be said to correspond to the environmental width  $w_r$  which we take to be fixed, but intra- and interspecific competition both shape and are shaped by intraand interspecific trait variation through eco-evolutionary feedbacks, so that neither can be said to be the strict cause of the other. In field studies, idiosyncratic patterns of trait variation are to some extent to be expected due to the myriad factors that can be present in natural systems. Interestingly, however, even for our simple model with just one parameter varied (Fig. 2A), ITV is sometimes, but not always, important for characterizing the trait variation in the community. When the width of the environment is small, yielding one or two species ( $w_r \le 2.3$ ), ITV is small so the trait means of the species of our model incorporating ITV agree very well with a model not incorporating ITV, implying that ITV is not important for characterizing the trait distribution in the community. For larger environmental widths, however, ITV becomes much more substantial, and the mean trait values, and even the number of species in the community, no longer agree with the model without ITV, implying that the role of ITV is crucial for characterizing the gest that whether ITV is important for characterizing communal trait variation could be highly system-specific and may resist broad-scale explanation. However, a more complete theoretical exploration of whether broad patterns in different models can be found that serve as good indicators for the importance of ITV is outside the scope of this paper, and more research will be required to determine the extent to which such patterns exist. Our framework would serve as a good tool for carrying out such explorations.

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Scaling up to structured communities, Albert et al. (2011) proposed that in a nested sampling design, ITV should saturate as the spatial or ecological scale is increased since at a sufficiently large scale, species will cover their entire range meaning that interspecific trait variation should become the more important factor. Although our two-patch Lotka-Volterra model (Eqs. 20, Fig. 3) is not set up for one-to-one comparisons with this hypothesis, we observe some related phenomena as the environments on the two patches become increasingly different (Fig. 3). Initially, ITV, mostly in the form of local adaptation, increases as the patches separate. More interspecific variation is then added as more species join the community, but beyond a certain point the patches are too different to permit local adaptation and interspecific variation dominates. To wit, not much theoretical attention has been payed to what conditions generically promote intra- vs. interspecific variation on the regional scale (but see Norberg et al., 2012; Edwards et al., 2018), and a more systematic exploration of this question would be an interesting application of our framework.

Regarding the second question concerned with how ITV affects higher-level outcomes, species coexistence has been proposed both to be negatively and positively related to ITV (Violle et al., 2012). In two theoretical models of competition with fixed intraspecific variances, Hart et al. (2016) and Barabás and D'Andrea (2016) found that coexistence is (mostly) hampered by ITV. In our framework, both the number of species and ITV are dynamic outcomes, and it is thus not strictly possible to speak causally about how species coexistence affects ITV or vice versa within the framework. As we have done, however, it is possible to compare a model that includes ITV (our framework) to one that does not (adaptive dynamics), and in this sense it seems unlikely

that the inclusion of ITV would yield a higher number of coexisting species. The available trait space must be apportioned, and if it can be effectively covered by fewer species by incorporating ITV, the number of coexisting species will be lower.

In a two-patch version of the Hart et al. (2016) model, Uriarte and Menge (2018) found that ITV could promote regional species coexistence. This contradicts our findings, and in our two-patch model, ITV in the form of local adaptation can preclude the coexistence of species by a single species covering more trait space. A crucial difference between our models is that Uriarte and Menge (2018) assumed that the trait means and variances were fixed on each patch, whereas in our models these are outcomes of the dynamics. As for the unstructured case, it is hard envisioning a scenario using our model where the inclusion of intraspecific variance would lead to more coexisting species than the reference model without ITV. A scenario like that of Uriarte and Menge (2018) is more likely if trait variation is plastic and driven by the environment as opposed to heritable. The nature of ITV could thus be an important factor too in determining whether ITV can promote coexistence, as has also been observed in an apparent-competition model (Schreiber et al., 2011).

Ecosystem functioning has also been shown to depend on the trait distributions of communities (Mouillot et al., 2011; Gross et al., 2017). Our modeling framework opens up the door for theoretical explorations of the relationship between trait variation both within and between species and various ecosystem functions. Similarly to coexistence, ecosystem function and the trait variation are both outcomes of the system's dynamics, so that neither is the strict cause of the other. However, this enables explorations of what mechanisms and environments create and sustain either, neither, or both of trait diversity and ecosystem functioning.

# Relationship to other theoretical approaches

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Our framework builds on, and connects to, several other strands of eco-evolutionary theory. Considering a single class and setting all mutations to zero, our framework reduces to the community-ecology framework of Wirtz and Eckhardt (1996) and Norberg et al. (2001), where

the moments of the trait distribution of an ensemble of species is tracked. This approach often includes an immigration term from a fixed species pool to maintain trait variance in the community. Such an immigration term could easily be incorporated into our framework by designating one of the classes a "species-pool class" and letting the internal rates of this class all be zero to keep the species pool fixed. Note that our formulation also includes cases where the species pool too consists of structured populations, so that, for example, juveniles and adults in a stage-structured model could immigrate at different rates from the species pool.

Although the assumptions going into the model at the outset are different, the moment equations derived for our model are also very similar to the equations derived under the assumptions of quantitative genetics. Assuming a single class, no mutations, and that phenotypic variation equals genetic variation (no environmental variation), our equations mirror those of Barabás et al. (2022), who derived equations for mean traits and trait variance-covariance under the assumptions of quantitative genetics for multiple traits. These similarities between trait-space approaches and quantitative genetics have been noted before (e.g., Débarre et al., 2013) and the two approaches have complementary strengths and weaknesses. Most notably, the assumptions of normality are less ad hoc in quantitative genetics, and each species is, as described by a normal distribution, well defined (Turelli and Barton, 1994; Barton et al., 2017). Similarly, the reproductive isolation of species, which in our moment equations is an approximation, is in quantitative genetics based on the biological species concept. This, however, comes at the cost that diversification into multiple peaks cannot be easily incorporated as opposed to our approach here.

Our moment equations also closely resemble those derived in trait-diffusion approaches (Merico et al., 2014; Le Gland et al., 2020), where mutations are generated by a diffusion process in trait space. Merico et al. (2014) derived the moment equations for well-mixed, single-species, single-trait populations and Le Gland et al. (2020) extended this to multiple traits and spatial structure by way of reaction-diffusion equations in continuous space. For mutation kernels with small variance-covariance matrices without covariances, our mutation convolution integral is well approximated by such trait-diffusion processes (Kimura, 1965; Débarre et al., 2013), and our

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assembly framework is easily adapted to this setting, equipping the trait-diffusion approaches with a way of assembling eco-evolutionarily stable communities of several species.

Finally, our framework also produces similar equations to those in 'oligomorphic dynamics' (Sasaki and Dieckmann, 2011; Débarre et al., 2014; Lion et al., 2022), where a trait-density distribution is also decomposed into a number of 'species' to track their moments. Compared to oligomorphic dynamics, the major innovation we present here is our invasion-analysis and community-assembly framework, but there are also differences in how the moment equations are derived. First, we assume that mutations are associated with some specific ecological process (typically births) whereas in oligomorphic dynamics, mutations are assumed to be an independent process. Second, rather than assuming that each species is reproductively isolated, in oligomorphic dynamics it is instead assumed that new individuals are allocated to each species in proportion to each species' density for given trait. For structured populations, additional assumptions are required (Lion et al., 2022). These assumptions do however ultimately produce the same general shapes for the moment equations as we derived here. Finally, rather than assuming that each species is normally distributed, oligomorphic dynamics assumes a small-variance approximation and can derive equations for an arbitrary set of moments under these assumptions. To get a closed system of moment equations a so-called moment-closure approximation is then used, where using normal distributions is one such possible closure.

Our choice of approximating each species' trait density as a normal distribution at the outset rather than expanding around the mean of each species for an arbitrary number of moments has both advantages and disadvantages. The advantages are that our moment equations are more stable when variances become large compared to a small-variance expansion, and that we can more easily integrate mutations into birth processes. The disadvantage is that the flexibility in shape is more limited. In principle, functions other than normal distributions could be used to derive the moment equations. For example, Klauschies et al. (2018) and Cropp and Norbury (2021) used beta distributions as the approximating distribution to close their moment equations, and there are also approaches that use more involved methods for making non-normal

approximations for the trait-space distributions at equilibrium (Mirrahimi and Gandon, 2020). Assumptions other than normality are likely possible while still retaining the core features of our approach, but each such differing assumption would require the re-derivation of nearly all moment equations. While a shortcoming, our comparisons between the trait-space equations and moment equations indicate that as long as normality in the distributions of birthed phenotypes from a parent phenotype is assumed, then our additional assumption that species' trait distributions are normal seem not to affect the accuracy of the moment approximations by any large degree, as our eco-evolutionarily stable communities assembled by moment equations agreed very well with the corresponding trait-space equations (Figs. 2D–F, 3C–F). We note that although we assume normality in each species, the community trait-density distribution is the sum of these normals, which makes the community distribution much more flexible, see Fig. 3D for an example. The primary exception to good accuracy in the moment equations is when the number of species is ambiguous. In these instances the trait-space equations would yield solutions that could not easily be approximated by a sum of normal distributions that were assumed to be reproductively isolated (see Supplementary S1 for examples).

While these drawbacks should be kept in mind, we nevertheless believe that our framework makes substantial progress in eco-evolutionary modeling with intraspecific trait variation. In a phytoplankton model Peeters and Straile (2018) compared trait-space equations without mutations to single-species moment equations, and concluded that single-species moment equations failed to provide any useful information when considering parts of parameter space where the trait-space equations diverged into multiple species. In a similar model using the trait-diffusion approach Le Gland et al. (2020) noted that their trait-space equations sometimes exhibited multimodality and speculated on the utility of modeling multiple modes, making the selection of how many modes to include based on functional groups. While multi-species moment models are not new (Sasaki and Dieckmann, 2011; Norberg et al., 2012; Barabás and D'Andrea, 2016), our assembly approach obviates the need for a-priori decisions on how many modes or species to include by using our assembly process. It also gives an alternate approach for deriving the equations for

moment dynamics for general class-structured populations, compared to Lion et al. (2022).

Taken together we believe that our framework of unifying the community-assembly techniques of adaptive dynamics with the moment-equation approach to including intraspecific trait
variation could be of great use to theoreticians and modelers seeking to take advantage of facets
of both eco-evolutionary modeling frameworks. We also believe that being able to assemble
eco-evolutionarily stable communities that accounts for intraspecific trait variation could help
address many ecological questions regarding the extent and importance of intra- and interspecific trait variation.

### Online Appendix A: Derivation of moment equations

In this appendix we will derive the generic moment equations (Eqs. 19 in the main text) from the generic trait-space equations (Eqs. 14 in the main text). However, we will here treat a more general case than we do in the main text for which there might be multiple traits under consideration. We will thus consider a *trait vector* x where each component of the trait vector  $x_1, x_2, \ldots, x_n$  describes some property of the organism such as body mass, the propensity to consume a particular resource, or anything that can be encoded by a real number. This means that we will have a *mean-trait vector*  $\bar{x}$ , and a *trait variance-covariance matrix* V, where, for example,  $V_{22}$  is the variance in trait  $x_2$ , and  $V_{12} = V_{21}$  is the covariance between  $x_1$  and  $x_2$ . This more general formulation reduces to the case we treat in the main text when the trait vector x is one dimensional.

### Calculating the time derivatives and general notation

Time derivatives of the moments

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Let the trait-density distribution of a community be given by v(x) where  $x \in \mathbb{R}^n$  is a trait vector. Let  $\psi$  and  $\omega$  index the trait components of x, and let dots over symbols denote time derivatives. We now wish to consider the following moments of the trait-density distribution v:

$$u = \int v(x) dx$$
 Total density (A.1a)

$$\bar{x}_{\psi} = \frac{1}{u} \int x_{\psi} v(x) dx$$
 Mean-trait vector component  $\psi$  (A.1b)

$$V_{\psi\omega} = \frac{1}{\mu} \int (x - \bar{x})_{\psi} (x - \psi)_{\omega} v(x) dx$$
 Variance-covariance component  $\psi\omega$  (A.1c)

All integrals are over the entirety of  $\mathbb{R}^n$ . Calculating the moment time derivatives then yields:

For the total density *u*:

$$\dot{u} = \frac{\mathrm{d}}{\mathrm{d}t} \left[ \int v(x) \mathrm{d}x \right] = \int \dot{v}(x) \mathrm{d}x \tag{A.2}$$

For the mean trait component  $\bar{x}_{\psi}$ :

$$\dot{x}_{\psi} = \frac{\mathrm{d}}{\mathrm{d}t} \left[ \frac{1}{u} \int x_{\psi} v(x) \mathrm{d}x \right] = -\frac{1}{u^2} \dot{u} \int x_{\psi} v(x) \mathrm{d}x + \frac{1}{u} \int x_{\psi} \dot{v}(x) \mathrm{d}x =$$
(A.3a)

$$= -\frac{1}{u} \int \dot{v} dx \bar{x}_{\psi} + \frac{1}{u} \int x_{\psi} \dot{v}(x) dx = \frac{1}{u} \int (x - \bar{x})_{\psi} \dot{v}(x) dx$$
 (A.3b)

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$$u\dot{\bar{x}}_{\psi} = \int (x - \bar{x})_{\psi}\dot{v}(x)dx \tag{A.3c}$$

For the variance-covariance component  $V_{\psi\omega}$ :

$$V_{\psi\omega} = \frac{1}{u} \int (x - \bar{x})_{\psi} (x - \bar{x})_{\omega} v(x) dx$$
 (A.4a)

 $\iff$ 

$$uV_{\psi\omega} = \int (x - \bar{x})_{\psi}(x - \bar{x})_{\omega}v(x)dx$$
(A.4b)

 $u\dot{V}_{\psi\omega} + V_{\psi\omega}\dot{u} = -\dot{x}_{\psi} \int (x - \bar{x})_{\omega}v(x)dx - \dot{\bar{x}}_{\omega} \int (x - \bar{x})_{\psi}v(x)dx + \int (x - \bar{x})_{\psi}(x - \bar{x})_{\omega}\dot{v}(x)dx$ (A.4c)

$$= \int (x - \bar{x})_{\psi} (x - \bar{x})_{\omega} \dot{v}(x) dx \tag{A.4d}$$

Together we thus have

$$\dot{u} = \int \dot{v}(x) dx \tag{A.5a}$$

$$u\dot{x}_{\psi} = \int (x - \bar{x})_{\psi} \dot{v}(x) dx \tag{A.5b}$$

$$u\dot{V}_{\psi\omega} + V_{\psi\omega}\dot{u} = \int (x - \bar{x})_{\psi}(x - \bar{x})_{\omega}\dot{v}(x)dx$$
 (A.5c)

This way of expressing the relationships between the time derivatives of the moments and the time derivative of the trait distribution makes it easier to derive the moment equations for the various models, as we can plug in the right-hand side of any equation in place of  $\dot{v}$  in Eqs. A.5.

A note on notation

The calculations for deriving the moment equations are not difficult in the sense that they require any complicated mathematical concepts or techniques. They are however rather complex in terms of notation and book keeping. To alleviate this problem, we introduce some useful notation.

First, we frequently employ so-called Einstein summation notation. This means that, unless otherwise indicated, repeated indices are summed over, so that for example

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$$A_{\alpha\beta}B_{\beta\gamma} := \sum_{\beta} A_{\alpha\beta}B_{\beta\gamma} \,. \tag{A.6}$$

Second, we let indices on scalar quantities denote components of gradients, i.e., if f is a function from  $\mathbb{R}^n$  to  $\mathbb{R}$ , then

$$f_{\alpha} = \frac{\partial f(x)}{\partial x_{\alpha}}, \quad \alpha \in \{1, 2, \dots, n\}$$
 (A.7)

Thus, for example, in index notation we would write  $\nabla_x g$  as  $g_\alpha$ . Combining these two notational conventions, we can for example write the matrix–vector product  $V\nabla_x g$  as  $V_{\psi\alpha}g_\alpha$  and the matrix–matrix product  $V\nabla_x^2 gV$  as  $V_{\psi\alpha}g_{\alpha\beta}V_{\beta\omega}$ .

We will use Greek letters to indicate trait components. For these indices the Einstein summation convention will always apply. We will use Latin indices i and j for species, and k and l for classes, and finally m for processes. The Einstein summation convention will not apply to these indices.

## Deriving the moment equations

To make it easier to derive the moment equations from the trait-space equations, we will first set out to derive some intermediate results.

First, let the probability-density function of an *n*-dimensional multivariate normal distribution be denoted by

$$\mathcal{N}(x, \bar{x}, V) = \frac{1}{\sqrt{(2\pi)^n \det(V)}} \exp\left(-\frac{1}{2}(x - \bar{x})^T V^{-1}(x - \bar{x})\right), \tag{A.8}$$

where x is the argument vector,  $\bar{x}$  is the mean vector, and V is the variance-covariance matrix of the multivariate normal distribution, and T denotes matrix transposition. We can then calculate the first and second derivatives of this normal distribution with respect to its argument components:

$$\mathcal{N}_{\psi} = \frac{\partial \mathcal{N}}{\partial x_{\psi}} = -V_{\psi\alpha}^{-1}(x - \bar{x})_{\alpha} \mathcal{N}(x, \bar{x}, V)$$
(A.9a)

$$\mathcal{N}_{\psi\omega} = \frac{\partial^2 \mathcal{N}}{\partial x_{\psi} \partial x_{\omega}} = \left[ V_{\psi\alpha}^{-1} (x - \bar{x})_{\alpha} V_{\omega\beta}^{-1} (x - \bar{x})_{\beta} - V_{\psi\omega}^{-1} \right] \mathcal{N}(x, \bar{x}, V) \tag{A.9b}$$

Furthermore, if f(y) is the rate of an ecological process for an individual with trait y, let the population level per capita rate for a population with mean-trait vector x and variance-covariance matrix W be given by

$$\hat{f}(x,W) = \int f(y)\mathcal{N}(y,x,W)dy. \tag{A.10}$$

We can now differentiate the population-level rate  $\hat{f}$  with respect to the mean-trait components:

$$\hat{f}_{\psi} = \frac{\partial \hat{f}}{\partial x_{\psi}} = W_{\psi\alpha}^{-1} \int (y - x)_{\alpha} f(y) \mathcal{N}(y, x, W) dy$$
(A.11a)

$$\hat{f}_{\psi\omega} = \frac{\partial^2 \hat{f}}{\partial x_{\psi} \partial x_{\omega}} = \int \left[ W_{\psi\alpha}^{-1} (y - x)_{\alpha} W_{\omega\beta}^{-1} (x - y)_{\beta} - W_{\psi\omega}^{-1} \right] f(y) \mathcal{N}(y, x, W) dy$$
 (A.11b)

Using these results we can calculate two integrals that will appear later in our derivation:

$$\int (x - \bar{x})_{\psi} f(x) \mathcal{N}(x, \bar{x}, V) dx = V_{\psi \alpha} V_{\alpha \beta}^{-1} \int (x - \bar{x})_{\beta} f(x) \mathcal{N}(x, \bar{x}, V) dx$$
 (A.12a)

$$=V_{\psi\alpha}\hat{f}_{\alpha}(\bar{x},V) \tag{A.12b}$$

and

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$$\int (x - \bar{x})_{\psi}(x - \bar{x})_{\omega} f(x) \mathcal{N}(x, \bar{x}, V) dx$$
(A.13a)

$$= V_{\psi\alpha}V_{\omega\beta} \int V_{\alpha\gamma}^{-1}(x-\bar{x})_{\gamma}V_{\beta\epsilon}^{-1}(x-\omega)_{\epsilon}f(x)\mathcal{N}(x,\bar{x},V)\mathrm{d}x \tag{A.13b}$$

$$=V_{\psi\alpha}V_{\omega\beta}\int[V_{\alpha\gamma}^{-1}(x-\bar{x})_{\gamma}V_{\beta\epsilon}^{-1}(x-\omega)_{\epsilon}-V_{\alpha\beta}^{-1}+V_{\alpha\beta}^{-1}]f(x)\mathcal{N}(x,\bar{x},V)\mathrm{d}x\tag{A.13c}$$

$$= V_{\psi\alpha} \hat{f}_{\alpha\beta}(\bar{x}, V) V_{\beta\omega} + \hat{f}(\bar{x}, V) V_{\psi\omega} \tag{A.13d}$$

where we have used that V is symmetric so that  $V_{\psi\omega} = V_{\omega\psi}$ .

Assuming that we have a (multi-)normally distributed trait-density distribution  $v(x) := u\mathcal{N}(x,\bar{x},V)$  with total density u, mean  $\bar{x}$ , and variance-covariance V we can use the above results in turn to calculate three integrals that will appear in the derivation of the moment equations:

$$\int f(x)v(x)dx = \int f(x)u\mathcal{N}(x,\bar{x},V)dx = \hat{f}(\bar{x},V)u$$
(A.14)

$$\int (x - \bar{x})_{\psi} f(x) v(x) dx = \int (x - \bar{x})_{\psi} f(x) u \mathcal{N}(x, \bar{x}, V) dx$$
(A.15a)

$$= uV_{\psi\alpha}\hat{f}_{\alpha}(\bar{x}, V) \tag{A.15b}$$

$$\int (x - \bar{x})_{\psi}(x - \bar{x})_{\omega} f(x) v(x) dx = \int (x - \bar{x})_{\psi}(x - \bar{x})_{\omega} f(x) u \mathcal{N}(x, \bar{x}, V) dx$$
(A.16a)

$$= u \left( V_{\psi\alpha} \hat{f}_{\alpha\beta}(\bar{x}, V) V_{\beta\omega} + \hat{f}(\bar{x}, V) V_{\psi\omega} \right)$$
 (A.16b)

In the trait-space equations, we also need to evaluate the integrals over the normally distributed mutation kernels. In total, three such integrals will need to be evaluated, the first of which is:

$$\int \int f(y)v(y)\mathcal{N}(y,x,M)\mathrm{d}y\mathrm{d}x = \tag{A.17a}$$

$$= \int f(y)v(y) \int \mathcal{N}(y, x, M) dxdy$$
 (A.17b)

$$= \int f(y)v(y)dy = \{ \text{Eq. A.14} \} = \hat{f}(\bar{x}, V)u$$
 (A.17c)

1020 The second integral is

$$\int (x - \bar{x})_{\psi} \int f(y)v(y)\mathcal{N}(y, x, M) dy dx = \int f(y)v(y) \int (x - \bar{x})_{\psi} \mathcal{N}(y, x, M) dx dy \qquad (A.18a)$$

$$= \int f(y)v(y) \int [(x-y)_{\psi} + (y-\bar{x})_{\psi}] \mathcal{N}(x,y,M) dxdy$$
(A.18b)

$$= \int (y - \bar{x})_{\psi} f(y) v(y) dy = \{ \text{Eqs. A.15} \} = u V_{\psi \alpha} \hat{f}_{\alpha}(\bar{x}, V)$$
(A.18c)

The third integral is

$$\int (x - \bar{x})_{\psi}(x - \bar{x})_{\omega} \int f(y)v(y)\mathcal{N}(y, x, M) dy dx$$
(A.19a)

$$= \int f(y)v(y) \int (x - \bar{x})_{\psi}(x - \bar{x})_{\omega} \mathcal{N}(x, y, M) dxdy$$
(A.19b)

$$= \int f(y)v(y) \int [(x-y)_{\psi}(x-y)_{\omega} + (y-\bar{x})_{\psi}(x-y)_{\omega}$$
 (A.19c)

$$+(x-y)_{\psi}(y-\bar{x})_{\omega}+(y-\bar{x})_{\psi}(y-\bar{x})_{\omega}]\mathcal{N}(x,y,M)\mathrm{d}x\mathrm{d}y\tag{A.19d}$$

$$= M_{\psi\omega} \int f(y)v(y)dy + \int (y - \bar{x})_{\psi}(y - \bar{x})_{\omega}f(y)v(y)dy$$
(A.19e)

$$= \{ Eq. A.14 \text{ and } Eqs. A.16 \}$$
 (A.19f)

$$= u \left( M_{\psi\omega} \hat{f}(\bar{x}, V) + V_{\psi\alpha} \hat{f}_{\alpha\beta}(\bar{x}, V) V_{\beta\omega} + \hat{f}(\bar{x}, V) V_{\psi\omega} \right)$$
(A.19g)

We will here formulate a more explicit version of the trait-space and moment equations (Eqs. 14 and 19 respectively in the main text). We assume that there are K classes, that  $v_k(x)$  is the trait-density distribution in class k, and that for each class pair there are  $N_{kl}$  processes where l is the source class and k is the destination class. We index each such process by  $f_{klm}(x, \mathbf{v})$ ,  $m \in \{1, ..., N_{kl}\}$ , where  $\mathbf{v} := (v_1, v_2, ..., v_K)$ . For each process we let  $M_{klm}$  be the mutation variance-covariance matrix associated with that process, which for most processes will be  $M_{klm} = 0$ . By summing over all processes the trait-space equations are then given by

$$\frac{dv_k(x)}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \int f_{klm}(y) v_l(y) \mathcal{N}(x, y, M_{klm}) dy.$$
 (A.20)

Comparing with the trait-space equations in the main text (Eq. 14), we here make explicit the summation over all the processes that we left implicit in the main text to obviate the need for excessive notational clutter. For the purposes of deriving the moment equations however, it is clearer to leave these summations in explicitly.

We now make the assumptions that the trait-density distribution in each class  $v_k(x)$  can be decomposed into a sum of component distributions (species)

$$v_k(x) = \sum_{i=1}^{S} v_{ik}(x),$$
 (A.21)

that each such component distribution can be approximated with a normal distribution

$$v_{ik}(x) \approx \tilde{v}_{ik}(x) := u_{ik} \mathcal{N}(x, \bar{x}_{ik}, V_{ik}) \tag{A.22}$$

and that each species is reproductively isolated so that each species can be treated separately. Using the results derived above we can now calculate the moment equations for these trait-space equations.

For *u*:

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$$\frac{\mathrm{d}u_{ik}}{\mathrm{d}t} = \int \dot{v}_{ik}(x)\mathrm{d}x \approx \int \dot{\tilde{v}}_{ik}(x)\mathrm{d}x = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \int \int f_{klm}(y)\tilde{v}_{il}(y)\mathcal{N}(x,y,M_{klm})\mathrm{d}y\mathrm{d}x \qquad (A.23a)$$

$$= \{ \text{Eqs. A.17} \} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \hat{f}_{klm}(\bar{x}_{il}, V_{il}) u_{il}$$
(A.23b)

For  $\bar{x}$ :

$$u_{ik}\frac{\mathrm{d}\bar{x}_{ik\psi}}{\mathrm{d}t} = \int (x - \bar{x}_{ik})_{\psi}\dot{v}_{ik}(x)\mathrm{d}x \approx \int (x - \bar{x}_{ik})_{\psi}\dot{\tilde{v}}_{ik}(x)\mathrm{d}x \tag{A.24a}$$

$$= \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \int (x - \bar{x}_{ik})_{\psi} \int f_{klm}(y) \tilde{v}_{il}(y) \mathcal{N}(x, y, M_{klm}) dy dx$$
 (A.24b)

$$= \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \int [(x - \bar{x}_{il})_{\psi} + (\bar{x}_{il} - \bar{x}_{ik})_{\psi}] \int f_{klm}(y) \tilde{v}_{il}(y) \mathcal{N}(x, y, M_{klm}) dy dx$$
 (A.24c)

 $= \{ Eqs. A.17 \text{ and } Eqs. A.18 \}$ 

$$= \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} u_{il} \left( V_{\psi\alpha} \hat{f}_{klm\alpha}(\bar{x}_{il}, V_{il}) + \hat{f}_{klm}(\bar{x}_{il}, V_{il})(\bar{x}_{il} - \bar{x}_{ik})_{\psi} \right)$$
(A.24d)

 $\iff$ 

$$\frac{\mathrm{d}\bar{x}_{ik\psi}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{\psi\alpha} \hat{f}_{klm\alpha}(\bar{x}_{il}, V_{il}) + \hat{f}_{klm}(\bar{x}_{il}, V_{il})(\bar{x}_{il} - \bar{x}_{ik})_{\psi} \right)$$
(A.24e)

<u>For *V*</u>:

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$$u_{ik}\frac{\mathrm{d}V_{ik\psi\omega}}{\mathrm{d}t} + V_{ik\psi\omega}\frac{\mathrm{d}u_{ik}}{\mathrm{d}t} = \int (x - \bar{x}_{ik})_{\psi}(x - \bar{x}_{ik})_{\omega}\dot{v}_{ik}(x)\mathrm{d}x \tag{A.25a}$$

$$\approx \int (x - \bar{x}_{ik})_{\psi} (x - \bar{x}_{ik})_{\omega} \dot{\bar{\sigma}}_{ik}(x) dx \tag{A.25b}$$

$$= \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \int (x - \bar{x}_{ik})_{\psi} (x - \bar{x}_{ik})_{\omega} \int f_{klm}(y) \tilde{v}_{il}(y) \mathcal{N}(x, y, M_{klm}) dy dx$$
 (A.25c)

$$= \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \int [(x - \bar{x}_{il})_{\psi} (x - \bar{x}_{il})_{\omega} + (\bar{x}_{il} - \bar{x}_{ik})_{\psi} (x - \bar{x}_{il})_{\omega}$$

$$+ (x - \bar{x}_{il})_{\psi}(\bar{x}_{il} - \bar{x}_{ik})_{\omega} + (\bar{x}_{il} - \bar{x}_{ik})_{\psi}(\bar{x}_{il} - \bar{x}_{ik})_{\omega}] \int f_{klm}(y) \tilde{v}_{il}(y) \mathcal{N}(x, y, M_{klm}) dy dx$$
(A.25d)

$$=\sum_{l=1}^K\sum_{m=1}^{N_{kl}}u_{il}\left[M_{klm\psi\omega}\hat{f}_{klm}(\bar{x}_{il},V_{il})+V_{il\psi\alpha}\hat{f}_{klm\alpha\beta}(\bar{x}_{il},V_{il})V_{il\beta\omega}+\hat{f}_{klm}(\bar{x}_{il},V_{il})V_{il\psi\omega}\right]$$

$$+ V_{il\psi\alpha} \hat{f}_{klm\alpha}(\bar{x}_{il}, V_{il})(\bar{x}_{il} - \bar{x}_{ik})_{\omega} + V_{il\omega\alpha} \hat{f}_{klm\alpha}(\bar{x}_{il}, V_{il})(\bar{x}_{il} - \bar{x}_{ik})_{\psi} + \hat{f}_{klm}(\bar{x}_{il}, V_{il})(\bar{x}_{il} - \bar{x}_{ik})_{\psi}(\bar{x}_{il} - \bar{x}_{ik})_{\omega}$$
(A.25e)

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$$\frac{\mathrm{d}V_{ik\psi\omega}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left[ M_{klm\psi\omega} \hat{f}_{klm}(\bar{x}_{il}, V_{il}) + V_{il\psi\alpha} \hat{f}_{klm\alpha\beta}(\bar{x}_{il}, V_{il}) V_{il\beta\omega} \right. \\
+ \hat{f}_{klm}(\bar{x}_{il}, V_{il}) (V_{il\psi\omega} - V_{ik\psi\omega}) \\
+ V_{il\psi\alpha} \hat{f}_{klm\alpha}(\bar{x}_{il}, V_{il}) (\bar{x}_{il} - \bar{x}_{ik})_{\omega} + V_{il\omega\alpha} \hat{f}_{klm\alpha}(\bar{x}_{il}, V_{il}) (\bar{x}_{il} - \bar{x}_{ik})_{\psi} \\
+ \hat{f}_{klm}(\bar{x}_{il}, V_{il}) (\bar{x}_{il} - \bar{x}_{ik})_{\psi} (\bar{x}_{il} - \bar{x}_{ik})_{\omega} \right]$$
(A.25f)

The complete moment equations for *S* species in *K* classes thus read

$$\frac{du_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \hat{f}_{iklm} u_{il}$$
 (A.26a)

$$\frac{d\bar{x}_{ik\psi}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il\psi\alpha} \hat{f}_{iklm\alpha} + \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik})_{\psi} \right)$$
(A.26b)

$$\frac{\mathrm{d}V_{ik\psi\omega}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left[ V_{il\psi\alpha} \hat{f}_{iklm\alpha\beta} V_{il\beta\omega} + \hat{f}_{iklm} (V_{il\psi\omega} - V_{ik\psi\omega}) + M_{klm\psi\omega} \hat{f}_{iklm} \right]$$
(A.26c)

$$+ V_{il\psi\alpha} \hat{f}_{iklm\alpha} (\bar{x}_{il} - \bar{x}_{ik})_{\omega} + V_{il\omega\alpha} \hat{f}_{iklm\alpha} (\bar{x}_{il} - \bar{x}_{ik})_{\psi}$$
(A.26d)

(A.25f)

$$+ \hat{f}_{iklm}(\bar{x}_{il} - \bar{x}_{ik})_{\psi}(\bar{x}_{il} - \bar{x}_{ik})_{\omega}$$
(A.26e)

$$\hat{f}_{iklm} := \hat{f}_{klm}(\bar{x}_{il}, V_{il}, \tilde{\mathbf{v}}) \tag{A.26f}$$

$$\hat{f}_{iklm\alpha} := \frac{\partial \hat{f}_{klm}}{\partial x_{\alpha}} (\bar{x}_{il}, V_{il}, \tilde{\mathbf{v}}) \tag{A.26g}$$

$$\hat{f}_{iklm\alpha\beta} := \frac{\partial^2 \hat{f}_{klm}}{\partial x_\alpha \partial x_\beta} (\bar{x}_{il}, V_{il}, \tilde{\mathbf{v}})$$
(A.26h)

Here, we have omitted the explicit dependence of the process rates on its arguments for notational clarity. We have also added the dependence of the process rates  $\hat{f}_{klm}$  on the approximate traitdensity distributions  $\tilde{\mathbf{v}}=(\tilde{v}_1,\ldots,\tilde{v}_K)$  where  $\tilde{v}_k(x)=\sum_{i=1}^S u_{ik}\mathcal{N}(x,\bar{x}_{ik},V_{ik})$ . For convenience we did not include this dependence during the derivation, as their inclusion does not affect the derivation. We do however make one note with regards to this. When we define the population-level rate

$$\hat{f}_{klm}(x, W, \tilde{\mathbf{v}}) = \int f_{klm}(y, \tilde{\mathbf{v}}) \mathcal{N}(y, x, W) dy$$
(A.27)

it technically describes the population-level per capita rate of a normally distributed population with mean-trait vector x and variance-covariance matrix W that is negligibly rare in the resident community whose trait-density distribution is given by  $\tilde{\mathbf{v}}$  across all classes. In other words, the rare population with mean x and variance-covariance W does not add to the trait-density distribution  $\tilde{\mathbf{v}}$ . This is analogous to how invasion fitness for a rare invader is defined in adaptive dynamics (Metz et al., 1992; Geritz et al., 1998). This notation helps us get frequency-dependent interactions (such as the competition in our Lotka-Volterra model examples) correct when we differentiate the population-level rates. Note also that while we in the appendices denote the rare invader's mean trait and variance by x and W for reasons of separating these abstract quantities of the invader from the realized quantities of an extant resident population, in the main text we instead use  $\bar{x}$  and V for the rare invader population to emphasize that they are the means and variance respectively.

It can be easier to interpret these equations when not written in index notation, and so we let  $\nabla_x f$  denote the gradient vector of f with respect to x, and let  $\nabla_x^2 f$  denote the Hessian matrix of f with respect to x, and rewrite the equations in the language of vectors and matrices which yields

$$\frac{du_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \hat{f}_{iklm} u_{il}$$
 (A.28a)

$$\frac{d\bar{x}_{ik\psi}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il} \nabla_x \hat{f}_{iklm} + \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik}) \right)$$
(A.28b)

$$\frac{dV_{ik\psi\omega}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left[ V_{il} \nabla_x^2 \hat{f}_{iklm} V_{il} + \hat{f}_{iklm} (V_{il} - V_{ik}) + M_{klm} \hat{f}_{iklm} \right]$$
(A.28c)

$$+ V_{il} \nabla_x \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik})^T + (\bar{x}_{il} - \bar{x}_{ik}) \left[ V_{il} \nabla_x \hat{f}_{iklm} \right]^T$$
(A.28d)

$$+\hat{f}_{iklm}(\bar{x}_{il}-\bar{x}_{ik})(\bar{x}_{il}-\bar{x}_{ik})^{T}$$
(A.28e)

$$\hat{f}_{iklm} := \hat{f}_{klm}(\bar{x}_{il}, V_{il}, \tilde{\mathbf{v}}) \tag{A.28f}$$

$$\nabla_{x}\hat{f}_{iklm} := \nabla_{x}\hat{f}_{klm}(\bar{x}_{il}, V_{il}, \tilde{\mathbf{v}}) \tag{A.28g}$$

$$\nabla_x^2 \hat{f}_{iklm} := \nabla_x^2 \hat{f}_{klm}(\bar{x}_{il}, V_{il}, \tilde{\mathbf{v}}) \tag{A.28h}$$

where  $^T$  denotes vector transpose, and all multiplication is taken to be matrix multiplication.

When the trait is scalar, i.e,  $x \in \mathbb{R}$ , these equations simplify to

$$\frac{\mathrm{d}u_{ik}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \hat{f}_{iklm} u_{il}$$
 (A.29a)

$$\frac{d\bar{x}_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il} \partial_x \hat{f}_{iklm} + \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik}) \right)$$
(A.29b)

$$\frac{dV_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left[ V_{il}^2 \partial_x^2 \hat{f}_{iklm} + \hat{f}_{iklm} (V_{il} - V_{ik}) + M_{klm} \hat{f}_{iklm} \right]$$
(A.29c)

$$+2V_{il}\partial_{x}\hat{f}_{iklm}(\bar{x}_{il}-\bar{x}_{ik})+\hat{f}_{iklm}(\bar{x}_{il}-\bar{x}_{ik})^{2}$$
 (A.29d)

$$\hat{f}_{klm}(x, W, \tilde{\mathbf{v}}) = \int f(y, \tilde{\mathbf{v}}) \mathcal{N}(y, x, W) dy$$
(A.29e)

$$\hat{f}_{iklm} := \hat{f}_{klm}(\bar{x}_{il}, V_{il}, \tilde{\mathbf{v}}) \tag{A.29f}$$

$$\partial_x \hat{f}_{iklm} := \frac{\partial \hat{f}_{klm}}{\partial x} (\bar{x}_{il}, V_{il}, \tilde{\mathbf{v}})$$
(A.29g)

$$\partial_x^2 \hat{f}_{iklm} := \frac{\partial^2 \hat{f}_{klm}}{\partial x^2} (\bar{x}_{il}, V_{il}, \tilde{\mathbf{v}}) \tag{A.29h}$$

Finally, we can describe the double summation over source classes l and processes m implicitly by letting d be the index for destination classes, s be the index for source classes, f be any process to be summed over, and M be its associated mutation variance, and  $\stackrel{+}{=}$  be the operator that describes addition to. This then yields

$$\frac{\mathrm{d}u_{id}}{\mathrm{d}t} \stackrel{+}{=} \hat{f}(\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}})u_{is}, \tag{A.30a}$$

$$\frac{\mathrm{d}\bar{x}_{id}}{\mathrm{d}t} \stackrel{+}{=} \frac{u_{is}}{u_{id}} \left[ V_{is} \frac{\partial \hat{f}}{\partial \bar{x}} (\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}}) + \hat{f}(\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}}) (\bar{x}_{is} - \bar{x}_{id}) \right], \tag{A.30b}$$

$$\frac{\mathrm{d}V_{id}}{\mathrm{d}t} \stackrel{+}{=} \frac{u_{is}}{u_{id}} \left[ V_{is}^2 \frac{\partial^2 \hat{f}}{\partial \bar{x}^2} (\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}}) + \hat{f}(\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}}) (V_{is} - V_{id}) \right]$$

$$+\hat{f}(\bar{x}_{is},V_{is},\tilde{\mathbf{v}})(\bar{x}_{is}-\bar{x}_{id})^2+2V_{is}\frac{\partial\hat{f}}{\partial\bar{x}}(\bar{x}_{is},V_{is},\tilde{\mathbf{v}})(\bar{x}_{is}-\bar{x}_{id})$$

$$+\hat{f}(\bar{x}_{is}, V_{is}, \tilde{\mathbf{v}})M$$
, (A.30c)

$$\hat{f}(\bar{x}, V, \tilde{\mathbf{v}}) = \int f(x, \tilde{\mathbf{v}}) \mathcal{N}(x, \bar{x}, V) dx.$$
(A.30d)

These correspond to Eq. 19 in the main text.

### Series solutions and Taylor approximations

The population per capita rates

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$$\hat{f}(x,W) = \int f(y)\mathcal{N}(y,x,W)dy$$
 (A.31)

are in most cases not going to be analytically computable. Owen (1980) contains a large list of Gaussian integrals. Here, we briefly note that for example exponential functions, Gaussian functions, and polynomials can be analytically integrated against a Gaussian, whereas, for example, a Type-II functional response of an organism with trait  $x \in \mathbb{R}$  consuming a resource R where the affinities depend on the trait x

$$f(x) = \frac{a(x)R}{1 + a(x)hR} \tag{A.32}$$

has, to wit, no analytically closed expression for simple forms for a(x) such as linear or exponential when the functional response is integrated against the Gaussian.

For the cases where the population-rate integrals cannot be evaluated directly, we may Taylor expand the process rates. To this end let  $\alpha^n$  denote an ordered set of indices such that

$$\alpha^n := \alpha_1 \alpha_2 \cdots \alpha_n \tag{A.33}$$

where each  $\alpha_i$  indexes the trait-components. Thus, for example

$$f_{\alpha^4} = f_{\alpha_1 \alpha_2 \alpha_2 \alpha_4} \tag{A.34}$$

denotes the 4-tensor of mixed partial derivatives of order 4 of f. For a vector x in trait space we let

$$x^{\alpha^n} := x_{\alpha_1} x_{\alpha_2} \cdots x_{\alpha_n} \tag{A.35}$$

denote the outer product of n copies of the vector. For a matrix W acting on trait space we also let

$$W^{\alpha^{2n}} := W_{\alpha_1 \alpha_2} W_{\alpha_3 \alpha_4} \cdots W_{\alpha_{2n-1} \alpha_{2n}} \tag{A.36}$$

denote the outer product of n copies of the matrices.

We can now Taylor-expand

$$\hat{f}(x,W) = \int f(y)\mathcal{N}(y,x,W)dy = \int \sum_{n=0}^{\infty} \frac{f_{\alpha^n}(x)}{n!} (y-x)^{\alpha^n} \mathcal{N}(y,x,W)dy$$
 (A.37a)

The central moments of a multivariate normal distribution are n-tensors and are given in e.g., Triantafyllopoulos (2002). However, when contracted against the fully symmetric tensor  $f_{\alpha^n}$  these expressions simplify considerably so that

$$\int f_{\alpha^n}(x)(y-x)^{\alpha^n} \mathcal{N}(y,x,W) dy = \begin{cases} 0 & \text{if } n \text{ is odd} \\ (n-1)!! f_{\alpha^n} W^{\alpha^n} & \text{if } n \text{ is even} \end{cases}$$
(A.38)

where "!!" is the double factorial, which is defined by

$$n!! = n(n-2)(n-4)\cdots 1, \ 0!! = 1, \ (-1)!! = 1$$
 (A.39)

1170 For the Taylor expansion we thus have

$$\int \sum_{n=0}^{\infty} \frac{f_{\alpha^n}(x)}{n!} (y-x)^{\alpha^n} \mathcal{N}(y,x,W) dy = \sum_{\substack{n=0\\ n \text{ even}}}^{\infty} \frac{f_{\alpha^n}(x)}{n!} (n-1)!! W^{\alpha^n}$$
(A.40a)

$$=\sum_{n=0}^{\infty} \frac{f_{\alpha^{2n}}(x)}{(2n)!} (2n-1)!! W^{\alpha^{2n}} = \sum_{n=0}^{\infty} \frac{f_{\alpha^{2n}}(x)}{2^n n!} W^{\alpha^{2n}}$$
(A.40b)

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$$\hat{f}(x,W) = \sum_{n=0}^{\infty} \frac{f_{\alpha^{2n}}(x)}{2^n n!} W^{\alpha^{2n}} = f(x) + \frac{1}{2} f_{\alpha\beta}(x) W_{\alpha\beta} + \frac{1}{8} f_{\alpha\beta\gamma\epsilon}(x) W_{\alpha\beta} W_{\gamma\epsilon} + \dots$$
 (A.41a)

$$\hat{f}_{\psi}(x,W) = \sum_{n=0}^{\infty} \frac{f_{\alpha^{2n}\psi}(x)}{2^n n!} W^{\alpha^{2n}} = f_{\psi}(x) + \frac{1}{2} f_{\psi\alpha\beta}(x) W_{\alpha\beta} + \frac{1}{8} f_{\psi\alpha\beta\gamma\epsilon}(x) W_{\alpha\beta} W_{\gamma\epsilon} + \dots$$
 (A.41b)

$$\hat{f}_{\psi\omega}(x,W) = \sum_{n=0}^{\infty} \frac{f_{\alpha^{2n}\psi\omega}(x)}{2^n n!} W^{\alpha^{2n}} = f_{\psi\omega}(x) + \frac{1}{2} f_{\psi\omega\alpha\beta}(x) W_{\alpha\beta} + \frac{1}{8} f_{\psi\omega\alpha\beta\gamma\epsilon}(x) W_{\alpha\beta} W_{\gamma\epsilon} + \dots \quad (A.41c)$$

A Taylor expansion of order n then corresponds to truncating to derivatives of f with no higher order than n, so that e.g., a Taylor-approximation of order three would yield

$$\hat{f}(x,W) = \sum_{n=0}^{\infty} \frac{f_{\alpha^{2n}}(x)}{2^n n!} W^{\alpha^{2n}} \approx f(x) + \frac{1}{2} f_{\alpha\beta}(x) W_{\alpha\beta}$$
 (A.42a)

$$\hat{f}_{\psi}(x,W) = \sum_{n=0}^{\infty} \frac{f_{\alpha^{2n}\psi}(x)}{2^{n} n!} W^{\alpha^{2n}} \approx f_{\psi}(x) + \frac{1}{2} f_{\psi\alpha\beta}(x) W_{\alpha\beta}$$
 (A.42b)

$$\hat{f}_{\psi\omega}(x,W) = \sum_{n=0}^{\infty} \frac{f_{\alpha^{2n}\psi\omega}(x)}{2^n n!} W^{\alpha^{2n}} \approx f_{\psi\omega}(x)$$
(A.42c)

For a scalar trait, let  $f^{(n)}$  denote the nth derivative of f with respect to x. The expressions then simplify to

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$$\hat{f}(x,W) = \sum_{n=0}^{\infty} \frac{f^{(2n)}(x)}{2^n n!} W^n = f(x) + \frac{1}{2} f^{(2)}(x) W + \frac{1}{8} f^{(4)}(x) W^2 + \dots$$
(A.43a)

$$\hat{f}^{(1)}(x,W) = \sum_{n=0}^{\infty} \frac{f^{(2n+1)}(x)}{2^n n!} W^n = f^{(1)}(x) + \frac{1}{2} f^{(3)}(x) W + \frac{1}{8} f^{(5)}(x) W^2 + \dots$$
 (A.43b)

$$\hat{f}^{(2)}(x,W) = \sum_{n=0}^{\infty} \frac{f^{(2n+2)}(x)}{2^n n!} W^n = f^{(2)}(x) + \frac{1}{2} f^{(4)}(x) W + \frac{1}{8} f^{(6)}(x) W^2 + \dots$$
 (A.43c)

#### Variable mutation variance-covariance matrices and mutation bias

For completeness we here presents result of more complicated mutation dynamics where the mutation variance-covariance matrix is allowed to depend on the trait of the parent so that some phenotypes generate a wider array of offspring than others in trait space, and where mutations are not symmetric so that there is a bias of mutations in some direction in trait space.

First, we let the mutation variance-covariance matrix vary with trait so that M(y) is a positive-definite matrix for all y. The mutation kernel is then given by  $\mathcal{N}(x, y, M(y))$ . Note that for each fixed y, this is just the probability density function of a normal distribution over x.

Working through the problem in the same way as we did for constant mutation matrices (Eqs. A.17–A.18) we can then evaluate the three integrals used to account for mutation, the first of which is:

$$\int \int f(y)\mathcal{N}(y,\bar{x},V)(y,x,M(y))\mathrm{d}y\mathrm{d}x = \int f(y)\mathcal{N}(y,\bar{x},V)\int \mathcal{N}(y,x,M(y))\mathrm{d}x\mathrm{d}y \qquad (A.44a)$$

$$= \int f(y)\mathcal{N}(y,\bar{x},V)dy = \int f(x)\mathcal{N}(x,\bar{x},V)dx = \hat{f}(\bar{x},V)$$
(A.44b)

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$$\int (x - \bar{x})_{\psi} \int f(y) \mathcal{N}(y, \bar{x}, V)(y, x, M(y)) dy dx = \int f(y) \mathcal{N}(y, \bar{x}, V) \int (x - \bar{x})_{\psi} \mathcal{N}(y, x, M(y)) dx dy$$
(A.45a)

$$= \int f(y)\mathcal{N}(y,\bar{x},V) \int [(x-y)_{\psi} + (y-\bar{x})_{\psi}]\mathcal{N}(x,y,M(y)) dxdy$$
(A.45b)

$$= \int (y - \bar{x})_{\psi} f(y) \mathcal{N}(y, \bar{x}, V) dy = \int (x - \bar{x})_{\psi} f(x) \mathcal{N}(x, \bar{x}, V) dx = V_{\psi \alpha} \hat{f}_{\alpha}(\bar{x}, V)$$
(A.45c)

The third integral is

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$$\int (x - \bar{x})_{\psi}(x - \bar{x})_{\omega} \int f(y) \mathcal{N}(y, \bar{x}, V)(y, x, M(y)) dy dx$$
(A.46a)

$$= \int f(y)\mathcal{N}(y,\bar{x},V) \int (x-\bar{x})_{\psi}(x-\bar{x})_{\omega} \mathcal{N}(x,y,M(y)) dxdy$$
(A.46b)

$$= \int f(y)\mathcal{N}(y,\bar{x},V) \int [(x-y)_{\psi}(x-y)_{\omega} + (y-\bar{x})_{\psi}(x-y)_{\omega}$$
(A.46c)

$$+ (x - y)_{\psi}(y - \bar{x})_{\omega} + (y - \bar{x})_{\psi}(y - \bar{x})_{\omega}]\mathcal{N}(x, y, M(y)) dxdy$$
(A.46d)

$$= \int f(y)M_{\psi\omega}(y)\mathcal{N}(y,\bar{x},V)\mathrm{d}y + \int (y-\bar{x})_{\psi}(y-\bar{x})_{\omega}f(y)\mathcal{N}(y,\bar{x},M)\mathrm{d}y$$
(A.46e)

$$= f\widehat{M}_{\psi\omega}(\bar{x}, V) + V_{\psi\alpha}\widehat{f}_{\alpha\beta}(\bar{x}, V)V_{\beta\omega} + \widehat{f}(\bar{x}, V)V_{\psi\omega}$$
(A.46f)

The mutation term in the moment equations when the mutation variance-covariance matrix is
trait-dependent will thus read

$$(\widehat{fM})_{iklm\psi\omega} = \int f_{klm}(x) M_{klm\psi\omega}(x) \mathcal{N}(x, \bar{x}_{il}, V_{il}) dx$$
(A.47)

To second order we have

$$\int f(y)M_{\psi\omega}(y)\mathcal{N}(y,\bar{x},V)\mathrm{d}y \tag{A.48a}$$

$$\approx f(\bar{x})M_{\psi\omega}(\bar{x}) + \frac{1}{2}V_{\alpha\beta} \left[ f M_{\psi\omega} \right]_{\alpha\beta} (\bar{x}) \tag{A.48b}$$

$$= f(\bar{x})M_{\psi\omega}(\bar{x}) + \frac{1}{2}V_{\alpha\beta} \left[ f_{\alpha\beta}(\bar{x})M_{\psi\omega}(\bar{x}) + f_{\alpha}(\bar{x})M_{\psi\omega\beta}(\bar{x}) + f_{\beta}(\bar{x})M_{\psi\omega\alpha}(\bar{x}) + f(\bar{x})M_{\psi\omega\alpha\beta}(\bar{x}) \right]$$
(A.48c)

Apart from the term in the moment equations that add to variance-covariance through mutation, which is now given by Eq. A.47, the rest of the moment equations remain unchanged under the assumption that the variance-covariance matrix is trait dependent.

We now turn to the case where there is also mutation bias so that a parent with trait y on average produces offspring with trait  $y + \mu(y)$  with variance-covariance M(y). Mathematically, this implies that a rate f produces new individuals with trait x at a rate

$$\int f(y)v(y)\mathcal{N}(y,x-\mu(y),M(y))\mathrm{d}y \tag{A.49}$$

Once again, we can evaluate the mutation integrals, the first of which yields

$$\int \int f(y)\mathcal{N}(y,\bar{x},V)(y,x-\mu(y),M(y))\mathrm{d}y\mathrm{d}x = \int f(y)\mathcal{N}(y,\bar{x},V)\int \mathcal{N}(x,y+\mu(y),M(y))\mathrm{d}x\mathrm{d}y$$
(A.50a)

$$= \int f(y)\mathcal{N}(y,\bar{x},V)\mathrm{d}y = \int f(x)\mathcal{N}(x,\bar{x},V)\mathrm{d}x = \hat{f}(\bar{x},V)$$
(A.50b)

The second mutation integral is

$$\int (x - \bar{x})_{\psi} \int f(y) \mathcal{N}(y, \bar{x}, V)(y, x - \mu(y), M(y)) dy dx$$
(A.51a)

$$= \int f(y)\mathcal{N}(y,\bar{x},V) \int (x-\bar{x})_{\psi} \mathcal{N}(x,y+\mu(y),M(y)) dxdy$$
(A.51b)

$$= \int f(y) \mathcal{N}(y, \bar{x}, V) \int [(x - (y + \mu(y)))_{\psi} + (y + \mu(y) - \bar{x})_{\psi}] \mathcal{N}(x, y + \mu(y), M(y)) dxdy \quad (A.51c)$$

$$= \int [(y - \bar{x})_{\psi} + \mu(y)_{\psi}] f(y) \mathcal{N}(y, \bar{x}, V) dy = V_{\psi\alpha} \hat{f}_{\alpha}(\bar{x}, V) + \widehat{f}_{\mu\psi}(\bar{x}, V)$$
(A.51d)

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$$\widehat{f\mu_{\psi}}(\bar{x}, V) = \int f(y)\mu_{\psi}(y)\mathcal{N}(y, \bar{x}, V)dy$$
(A.52)

For the third mutation integral, let  $\tilde{y} := y + \mu(y)$ . We then get

$$\int (x-\bar{x})_{\psi}(x-\bar{x})_{\omega} \int f(y)\mathcal{N}(y,\bar{x},V)(y,x-\mu(y),M(y))\mathrm{d}y\mathrm{d}x \tag{A.53a}$$

$$= \int f(y)\mathcal{N}(y,\bar{x},V) \int (x-\bar{x})_{\psi}(x-\bar{x})_{\omega}\mathcal{N}(x,\tilde{y},M(y)) dxdy$$
(A.53b)

$$= \int f(y)\mathcal{N}(y,\bar{x},V) \int [(x-\tilde{y})_{\psi}(x-\tilde{y})_{\omega} + (\tilde{y}-\bar{x})_{\psi}(x-\tilde{y})_{\omega}$$
(A.53c)

$$+(x-\tilde{y})_{\psi}(\tilde{y}-\bar{x})_{\omega}+(\tilde{y}-\bar{x})_{\psi}(\tilde{y}-\bar{x})_{\omega}]\mathcal{N}(x,\tilde{y},M(y))\mathrm{d}x\mathrm{d}y\tag{A.53d}$$

$$= \int f(y) M_{\psi\omega}(y) \mathcal{N}(y, \bar{x}, V) dy + \int (\tilde{y} - \bar{x})_{\psi} (\tilde{y} - \bar{x})_{\omega} f(y) \mathcal{N}(y, \bar{x}, V) dy$$
(A.53e)

$$= \widehat{fM_{\psi\omega}}(\bar{x}, V) + \int (y - \bar{x})_{\psi}(y - \bar{x})_{\omega} f(y) \mathcal{N}(y, \bar{x}, V) dy$$
(A.53f)

$$+ \int \mu(y)_{\psi}(y-\bar{x})_{\omega}f(y)\mathcal{N}(y,\bar{x},V)\mathrm{d}y + \int (y-\bar{x})_{\psi}\mu(y)_{\omega}f(y)\mathcal{N}(y,\bar{x},V)\mathrm{d}y \tag{A.53g}$$

$$+ \int \mu(y)_{\psi} \mu(y)_{\omega} f(y) \mathcal{N}(y, \bar{x}, V) dy$$
 (A.53h)

$$= \widehat{fM_{\psi\omega}}(\bar{x}, V) + V_{\psi\alpha}\widehat{f}_{\alpha\beta}(\bar{x}, V)V_{\beta\omega} + \widehat{f}(\bar{x}, V)V_{\psi\omega}$$
(A.53i)

$$+ V_{\psi\alpha}(\widehat{\mu_{\omega}f})_{\alpha}(\bar{x}, V) + V_{\omega\alpha}(\widehat{\mu_{\psi}f})_{\alpha}(\bar{x}, V) + \widehat{\mu_{\psi}\mu_{\omega}f}(\bar{x}, V)$$
(A.53j)

When inserted into the full moment equations where each process  $f_{klm}$  has an attached mutation bias vector  $\mu_{klm}(y)$  for the class-structured community this yields the moment equations

$$\frac{\mathrm{d}u_{ik}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \hat{f}_{iklm} u_{il}$$
 (A.54a)

$$\frac{\mathrm{d}\bar{x}_{ik\psi}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il\psi\alpha} \hat{f}_{iklm\alpha} + \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik})_{\psi} + \widehat{f} \mu_{iklm\psi} \right) \tag{A.54b}$$

$$\frac{\mathrm{d}V_{ik\psi\omega}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( \widehat{fM}_{iklm\psi\omega} + V_{il\psi\alpha} \hat{f}_{iklm\alpha\beta} V_{il\beta\omega} + \hat{f}_{iklm} (V_{il\psi\omega} - V_{ik\psi\omega}) \right)$$
(A.54c)

$$+V_{il\psi\alpha}(\widehat{f\mu}_{iklm\omega})_{\alpha} + V_{il\omega\alpha}(\widehat{f\mu}_{iklm\psi})_{\alpha} + \widehat{\mu\mu f}_{iklm\psi\omega}$$
(A.54d)

$$+ (\bar{x}_{il} - \bar{x}_{ik})_{\psi} (V_{il\omega\alpha} \hat{f}_{iklm\alpha} + \widehat{f} \mu_{iklm\omega}) + (\bar{x}_{il} - \bar{x}_{ik})_{\omega} (V_{il\psi\alpha} \hat{f}_{iklm\alpha} + \widehat{f} \mu_{iklm\psi})$$
(A.54e)

$$+\hat{f}_{iklm}(\bar{x}_{il}-\bar{x}_{ik})_{\psi}(\bar{x}_{il}-\bar{x}_{ik})_{\omega}$$
(A.54f)

Here, all functions with subscript iklm are evaluated at  $\bar{x}_{il}$  and  $V_{il}$ .

In vector-matrix form these equations are written as

$$\frac{du_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \hat{f}_{iklm} u_{il}$$
 (A.55a)

$$\frac{d\bar{x}_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il} \nabla_x \hat{f}_{iklm} + \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik}) + \widehat{f} \mu_{iklm} \right)$$
(A.55b)

$$\frac{dV_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( \widehat{fM}_{iklm} + V_{il} \nabla_x^2 \hat{f}_{iklm} V_{il} + \hat{f}_{iklm} (V_{il} - V_{ik}) \right)$$
(A.55c)

$$+ V_{il} \nabla_x \widehat{f} \widehat{\mu}_{iklm} + [V_{il} \nabla_x \widehat{f} \widehat{\mu}_{iklm}]^T + \widehat{\mu} \widehat{\mu}^T f_{iklm}$$
(A.55d)

$$+ (\bar{x}_{il} - \bar{x}_{ik})(V_{il}\nabla_x \hat{f}_{iklm} + \widehat{f}\mu_{iklm})^T + (V_{il}\nabla_x \hat{f}_{iklm} + \widehat{f}\mu_{iklm})(\bar{x}_{il} - \bar{x}_{ik})^T$$
(A.55e)

$$+\hat{f}_{iklm}(\bar{x}_{il}-\bar{x}_{ik})(\bar{x}_{il}-\bar{x}_{ik})^T$$
(A.55f)

For scalar traits, these simplify somewhat to

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$$\frac{\mathrm{d}u_{ik}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \hat{f}_{iklm} u_{il} \tag{A.56a}$$

$$\frac{d\bar{x}_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il} \partial_x \hat{f}_{iklm} + \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik}) + \widehat{f} \mu_{iklm} \right)$$
(A.56b)

$$\frac{dV_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( \widehat{fM}_{iklm} + V_{il}^2 \partial_x^2 \hat{f}_{iklm} + \hat{f}_{iklm} (V_{il} - V_{ik}) \right)$$
(A.56c)

$$+2V_{il}\partial_x\widehat{f}\mu_{iklm}+\widehat{\mu^2f}_{iklm} \tag{A.56d}$$

$$+2(\bar{x}_{il}-\bar{x}_{ik})(V_{il}\partial_x\hat{f}_{iklm}+\widehat{f}\widehat{\mu}_{iklm}) \tag{A.56e}$$

$$+\hat{f}_{iklm}(\bar{x}_{il}-\bar{x}_{ik})^2\bigg) \tag{A.56f}$$

#### Environmental variables

In our examples in the main text we have not included non-evolving environmental variables (but see Appendix D). Such environmental variables include e.g., abiotic resources, toxins, or natural enemies whose traits can be considered fixed over the time-scale of interest. Here we present a brief account of how these are included in the trait-space and moment equations when the rate functions of the environmental variables depend linearly on the species' trait-density distributions, as would be the case in classical resource-competition theory (Tilman, 1982) and contemporary niche theory (Chase and Leibold, 2003; Koffel et al., 2021).

Environmental variables may or may not follow the same class structure as the ecological communities. For example, in a two-patch model, resources may follow the same class structure as the species and are distributed among the patches, but in our stage-structured model (Appendix D) the resources are unstructured. Furthermore, each environmental variable might have its own structure. Thus, let  $E_{jn_j}$  be the density of environmental variable j in environmental class  $n_j$ , with  $N_E$  total environmental variables and  $K_{Ej}$  environmental variable classes for environmental

variable j. We let **E** denote the vector of all environmental variable densities in all environmental classes. We note here that it would be equally possible to simply enumerate all environmental variables  $E_1, E_2, \ldots$  without loss of generality. However, for the times when the structure for the species mirrors that of the environmental variables (as in e.g., a patch model where each patch has, say, a resource and a natural enemy) structuring the environmental variables is useful.

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Together with the trait-space equations for the ecological communities this yields the equation system

$$\frac{\mathrm{d}v_k(x)}{\mathrm{d}t} = \sum_{l=1}^K \sum_{m=1}^{N_{kl}} \int f_{klm}(y, \mathbf{v}, \mathbf{E}) v_l(y) \mathcal{N}(x, y, M_{klm}) \mathrm{d}y$$
 (A.57a)

$$\frac{\mathrm{d}E_{jn_j}}{\mathrm{d}t} = \rho_{jn_j}(\mathbf{E}) + \sum_{l=1}^K \int I_{jn_jl}(\mathbf{E}, x) v_l(x) \mathrm{d}x \tag{A.57b}$$

Here,  $\rho_{jn_j}(\mathbf{E})$  represent the dynamics of environmental variable j in environmental class  $n_j$  in the absence of any species, and  $I_{jn_jl}(\mathbf{E}, y)$  is the impact of an individual in class l with trait y on environmental variable j in environmental class  $n_j$ .

As before, we now make the assumption that the trait-density distribution  $v_l(x)$  can be approximated by a sum of normal distributions:

$$v_l(x) \approx \tilde{v}_l(x) = \sum_{i=1}^{S} u_{il} \mathcal{N}(x, \bar{x}_{il}, V_{il})$$
(A.58)

and, similarly to how we derived the moment equations, introduce the population-level per capita impact from a population with mean trait  $\bar{x}_{il}$  and variance-covariance  $V_{il}$ :

$$\hat{I}_{ijn_jl} := \int I_{jn_jl}(\mathbf{E}, x) \mathcal{N}(x, \bar{x}_{il}, V_{il}) dx$$
(A.59)

If necessary, this can then be Taylor-expanded to arbitrary order. In particular, to second order this yields:

$$\hat{I}_{ijn_{j}l} \approx I_{jn_{j}l}(\mathbf{E}, \bar{x}_{il}) + \frac{1}{2} \nabla_{x}^{2} I_{jn_{j}l}(\mathbf{E}, \bar{x}_{il}) : V_{il}$$
 (A.60)

Thus, the moment equations including environmental variables read

$$\frac{du_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \hat{f}_{iklm} u_{il}$$
 (A.61a)

$$\frac{d\bar{x}_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il} \nabla_x \hat{f}_{iklm} + \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik}) \right)$$
(A.61b)

$$\frac{dV_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il} \nabla_x^2 \hat{f}_{iklm} V_{il} + \hat{f}_{iklm} (V_{il} - V_{ik}) + \hat{f}_{iklm} M_{klm} \right)$$

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$$+\hat{f}_{iklm}(\bar{x}_{il}-\bar{x}_{ik})(\bar{x}_{il}-\bar{x}_{ik})^{T}$$
(A.61c)

$$+ \left. V_{il} 
abla_x \hat{f}_{iklm} (ar{x}_{il} - ar{x}_{ik})^T + (ar{x}_{il} - ar{x}_{ik}) \left[ V_{il} 
abla_x \hat{f}_{iklm} 
ight]^T 
ight)$$

$$\frac{dE_{jn_j}}{dt} = \rho_{jn_j} + \sum_{i=1}^{S} \sum_{l=1}^{K} \hat{I}_{jn_jil} u_{il}$$
(A.61d)

Here, the arguments of all rate functions have been suppressed for notational clarity, and functions are evaluated at  $\bar{x}_{il}$ ,  $V_{il}$ , and  $\mathbf{E}$ .

#### Environmental, non-heritable trait variation

We have throughout this work assumed that all trait variation is heritable, but our framework can be extended to include non-heritable environmental variation. While we have not worked out how to incorporate environmental variation to the same detail and generality as for the case without it, below we present a sketch of one way of incorporating environmental variation for the simplest case of a single trait in an unstructured community, and derive moment equations for this case.

To derive equations that include environmental variation, we must consider the joint genotype—phenotype distribution  $v(x,\xi)$ , where x is a genotype value and  $\xi$  is a phenotype value. The distribution  $v(x,\xi)$  thus describes how many individuals there are with genotype value x and phenotype value  $\xi$ , or, perhaps more intuitively, for any fixed x,  $v(x,\xi)$  gives the distribution of phenotype values for the genotype value x. Furthermore, we will define

$$v_G(x) := \int_{-\infty}^{\infty} v(x, \xi) d\xi, \qquad (A.62a)$$

$$v_P(\xi) := \int_{-\infty}^{\infty} v(x, \xi) dx, \qquad (A.62b)$$

to be the distributions of genotypes and phenotypes in the community respectively.

Next, we must make assumptions regarding how environmental variation is generated in the community. We will do this in a similar manner to how we incorporated mutations into our trait-space equations. We will assume that the per capita birth rate is given by  $b(\xi, v_P)$  and thus depends on the phenotype value of the individual and the distribution of phenotype values in the community,  $v_P(\xi)$ . Thus, the total rate at which parents with genotype y birth offspring is

$$\int_{-\infty}^{\infty} b(\eta, v_P) v(y, \eta) d\eta, \qquad (A.63)$$

where we have integrated over all phenotypes  $\eta$  for the given genotype y. Assuming once again that each parent with genotype y gives birth to a normally-distributed clutch of offspring due to mutations, the distribution of birthed genotypes in the community can then be calculated to be

$$B(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} b(\eta, v_P) v(y, \eta) d\eta \mathcal{N}(x, y, M) dy.$$
 (A.64)

Finally, we will assume that there is some fixed amount of normal environmental variation  $E_b$  assigned at birth around each genotype value. This means that new offspring will be produced at a rate for the joint distribution given by

$$B(x)\mathcal{N}(\xi, x, E_b). \tag{A.65}$$

Assuming that mortality rates as well as birth rates depend only on individuals' phenotype values and the phenotype distribution in the community we can thus write down how the joint genotype–phenotype distribution will change over time:

$$\frac{\mathrm{d}v(x,\xi)}{\mathrm{d}t} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} b(\eta,v_P)v(y,\eta)\mathrm{d}\eta \mathcal{N}(x,y,M)\mathrm{d}y \mathcal{N}(\xi,x,E_b) - m(\xi,v_P)v(x,\xi). \tag{A.66}$$

This is the trait-space equation for the case where environmental variation is included.

Moment equations with environmental variation

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Just as we did without environmental variation, we will assume that the joint genotype–phenotype distribution  $v(x, \xi)$  can be broken up into S 'species', or peaks, so that

$$v(x,\xi) = \sum_{i=1}^{S} v_i(x,\xi)$$
 (A.67)

and we will then approximate each peak by

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$$\tilde{v}_i(x,\xi) := u_i \mathcal{N}(x,\bar{x}_i,G_i) \mathcal{N}(\xi,x,E_i) \approx v_i(x,\xi), \qquad (A.68)$$

where  $u_i$  is the total density of individuals in species i,  $\bar{x}_i$  is the mean genotype of species i,  $G_i$  is the genetic variance in species i, and  $E_i$  is the environmental variance in species i. In words, each species is assumed to have a normal distribution of genotype values, and to have a normal distribution of phenotype values around each genotype value. We write

$$\tilde{v}(x,\xi) := \sum_{i=1}^{S} \tilde{v}_i(x,\xi) \approx v(x,\xi)$$
(A.69)

for the approximated trait-density distribution. The distribution of phenotype values in each species is given by

$$\tilde{v}_{Pi}(\xi) = \int_{-\infty}^{\infty} \tilde{v}_i(x,\xi) dx = \int_{-\infty}^{\infty} u_i \mathcal{N}(x,\bar{x}_i,G_i) \mathcal{N}(\xi,x,E_i) dx = u_i \mathcal{N}(\xi,\bar{x},G_i+E_i)$$
(A.70)

and we thus let  $V_i := G_i + E_i$  be the phenotypic trait variance in species i. Note that under these assumptions, the mean phenotype in species i,  $\bar{\xi}_i$ , is equal to the mean genotype in species i,  $\bar{x}_i$ , and so we shall only need to track the mean genotype  $\bar{x}_i$  for each species, and can refer to  $\bar{x}_i$  as simply the "mean trait" in species i, as we did for the case with no environmental variation.

Like for the case without environmental variation we need to define population-level rates for a normally-distributed population with mean trait  $\bar{x}$  and phenotypic variance V, which are given by

$$\hat{b}(\bar{x}, V, \tilde{v}_P) = \int_{-\infty}^{\infty} b(\xi, \tilde{v}_P) \mathcal{N}(\xi, \bar{x}, V) d\xi, \qquad (A.71a)$$

$$\hat{m}(\bar{x}, V, \tilde{v}_P) = \int_{-\infty}^{\infty} m(\xi, \tilde{v}_P) \mathcal{N}(\xi, \bar{x}, V) d\xi.$$
(A.71b)

Given this, we can derive (see subsection below) the moment equations for the total densities  $u_i$ ,
mean traits  $\bar{x}_i$ , genetic variance  $G_i$ , and environmental variance  $E_i$  to be

$$\frac{\mathrm{d}u_i}{\mathrm{d}t} = \left[\hat{b}(\bar{x}_i, V_i, \tilde{v}_P) - \hat{m}(\bar{x}_i, V_i, \tilde{v}_P)\right] u_i, \tag{A.72a}$$

$$\frac{\mathrm{d}\bar{x}_i}{\mathrm{d}t} = G_i \left[ \frac{\partial \hat{b}}{\partial \bar{x}} (\bar{x}_i, V_i, \tilde{v}_P) - \frac{\partial \hat{m}}{\partial \bar{x}} (\bar{x}_i, V_i, \tilde{v}_P) \right], \tag{A.72b}$$

$$\frac{\mathrm{d}G_i}{\mathrm{d}t} = G_i^2 \left[ \frac{\partial^2 \hat{b}}{\partial \bar{x}^2} (\bar{x}_i, V_i, \tilde{v}_P) - \frac{\partial^2 \hat{m}}{\partial \bar{x}^2} (\bar{x}_i, V_i, \tilde{v}_P) \right] + \hat{b}(\bar{x}_i, V_i, \tilde{v}_P) M, \tag{A.72c}$$

$$\frac{\mathrm{d}E_i}{\mathrm{d}t} = \hat{b}(\bar{x}_i, V_i, \tilde{v}_P) \left( E_b - E_i \right) - \left( V_i^2 - G_i^2 \right) \frac{\partial^2 \hat{m}}{\partial \bar{x}^2} (\bar{x}_i, V_i, \tilde{v}_P) , \tag{A.72d}$$

$$V_i = G_i + E_i. (A.72e)$$

The first three equations for  $u_i$ ,  $\bar{x}_i$ , and  $G_i$  closely mirror those we derived without environmental variation, but the population-level birth and mortality rates and their derivatives must be evaluated using the total phenotypic variance  $V_i$ . When  $E_i = 0$ ,  $V_i = G_i$  and we have complete agreement with our equations that do not incorporate environmental variation as expected. 1380 More notably, under our assumption of constant environmental variation generated at birth  $E_b$ , we must take the standing environmental variance  $E_i$  for each species to be a dynamic variable that changes over time in response to births and deaths. Roughly speaking, the first term of 1383 Eq. A.72d describes how births change the standing environmental variation  $E_i$  to become closer to the amount generated at birth,  $E_b$ . The second term of Eq. A.72d describes the effects of traitdependent mortality on the standing environmental variation. If mortality is trait independent 1386 so that  $\partial^2 \hat{m}/\partial \bar{x}^2 = 0$ , then the standing environmental variation will only be driven by the birth process, and  $E_i$  will settle onto becoming equal to  $E_b$  for all species, and once  $E_i = E_b$ , it will remain so regardless of how the other state variables may change over time. If, however, there is 1389 stabilizing selection due to trait dependence of the mortality term so that  $-\partial^2\hat{m}/\partial\bar{x}^2<0$ , then this will have the effect of reducing the standing environmental variation over time, and in equilibrium there will be a balance between the environmental variation generated through births and the reduction of environmental variation due to stabilizing mortality selection.

While outside the scope of this paper, using the same basic idea one could work out the moment equations for class-structured populations with multiple traits including environmental variation, and invasion and branching criteria could be worked out in analogous ways to how we did so for the case without environmental variation.

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Deriving the moment equations when including environmental variation

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Before we derive the expressions for the rates of change for the moments, we must compute some intermediary results that will be useful in computing the various integrals involved when calculating the moment equations.

First, let  $f \in \{b, m\}$  be either the function describing the birth rate or the mortality rate. We then define

$$\hat{f}(\bar{x}, G, E, v_P) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\xi, v_P) \mathcal{N}(x, \bar{x}, G) \mathcal{N}(\xi, x, E) d\xi dx, \qquad (A.73a)$$

$$\hat{f}(\bar{x}, V, v_P) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\xi, v_P) \mathcal{N}(\xi, \bar{x}, V) d\xi, \qquad (A.73b)$$

and note that when V=G+E these expressions are equal. For the first derivative of  $\hat{f}$  we calculate

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x}) f(\xi, v_P) \mathcal{N}(x, \bar{x}, G) \mathcal{N}(\xi, x, E) d\xi dx$$
(A.74a)

$$=G\int_{-\infty}^{\infty} f(\xi, v_P) \frac{\xi - \bar{x}}{V} \mathcal{N}(\xi, \bar{x}, V) d\xi = G \frac{\partial \hat{f}}{\partial \bar{x}}(\bar{x}, V, v_P). \tag{A.74b}$$

For the second derivatives of  $\hat{f}$  we may similarly calculate

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^2 f(\xi, v_P) \mathcal{N}(x, \bar{x}, G) \mathcal{N}(\xi, x, E) d\xi dx = G^2 \frac{\partial^2 \hat{f}}{\partial \bar{x}^2} (\bar{x}, V, v_P) + G \hat{f}(\bar{x}, V, \tilde{v}_P), \quad (A.75a)$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (\xi - \bar{x})^2 f(\xi, v_P) \mathcal{N}(x, \bar{x}, G) \mathcal{N}(\xi, x, E) d\xi dx = V^2 \frac{\partial^2 \hat{f}}{\partial \bar{x}^2} (\bar{x}, V, v_P) + V \hat{f}(\bar{x}, V, \tilde{v}_P). \quad (A.75b)$$

Under the assumption that the mean genotype  $\bar{x}_i$  equals the mean phenotype  $\bar{\xi}_i$  (or simply, the mean trait) the moments are given by

$$u_i = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} v_i(x,\xi) dx d\xi, \qquad (A.76a)$$

$$\bar{x}_i = \frac{1}{u_i} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x v_i(x, \xi) dx d\xi, \qquad (A.76b)$$

$$G_i = \frac{1}{u_i} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x}_i)^2 v_i(x, \xi) dx d\xi, \qquad (A.76c)$$

$$V_i = \frac{1}{u_i} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (\xi - \bar{x}_i)^2 v_i(x, \xi) dx d\xi, \qquad (A.76d)$$

$$E_{i} = V_{i} - G_{i} = \frac{1}{u_{i}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ (\xi - \bar{x}_{i})^{2} - (x - \bar{x}_{i})^{2} \right] v_{i}(x, \xi) dx d\xi$$
 (A.76e)

$$= \frac{1}{u_i} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ 2(\xi - x)(x - \bar{x}_i) + (\xi - x)^2 \right] v_i(x, \xi) dx d\xi.$$
 (A.76f)

Now, assuming our normal approximations so that

$$\tilde{v}_i(x,\xi) := u_i \mathcal{N}(x,\bar{x}_i,G_i) \mathcal{N}(\xi,x,E_i) \approx v_i(x,\xi),$$
(A.77a)

$$\tilde{v}(x,\xi) := \sum_{i=1}^{S} \tilde{v}_i(x,\xi) \approx v(x,\xi), \tag{A.77b}$$

$$\tilde{v}_P(\xi) := \int_{-\infty}^{\infty} \tilde{v}(x, \xi) dx, \qquad (A.77c)$$

we can derive the moment equations. Below, we calculate in turn the moment equations for the total density  $u_i$ , the mean trait  $\bar{x}_i$ , the genetic variance  $G_i$ , and the environmental variance  $E_i$  for each species i.

Total density,  $u_i$ :

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$$\frac{\mathrm{d}u_{i}}{\mathrm{d}t} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{\mathrm{d}v_{i}(x,\xi)}{\mathrm{d}t} \mathrm{d}\xi \mathrm{d}x \approx \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{\mathrm{d}\tilde{v}_{i}(x,\xi)}{\mathrm{d}t} \mathrm{d}\xi \mathrm{d}x \qquad (A.78a)$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} b(\eta,\tilde{v}_{P})\tilde{v}_{i}(y,\eta) \mathrm{d}\eta \mathcal{N}(x,y,M) \mathrm{d}y \mathcal{N}(\xi,x,E_{b}) \right]$$

$$- m(\xi,\tilde{v}_{P})\tilde{v}_{i}(x,\xi) \, \mathrm{d}\xi \mathrm{d}x = \qquad (A.78b)$$

{integrate in order  $\xi \to x \to y$  in birth term}

$$= \left[\hat{b}(\bar{x}_i, V_i, \tilde{v}_P) - \hat{m}(\bar{x}_i, V_i, \tilde{v}_P)\right] u_i \tag{A.78c}$$

Mean trait,  $\bar{x}_i$ :

$$\frac{\mathrm{d}}{\mathrm{d}t}(u_i\bar{x}_i) = u_i\frac{\mathrm{d}\bar{x}_i}{\mathrm{d}t} + \bar{x}_i\frac{\mathrm{d}u_i}{\mathrm{d}t} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x\frac{\mathrm{d}v_i(x,\xi)}{\mathrm{d}t} \mathrm{d}\xi \mathrm{d}x \tag{A.79a}$$

 $= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x}_i) \frac{\mathrm{d}v_i(x, \xi)}{\mathrm{d}t} \mathrm{d}\xi \mathrm{d}x + \bar{x}_i \frac{\mathrm{d}u_i}{\mathrm{d}t}$ (A.79b)

and we thus get

$$u\frac{\mathrm{d}\bar{x}_{i}}{\mathrm{d}t} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x}_{i}) \frac{\mathrm{d}v_{i}(x, \xi)}{\mathrm{d}t} \mathrm{d}\xi \mathrm{d}x \approx \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x}_{i}) \frac{\mathrm{d}\tilde{v}_{i}(x, \xi)}{\mathrm{d}t} \mathrm{d}\xi \mathrm{d}x$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x}_{i}) \left[ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} b(\eta, \tilde{v}_{P}) \tilde{v}_{i}(y, \eta) \mathrm{d}\eta \mathcal{N}(x, y, M) \mathrm{d}y \mathcal{N}(\xi, x, E_{b}) \right]$$

$$- m(\xi, \tilde{v}_{P}) \tilde{v}_{i}(x, \xi) \mathrm{d}\xi \mathrm{d}x =$$
(A.80b)

{integrate in order  $\xi \to x$  in birth term}

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (y - \bar{x}_i) b(\eta, \tilde{v}_P) \tilde{v}_i(y, \eta) d\eta dy - \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x}_i) m(\xi, \tilde{v}_P) \tilde{v}_i(x, \eta) d\xi dx \quad (A.80c)$$

{Eqs. A.74}

$$= u_i G_i \frac{\partial \hat{b}}{\partial \bar{x}} (\bar{x}_i, V_i, \tilde{v}_P) - u_i G_i \frac{\partial \hat{m}}{\partial \bar{x}} (\bar{x}_i, V_i, \tilde{v}_P)$$
(A.80d)

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$$\frac{\mathrm{d}\bar{x}_i}{\mathrm{d}t} = G_i \left[ \frac{\partial \hat{b}}{\partial \bar{x}} (\bar{x}_i, V_i, \bar{v}_P) - \frac{\partial \hat{m}}{\partial \bar{x}} (\bar{x}_i, V_i, \bar{v}_P) \right] \tag{A.80e}$$

Genetic variance, G<sub>i</sub>:

$$\frac{\mathrm{d}}{\mathrm{d}t}(u_iG_i) = u_i\frac{\mathrm{d}G_i}{\mathrm{d}t} + G_i\frac{\mathrm{d}u_i}{\mathrm{d}t} = \frac{\mathrm{d}}{\mathrm{d}t}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x-\bar{x}_i)^2v_i(x,\xi)\mathrm{d}\xi\mathrm{d}x \tag{A.81a}$$

$$\approx \frac{\mathrm{d}}{\mathrm{d}t} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x}_i)^2 \tilde{v}_i(x, \xi) \mathrm{d}\xi \mathrm{d}x \tag{A.81b}$$

$$= \frac{\mathrm{d}\bar{x}_i}{\mathrm{d}t} \underbrace{\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} 2(x - \bar{x}_i) \tilde{v}_i(x, \xi) \mathrm{d}\xi \mathrm{d}x}_{\text{c}} + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x}_i)^2 \frac{\mathrm{d}\tilde{v}_i}{\mathrm{d}t} \mathrm{d}\xi \mathrm{d}x \tag{A.81c}$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x}_i)^2 \left[ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} b(\eta, \tilde{v}_P) \tilde{v}_i(y, \eta) d\eta \mathcal{N}(x, y, M) dy \mathcal{N}(\xi, x, E_b) \right] d\xi dx =$$
(A.81d)

{integrate in order  $\xi \to x$  in birth term}

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} b(\eta, \tilde{v}_P) \tilde{v}_i(y, \eta) \left[ M + (y - \bar{x}_i)^2 \right] d\eta dy$$
$$- \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} m(\xi, \tilde{v}_P) \tilde{v}_i(x, \xi) (x - \bar{x}_i)^2 d\xi dx \tag{A.81e}$$

{Eq. A.75}

$$= u_i \left[ \hat{b}(\bar{x}_i, V_i, \tilde{v}_P) M + G_i^2 \frac{\partial^2 \hat{b}}{\partial \bar{x}^2} (\bar{x}_i, V_i, \tilde{v}_P) + G_i \hat{b}(\bar{x}_i, V_i, \tilde{v}_P) \right.$$

$$\left. - G_i^2 \frac{\partial^2 \hat{m}}{\partial \bar{x}^2} (\bar{x}_i, V_i, \tilde{v}_P) - G_i \hat{m}(\bar{x}_i, V_i, \tilde{v}_P) \right]$$
(A.81f)

 $\iff$ 

$$\frac{\mathrm{d}G_i}{\mathrm{d}t} = G_i^2 \left[ \frac{\partial^2 \hat{b}}{\partial \bar{x}^2} (\bar{x}_i, V_i, \tilde{v}_P) - \frac{\partial^2 \hat{m}}{\partial \bar{x}^2} (\bar{x}_i, V_i, \tilde{v}_P) \right] + \hat{b}(\bar{x}_i, V_i, \tilde{v}_P) M \tag{A.81g}$$

Environmental variance,  $E_i$ :

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$$\frac{\mathrm{d}}{\mathrm{d}t}(u_{i}E_{i}) = u_{i}\frac{\mathrm{d}E_{i}}{\mathrm{d}t} + E_{i}\frac{\mathrm{d}u_{i}}{\mathrm{d}t} \tag{A.82a}$$

$$= \frac{\mathrm{d}}{\mathrm{d}t} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ 2(\xi - x)(x - \bar{x}_{i}) + (\xi - x)^{2} \right] v_{i}(x, \xi) \mathrm{d}x \mathrm{d}\xi \tag{A.82b}$$

$$\approx \frac{\mathrm{d}}{\mathrm{d}t} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ 2(\xi - x)(x - \bar{x}_{i}) + (\xi - x)^{2} \right] \tilde{v}_{i}(x, \xi) \mathrm{d}x \mathrm{d}\xi \tag{A.82c}$$

$$= -\frac{\mathrm{d}\bar{x}_{i}}{\mathrm{d}t} \underbrace{\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} 2(\xi - x)\tilde{v}_{i}(x, \xi) \mathrm{d}x \mathrm{d}\xi}_{=0}$$

$$+ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ 2(\xi - x)(x - \bar{x}_{i}) + (\xi - x)^{2} \right] \frac{\mathrm{d}\tilde{v}_{i}(x, \xi)}{\mathrm{d}t} \mathrm{d}x \mathrm{d}\xi \tag{A.82d}$$

$$+ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ 2(\xi - x)(x - \bar{x}_i) + (\xi - x)^2 \right] \frac{\mathrm{d}\tilde{v}_i(x, \xi)}{\mathrm{d}t} \mathrm{d}x \mathrm{d}\xi$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ 2(\xi - x)(x - \bar{x}_i) + (\xi - x)^2 \right] \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} b(\eta, \tilde{v}_P) \tilde{v}_i(y, \eta) \mathrm{d}\eta \mathcal{N}(x, y, M) \mathrm{d}y \mathcal{N}(\xi, x, E_b) \mathrm{d}\xi \mathrm{d}x$$

$$- \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[ (\xi - \bar{x}_i)^2 - (x - \bar{x}_i)^2 \right] m(\xi, \tilde{v}_P) \tilde{v}_i(x, \xi) \mathrm{d}\xi \mathrm{d}x$$
(A.82e)

{integrate in order  $\xi \to x$  in birth term, use Eqs. A.75 in mortality term}

$$= E_{b} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} b(\eta, \tilde{v}_{P}) \tilde{v}_{i}(y, \eta) d\eta dy$$

$$- u_{i} \left[ V_{i}^{2} \frac{\partial^{2} \hat{m}}{\partial \bar{x}^{2}} (\bar{x}_{i}, V_{i}, \tilde{v}_{P}) + V_{i} \hat{m}(\bar{x}_{i}, V_{i}, \tilde{v}_{P}) - G_{i}^{2} \frac{\partial^{2} \hat{m}}{\partial \bar{x}^{2}} (\bar{x}_{i}, V_{i}, \tilde{v}_{P}) - G_{i} \hat{m}(\bar{x}_{i}, V_{i}, \tilde{v}_{P}) \right]$$

$$= u_{i} E_{b} \hat{b}(\bar{x}_{i}, V_{i}, \tilde{v}_{P}) - u_{i} (V_{i}^{2} - G_{i}^{2}) \frac{\partial^{2} \hat{m}}{\partial \bar{x}^{2}} (\bar{x}_{i}, V_{i}, \tilde{v}_{P}) - u_{i} E_{i} \hat{m}(\bar{x}_{i}, V_{i}, \tilde{v}_{P})$$

$$(A.82g)$$

 $\frac{\mathrm{d}E_i}{\mathrm{d}t} = \hat{b}(\bar{x}_i, V_i, \tilde{v}_P)(E_b - E_i) - (V_i^2 - G_i^2) \frac{\partial^2 \hat{m}}{\partial \bar{x}^2}(\bar{x}_i, V_i, \tilde{v}_P)$ (A.82h)

Together, these are the moment equations (Eqs. A.72) when environmental variance is included.

### Online Appendix B: Evolutionary branching and invasion analysis

In this appendix we will derive ways of examining whether a community of species at ecoevolutionary equilibrium is closed to invasion by further species. We refer to these methods
as heuristics since following these procedures cannot guarantee a complete closure to further
invasions, and because the methodology is somewhat *ad hoc*. Nevertheless, in the examples we
have tested (see the main text) these methods have so far proven to be highly accurate in the
sense that they almost always produce communities with the same number of species for the
moment equations as the trait-space equations produce peaks in eco-evolutionary equilibrium.
The exceptions, as shown for the two-patch example in the main text, primarily happen when
the number of species is ambiguous (a distribution with several peaks, but where the peaks are
not well separated), for narrow ranges of parameters near bifurcation points.

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We shall follow the general ideas of adaptive dynamics (Metz et al., 1992; Dieckmann and Law, 1996; Geritz et al., 1998; Dercole and Rinaldi, 2008; Brännström et al., 2013) and work out two different ways of investigating when bifurcation into more species can take place. The first condition is local in trait space and known as an *evolutionary branching* where a species splits into two new species that subsequently diverge in trait space. It is easier to calculate than the second condition, which treats global invasion analysis where the invader does not necessarily have a trait that is close to any resident species. The first condition implies the second, but not necessarily vice versa.

## Evolutionary branchings

We shall here work out a criterion for when a species characterized by the moment equations can be split into two new species locally in trait space in such a way that they subsequently diverge in their traits.

Consider a community of S species in K classes being in a convergence-stable eco-evolutionary

equilibrium so that

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$$0 = \frac{\mathrm{d}u_{ik}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \hat{f}_{iklm} u_{il}$$
(B.1a)

$$0 = \frac{\mathrm{d}\bar{x}_{ik}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il} \nabla_x \hat{f}_{iklm} + \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik}) \right)$$
(B.1b)

$$0 = \frac{dV_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il} \nabla_x^2 \hat{f}_{iklm} V_{il} + \hat{f}_{iklm} M_{klm} + \right)$$
(B.1c)

$$+ V_{il} \nabla_x \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik})^T + (\bar{x}_{il} - \bar{x}_{ik}) \left[ V_{il} \nabla_x \hat{f}_{iklm} \right]^T +$$
 (B.1d)

$$+\hat{f}_{iklm}\left[V_{il}-V_{ik}+(\bar{x}_{il}-\bar{x}_{ik})(\bar{x}_{il}-\bar{x}_{ik})^{T}\right]$$
 (B.1e)

for all  $i \in \{1, 2, ..., S\}$  and  $k \in \{1, 2, ..., K\}$ .

To test whether a given species i within this community can undergo an evolutionary branching we first split this species into two new species  $i_1$  and  $i_2$  with densities, mean-trait vectors, and variance-covariances given by

$$u_{i_1k} = u_{i_2k} = \frac{u_{ik}}{2} \tag{B.2a}$$

$$\bar{x}_{i_1k} = \bar{x}_{i_2k} = \bar{x}_{ik}$$
 (B.2b)

$$V_{i_1k} = V_{i_2k} = V_{ik} (B.2c)$$

We then organize all the state variables, u,  $\bar{x}$ , and V into a vector w, so that the entries of w are the total densities, the mean trait components and the variance-covariance components for all species and classes in the split system. We let F(w) be the function given by the right-hand side of Eq. B.1 and linearize around the equilibrium  $w^*$ ,

$$0 = \frac{\mathrm{d}w}{\mathrm{d}t} \approx F(w^*) + J_F(w^*)(w - w^*)$$
(B.3)

where  $J_F(w^*)$  is the Jacobian matrix of F evaluated at  $w^*$ . Normally, in dynamical systems theory, we would say that the community with the split species is stable if the dominant eigenvalue (eigenvalue with largest real part) of the Jacobian matrix has a negative real part. However, here, due to the splitting, there will always be a neutral direction corresponding to shifting mass between species  $i_1$  and  $i_2$ , so there will always exist a zero eigenvalue of the Jacobian. Thus, if the

dominant eigenvalue is zero there is no branching. However, if there exists an eigenvalue with positive real part this indicates that the split-species equilibrium is unstable and that a branching in species i will take place.

Figure B.1 shows an evolutionary branching for the two-patch Lotka-Volterra model (Eqs. 20, Fig. 3, main text). The initial species evolves to an eco-evolutionary equilibrium with substantial variance and significant local adaptation between the two patches. There, we split the species and determine the dominant eigenvalue  $\lambda_d$  as described above. For this example, the dominant eigenvalue is positive showing that the one-species equilibrium is unstable to the addition of a species. Let  $\phi$  be the eigenvector associated with the dominant eigenvalue  $\lambda_d$ . The components of the eigenvector are

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	Patch 1	Patch 2	
1527	$u_{11}^{\phi} = 0.4468$	$u_{12}^{\phi} = -0.4468$	(B.4a)
	$u_{21}^{\phi} = -0.4468$	$u_{22}^{\phi} = 0.4468$	(B.4b)
	$\bar{x}_{11}^{\phi} = -0.2021$	$ar{x}_{12}^{\phi} = -0.2021$	(B.4c)
1530	$\bar{x}_{21}^{\phi} = 0.2021$	$\bar{x}_{22}^{\phi} = 0.2021$	(B.4d)
	$V_{11}^{\phi} = -0.09774$	$V_{12}^{\phi} = 0.09774$	(B.4e)
	$V_{21}^{\phi}=0.09774$	$V_{22}^{\phi} = -0.09774$	(B.4f)

In other words, the unstable direction corresponds to one species becoming relatively more abundant on patch 1 and with a lower trait, and one species becoming relatively more abundant on patch 2 with a higher trait. We construct the new two-species system after the branching by letting

$$w_{\text{new}} = w^* + \alpha \phi \tag{B.5}$$

where  $\alpha$  is some small number, for this example  $\alpha=0.05$ , then solve for the S+1-species eco-evolutionary equilibrium.

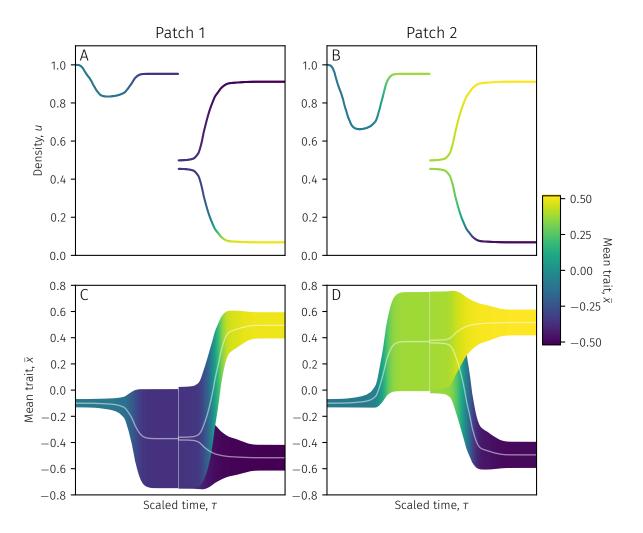


Figure B.1: Illustration of branching procedure for the two-patch Lotka-Volterra model (Eqs. 20, Fig. 3, main text). The panels depicts the densities (A–B) and mean traits (C–D) in the two-patch model on both patches where the left two panels depict patch 1 and the right two panels depict patch 2. Panels (C–D) also depict one standard deviation around the mean as filled areas. The initial species evolves to an eco-evolutionary equilibrium after which a branching takes place, the species is split, and the two new species once again evolve to an eco-evolutionary equilibrium. To illustrate the branching we have rescaled time non-uniformly to ensure the interesting aspects of the branching are clearly visible. **Parameter values**:  $x_1^{\text{opt}} = -0.5$ ,  $x_2^{\text{opt}} = 0.5$ ,  $V_r = 1.0$ ,  $V_c = 1.0$ ,  $V_c = 1.0$ ,  $V_c = 1.0$ , and  $V_c = 1.0$ , and

## Global invasion dynamics

Local branching in trait space will not always be sufficient to ensure that community is globally closed to further invasions. Here, we will work out a criterion for when an additional species with an arbitrary trait can be added to the community in such a way that this added species grows from being initially rare. This corresponds to local-but-not-global ESSs in adaptive dynamics (Geritz et al. 1999; Klausmeier et al. 2020).

Let a discrete structured community of *S* species in *K* classes be in eco-evolutionary equilibrium so that

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$$0 = \frac{\mathrm{d}u_{ik}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \hat{f}_{iklm} u_{il}$$
 (B.6a)

$$0 = \frac{\mathrm{d}\bar{x}_{ik}}{\mathrm{d}t} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il} \nabla_x \hat{f}_{iklm} + \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik}) \right)$$
(B.6b)

$$0 = \frac{dV_{ik}}{dt} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} \frac{u_{il}}{u_{ik}} \left( V_{il} \nabla_x^2 \hat{f}_{iklm} V_{il} + \hat{f}_{iklm} M_{klm} + \right)$$
(B.6c)

$$+ V_{il} \nabla_x \hat{f}_{iklm} (\bar{x}_{il} - \bar{x}_{ik})^T + (\bar{x}_{il} - \bar{x}_{ik}) \left[ V_{il} \nabla_x \hat{f}_{iklm} \right]^T +$$
 (B.6d)

$$+\hat{f}_{iklm}\left[V_{il}-V_{ik}+(\bar{x}_{il}-\bar{x}_{ik})(\bar{x}_{il}-\bar{x}_{ik})^{T}\right]$$
 (B.6e)

for all  $i \in \{1, 2, ..., S\}$  and  $k \in \{1, 2, ..., K\}$ . Denote the trait-density distributions of these resident populations in equilibrium by

$$\tilde{v}_k^{\text{res}}(x) = \sum_{i=1}^S u_{ik} \mathcal{N}(x, \bar{x}_{ik}, V_{ik})$$
(B.7)

and let  $\tilde{\mathbf{v}}^{\text{res}} = (\tilde{v}_1^{\text{res}}, ..., \tilde{v}_K^{\text{res}})$  be the vector of all resident trait-density distributions.

We would now like to devise a procedure to determine whether the resident community is closed to invasions. In analogy with adaptive dynamics (Metz et al., 1992; Dieckmann and Law, 1996; Geritz et al., 1998; Dercole and Rinaldi, 2008; Brännström et al., 2013) we will let a very rare invader enter this community, and try to determine whether this invader can grow in the environment set by the residents while still rare. However, we also need to account for the internal dynamics of the invader, i.e., its mean traits and variance-covariances across classes.

Although the invader will be assumed to be so rare that it does not effect its own dynamics or any of the residents, in the case of structured populations, we must still keep track of its distribution across classes to calculate the relative-density weight term in the mean trait and trait variance equations. To this end let the class-frequency of the invader in class k be given by

$$p_k^{\text{inv}} := \frac{u_k^{\text{inv}}}{\sum_{l=1}^K u_l^{\text{inv}}}, \tag{B.8}$$

where  $\sum_{k=1}^{K} p_k^{\text{inv}} \equiv 1$ . We can then calculate

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$$\frac{\mathrm{d}p_k^{\text{inv}}}{\mathrm{d}t} = \frac{\mathrm{d}}{\mathrm{d}t} \left( \frac{u_k^{\text{inv}}}{\sum_{l=1}^K u_l^{\text{inv}}} \right) = \sum_{l=1}^K \sum_{m=1}^{N_{kl}} \hat{f}_{klm}^{\text{inv}} p_l^{\text{inv}} - p_k^{\text{inv}} \sum_{j=1}^K \sum_{l=1}^K \sum_{m=1}^{N_{jl}} \hat{f}_{jlm}^{\text{inv}} p_l^{\text{inv}}.$$
(B.9)

We note that the mean-trait vector and variance-covariance matrix equations in the moment equations depend on the densities only through their ratios, and by construction we have that

$$\frac{p_l^{\text{inv}}}{p_l^{\text{inv}}} \equiv \frac{u_l^{\text{inv}}}{u_l^{\text{inv}}}.$$
 (B.10)

Let  $\bar{x}_k^{\text{inv}}$  and  $V_k^{\text{inv}}$  denote the mean-trait vector and variance-covariance matrix respectively of the rare invader in class k, and let  $\hat{f}_{klm}^{\text{inv}} := \hat{f}_{klm}(\bar{x}_l^{\text{inv}}, V_l^{\text{inv}}, \tilde{\mathbf{v}}^{\text{res}})$ . Note that because we assume that the invader is very rare, the per capita rates of the invader do not depend on the trait-density distribution of the invader itself. Similarly, we assume that the invader's rarity is such that it will not affect the residents, and  $\tilde{\mathbf{v}}^{\text{res}}$  will be constant.

We can then formulate the invader equations as

$$\frac{\mathrm{d}p_k^{\text{inv}}}{\mathrm{d}t} = \sum_{l=1}^K \sum_{m=1}^{N_{kl}} \hat{f}_{klm}^{\text{inv}} p_l^{\text{inv}} - p_k^{\text{inv}} \sum_{j=1}^K \sum_{l=1}^K \sum_{m=1}^{N_{jl}} \hat{f}_{jlm}^{\text{inv}} p_l^{\text{inv}},$$
(B.11a)

$$\frac{\mathrm{d}\bar{x}_k^{\mathrm{inv}}}{\mathrm{d}t} = \sum_{l=1}^K \sum_{m=1}^{N_{kl}} \frac{p_l^{\mathrm{inv}}}{p_k^{\mathrm{inv}}} \left( V_l^{\mathrm{inv}} \nabla_x \hat{f}_{klm}^{\mathrm{inv}} + \hat{f}_{klm}^{\mathrm{inv}} (\bar{x}_l^{\mathrm{inv}} - \bar{x}_k^{\mathrm{inv}}) \right)$$
(B.11b)

$$\frac{\mathrm{d}V_k^{\mathrm{inv}}}{\mathrm{d}t} = \sum_{l=1}^K \sum_{m=1}^{N_{kl}} \frac{p_l^{\mathrm{inv}}}{p_n^{\mathrm{inv}}} \left( V_l^{\mathrm{inv}} \nabla_x^2 \hat{f}_{klm}^{\mathrm{inv}} V_l^{\mathrm{inv}} + \hat{f}_{klm}^{\mathrm{inv}} M_{klm} + \right)$$

$$+ V_{l}^{\text{inv}} \nabla_{x} \hat{f}_{klm}^{\text{inv}} (\bar{x}_{l}^{\text{inv}} - \bar{x}_{k}^{\text{inv}})^{T} + (\bar{x}_{l}^{\text{inv}} - \bar{x}_{k}^{\text{inv}}) \left[ V_{l}^{\text{inv}} \nabla_{x} \hat{f}_{klm}^{\text{inv}} \right]^{T} +$$

$$+ \hat{f}_{klm}^{\text{inv}} \left[ V_{l}^{\text{inv}} - V_{k}^{\text{inv}} + (\bar{x}_{l}^{\text{inv}} - \bar{x}_{k}^{\text{inv}}) (\bar{x}_{l}^{\text{inv}} - \bar{x}_{k}^{\text{inv}})^{T} \right]$$
(B.11c)

Under equilibrium dynamics, an invader will eventually assume an equilibrium distribution, but the nonlinearity of the equations means that there could potentially exist several such equilibria. Assume that the invader equations have N total equilibria, and denote each such equilibrium by  $p_k^{\text{inv}*n}$ ,  $\bar{x}_k^{\text{inv}*n}$ ,  $V_k^{\text{inv}*n}$  for the class frequencies, mean trait vectors, and variance-covariance matrices of the invaders for equilibrium n = 1, ..., N and class k = 1, ..., K.

Now, let the  $K \times K$  matrix  $\hat{F}^{inv*n}$  with entries  $\hat{F}^{inv*n}_{kl}$  be defined by

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$$\hat{F}_{kl}^{\text{inv}*n} = \sum_{m=1}^{N_{kl}} \hat{f}_{klm}^{\text{inv}*n} = \sum_{m=1}^{N_{kl}} \hat{f}_{klm}(\bar{x}_l^{\text{inv}*n}, V_l^{\text{inv}*n}, \tilde{\mathbf{v}}^{\text{res}})$$
(B.12)

and let the vector  $\mathbf{p}^{\text{inv}*n} := (p_1^{\text{inv}*n}, p_2^{\text{inv}*n}, ..., p_K^{\text{inv}*n})$ . Then, from Eq. B.11a, we have in equilibrium that

$$\hat{F}^{\text{inv}*n}\mathbf{p}^{\text{inv}*n} = \left(\sum_{j=1}^{K}\sum_{l=1}^{K}\sum_{m=1}^{N_{jl}}\hat{f}_{jlm}^{\text{inv}*n}p_{l}^{\text{inv}*n}\right)\mathbf{p}^{\text{inv}*n}.$$
(B.13)

From this expression we see that  $\mathbf{p}^{\text{inv}*n}$  is an eigenvector of  $\hat{F}^{\text{inv}*n}$ , and we can see that the eigenvalue is

$$\lambda_n = \sum_{j=1}^K \sum_{l=1}^K \sum_{m=1}^{N_{jl}} \hat{f}_{jlm}^{\text{inv}*n} p_l^{\text{inv}*n} .$$
 (B.14)

If we now turn to the density dynamics of the invader we have that if the initial densities of the invader,  $\mathbf{u}_0^{\text{inv}*n}$ , are proportional to an equilibrium class-frequency distribution,  $\mathbf{u}_0^{\text{inv}*n} = c_0 \mathbf{p}^{\text{inv}*n}$ , then

$$\frac{\mathrm{d}u_k^{\mathrm{inv}*n}}{\mathrm{d}t} = \sum_{l=1}^K \sum_{m=1}^{N_{kl}} \hat{f}_{klm}^{\mathrm{inv}*n} u_l^{\mathrm{inv}*n} \iff \frac{\mathrm{d}\mathbf{u}^{\mathrm{inv}*n}}{\mathrm{d}t} = \hat{F}^{\mathrm{inv}*n} \mathbf{u}^{\mathrm{inv}*n} \implies \mathbf{u}^{\mathrm{inv}*n}(t) = c_0 e^{\lambda_n t} \mathbf{p}^{\mathrm{inv}*n}. \quad (B.15)$$

In other words,  $\lambda_n$  is the long-term exponential growth rate of the invader while still rare for equilibrium n. This means that  $\lambda_n$  is the invasion fitness of invader equilibrium n. Thus, if  $\lambda_n > 0$ , the invader can successfully invade the community of residents, and if  $\lambda_n \leq 0$  then the invasion will not succeed.

In principle, this then gives us a way of determining whether a resident community is invasible. For a given resident community, we find all the equilibria of the invader equations (Eqs. B.11), and then use Eq. B.14 to calculate the invasion fitness of each such equilibrium. If any positive invasion fitness is found, the community is invasible, and if no positive invasion

fitness equilibria are found, the community is not invasible. In practice, however, proving that one has found all the equilibria of the invader equations will in general not be feasible. Thus, we need some heuristic that is easy to carry out and can still find the relevant equilibria most of the time. To this end, we start by computing the adaptive-dynamics fitness landscape, where we consider the invaders to have no variance and fixed mean-trait vectors with no local adaptation so that  $V_k^{\text{inv}} = 0$  for all k and  $\bar{x}_k = \bar{x}^{\text{AD}}$  for all k. Then, we can immediately calculate the growth rate of this zero-variance invader as the dominant eigenvalue of the matrix  $F^{\text{AD}}$ , with entries given by

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$$F_{kl}^{\text{AD}} = \sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} f_{klm}(\bar{x}^{\text{AD}}, \tilde{\mathbf{v}}^{\text{res}}).$$
 (B.16)

See Caswell (2001) for details on invasion analysis in structured populations in the adaptive-dynamics framework. We can then calculate this adaptive-dynamics invasion fitness for a range of trait vectors  $\bar{x}^{AD}$  in some region of trait space that is pertinent to the problem at hand. We then find all mean-trait vectors that yield local maxima in the AD-fitness landscape. Let these be denoted by  $\bar{x}^{AD,\max,q}$  for the q:th such local maximum. Finally, we use these mean-trait vectors as initial conditions for the invader equations (Eqs. B.11) by setting

$$\mathbf{p}_{t=0}^{\text{inv},q} = \mathbf{p}^{\text{AD,max},q} \tag{B.17a}$$

$$\bar{x}_{k,t=0}^{\text{inv},q} = \bar{x}^{\text{AD,max},q}$$
 for all  $k$  (B.17b)

$$V_{k,t=0}^{\text{inv},q} = 0 \quad \text{for all } k \tag{B.17c}$$

where  $\mathbf{p}^{\text{AD,max},q}$  is the normalized eigenvector associated with dominant eigenvalue of the matrix with entries at k, l given by

$$\sum_{l=1}^{K} \sum_{m=1}^{N_{kl}} f_{klm}(\bar{x}^{\text{AD,max},q}, \tilde{\mathbf{v}}^{\text{res}}).$$
(B.18)

For each such initial condition we then solve the invader equations to equilibrium and compute that equilibrium's invasion fitness as described above. While not guaranteed to find every invader equilibrium, this method tends to work well in practice for finding the relevant equilibria as the zero-variance populations serve as good first approximations to where positive invasion fitness might be available.

# Online Appendix C: Additional details of the Lotka-Volterra competition models

In this appendix we provide some additional details of the two example models of Lotka-Volterra competition we use in the main text.

#### The unstructured Lotka-Volterra model

The trait-space equations of the model are given by

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$$\frac{\mathrm{d}v(x)}{\mathrm{d}t} = \int b(y)v(y)\mathcal{N}(x,y,M)\mathrm{d}y - \mu(x)v(x) - a(x,v)v(x), \tag{C.1a}$$

$$b(x) = r_0, \quad \mu(x) = \frac{(x - x^{\text{opt}})^2}{V_r},$$
 (C.1b)

$$r(x) := b(x) - \mu(x) = r_0 - \frac{(x - x^{\text{opt}})^2}{V_r},$$
 (C.1c)

$$a(x,v) = \int \alpha(y,x)v(y)dy, \quad \alpha(y,x) = \exp\left(-\frac{(y-x)^2}{2V_c}\right). \tag{C.1d}$$

Here, r(x) describes the intrinsic density-independent per capita net growth rate due to the environment. The strength of competition between two individuals with traits x and y is given by  $\alpha(y,x)$ , which means that the total per capita mortality experienced by an individual with trait x given the total trait-density distribution of the community is a(x,v). For the unstructured model, the value of  $x^{\text{opt}}$  can be set to be zero without loss of generality as we do in the main text. We include it here to more easily generalize to the two-patch model.

Using our general method, we can plug in these rates to get the moment equations for this system:

$$\frac{\mathrm{d}u_i}{\mathrm{d}t} = (\hat{r}(\bar{x}_i, V_i) - \hat{a}(\bar{x}_i, V_i, \tilde{v})) u_i \tag{C.2a}$$

$$\frac{\mathrm{d}\bar{x}_i}{\mathrm{d}t} = V_i \left( \frac{\partial \hat{r}}{\partial x} (\bar{x}_i, V_i) - \frac{\partial \hat{a}}{\partial x} (\bar{x}_i, V_i, \tilde{v}) \right) \tag{C.2b}$$

$$\frac{\mathrm{d}V_i}{\mathrm{d}t} = V_i^2 \left( \frac{\partial^2 \hat{r}}{\partial x^2} (\bar{x}_i, V_i) - \frac{\partial^2 \hat{a}}{\partial x^2} (\bar{x}_i, V_i, \tilde{v}) \right) + \hat{b}(\bar{x}_i, V_i) M \tag{C.2c}$$

From this, we see that we need to compute the population-level rates

$$\hat{r}(x,W) = \int r(y)\mathcal{N}(y,x,W)dy$$
 (C.3a)

$$\hat{a}(x, W, \tilde{v}) = \int a(y, \tilde{v}) \mathcal{N}(y, x, W) dy$$
 (C.3b)

$$\hat{b}(x,W) = \int b(y)\mathcal{N}(y,x,W)dy$$
 (C.3c)

The notation

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$$\frac{\partial \hat{r}}{\partial x}(\bar{x}_i, V_i) \tag{C.4}$$

means that we take the derivative of the function  $\hat{r}(x, W)$  with respect to x and evaluate the resulting function at  $x = \bar{x}_i$  and  $W = V_i$ .

Here, we compute the population-level rates in turn. First, the population-level rate for r can be computed as

$$\hat{r}(x,W) = \int r(y)\mathcal{N}(y,x,W)dy = \int \left(r_0 - \frac{(y - x^{\text{opt}})^2}{V_r}\right)\mathcal{N}(y,x,W)dy$$
 (C.5a)

$$= \int \left( r_0 - \frac{(y-x)^2 + 2(y-x)(x-x^{\text{opt}}) + (x-x^{\text{opt}})^2}{V_r} \right) \mathcal{N}(y,x,W) dy$$
 (C.5b)

$$= r_0 - \frac{(x - x^{\text{opt}})^2 + W}{V_r}$$
 (C.5c)

Next, we can compute the population-level rate for a. To do this, we first rewrite the competition kernel  $\alpha$  as

$$\alpha(x,y) = \exp\left(-\frac{(x-y)^2}{2V_c}\right) = \sqrt{2\pi V_c} \mathcal{N}(x,y,V_c)$$
 (C.6)

By a well known result we know that

$$\int \mathcal{N}(x,a,A)\mathcal{N}(x,b,B)dx = \mathcal{N}(a,b,A+B)$$
 (C.7)

which we can now use to calculate population-level competition. We use that the trait-density distribution  $\tilde{v}(x)$  is a sum of normals  $\tilde{v}(x)$  like

$$\tilde{v}(x) = \sum_{j=1}^{S} u_j \mathcal{N}(x, \bar{x}_j, V_j). \tag{C.8}$$

We can now compute the rate  $\hat{a}(x, W, \tilde{v})$ :

$$\hat{a}(x, W, \tilde{v}) = \int a(y, \tilde{v}) \mathcal{N}(y, x, W) dy = \int \int \alpha(z, y) \tilde{v}(z) dz \mathcal{N}(y, x, W) dy$$
 (C.9a)

$$= \int \int \sqrt{2\pi V_c} \mathcal{N}(z, y, V_c) \sum_{i=1}^{S} u_i \mathcal{N}(z, \bar{x}_i, V_j) dz \mathcal{N}(y, x, W) dy$$
 (C.9b)

$$= \sqrt{2\pi V_c} \sum_{j=1}^{S} u_j \int \mathcal{N}(y, \bar{x}_j, V_j + V_c) \mathcal{N}(y, x, W) dy$$
 (C.9c)

$$= \sqrt{2\pi V_c} \sum_{j=1}^{S} u_j \mathcal{N}(x, \bar{x}_j, V_j + V_c + W)$$
 (C.9d)

Finally, we need to compute the population-level birth rate  $\hat{b}$ , which is given by

$$\hat{b}(x,W) = \int b(y)\mathcal{N}(y,x,W)dy = \int r_0 \mathcal{N}(y,x,W)dy = r_0.$$
 (C.10)

Inserting the expressions for the population-level rates and their derivatives yields the equations for the unstructured Lotka-Volterra model shown in the main text (Eq. 10).

Adaptive-dynamics version of the unstructured Lotka-Volterra model

Under the assumptions of adaptive dynamics, each species i is characterized by its density  $u_i$  and its trait value  $\bar{x}_i$ , which is assumed to be the same for all individuals within a species. We can then get the rate functions for the density-dynamics for the adaptive-dynamics case by letting the trait-density distribution of each species be given by

$$v_i^{\rm AD}(x) = u_i \delta(x - \bar{x}_i), \qquad (C.11)$$

where  $\delta$  is the Dirac delta distribution. The total distribution will thus be given by summing over all S species,

$$v^{\text{AD}} = \sum_{i=1}^{S} u_i \delta(x - \bar{x}_i)$$
 (C.12)

Now, letting  $\hat{f}^{AD}(x)$  denote the population-level growth rate of a rare population with trait x, we have

$$\hat{f}^{\text{AD}}(x, v^{\text{AD}}) = \int_{-\infty}^{\infty} f(y, v^{\text{AD}}) \delta(y - x) dy$$
 (C.13)

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We thus have that the environmental rate for the adaptive-dynamics case are given by

$$\hat{r}^{AD}(x) = \int_{-\infty}^{\infty} \left( r_0 - \frac{(y - x^{\text{opt}})^2}{V_r} \right) \delta(y - x) dy = r_0 - \frac{(x - x^{\text{opt}})^2}{V_r}$$
 (C.14)

by the properties of the Dirac delta distribution. The competition can be computed as

$$\hat{a}^{\text{AD}}(x, v^{\text{AD}}) = \int_{-\infty}^{\infty} a(y, v^{\text{AD}}) \delta(y - x) dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \alpha(z, y) v^{\text{AD}}(z) dz \delta(y - x) dy$$

$$= \sqrt{2\pi V_c} \sum_{j=1}^{S} u_j \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathcal{N}(y, z, V_c) \delta(z - \bar{x}_j) dz \delta(y - x) dy$$

$$= \sqrt{2\pi V_c} \sum_{j=1}^{S} u_j \int_{-\infty}^{\infty} \mathcal{N}(y, \bar{x}_j, V_c) \delta(y - x) dy = \sqrt{2\pi V_c} \sum_{j=1}^{S} u_j \mathcal{N}(x, \bar{x}_j, V_c)$$
 (C.15a)

This yields the density dynamics

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$$\frac{du_i}{dt} = \left[\hat{r}^{AD}(\bar{x}_i) - \hat{a}^{AD}(\bar{x}_i, v^{AD})\right] u_i = \left[r_0 - \frac{\bar{x}_i^2}{V_r} - \sqrt{2\pi V_c} \sum_{i=1}^S u_i \mathcal{N}(\bar{x}_i, \bar{x}_j, V_c)\right] u_i$$
 (C.16)

Under the assumptions of adaptive dynamics, mutations are rare and of small phenotypic effect. Under these assumptions one can derive the canonical equations of adaptive dynamics, which describes how the mean traits of the species will change over time (Dieckmann and Law, 1996; Champagnat, 2003). However, since we are primarily interested in the eco-evolutionary equilibrium, we can here use a simplified version where we introduce a parameter  $\epsilon^{\text{evo}}$  which is a small number that characterizes the separation in time scale between ecological and evolutionary dynamics. Doing so yields the complete adaptive-dynamics equations

$$\frac{\mathrm{d}u_{i}}{\mathrm{d}t} = \left[\hat{r}^{\mathrm{AD}}(\bar{x}_{i}) - \hat{a}^{\mathrm{AD}}(\bar{x}_{i}, v^{\mathrm{AD}})\right] u_{i} = \left[r_{0} - \frac{\bar{x}_{i}^{2}}{V_{r}} - \sqrt{2\pi V_{c}} \sum_{j=1}^{S} u_{j} \mathcal{N}(\bar{x}_{i}, \bar{x}_{j}, V_{c})\right] u_{i} \qquad (C.17a)$$

$$\frac{\mathrm{d}\bar{x}_{i}}{\mathrm{d}t} = \epsilon^{\mathrm{evo}} \left[\frac{\partial \hat{r}^{\mathrm{AD}}}{\partial x}(\bar{x}_{i}) - \frac{\partial \hat{a}^{\mathrm{AD}}}{\partial x}(\bar{x}_{i}, v^{\mathrm{AD}})\right] = \epsilon^{\mathrm{evo}} \left[-\frac{2\bar{x}_{i}}{V_{r}} + \sqrt{2\pi V_{c}} \sum_{j=1}^{S} u_{j} \frac{\bar{x}_{i} - \bar{x}_{j}}{V_{c}} \mathcal{N}(\bar{x}_{i}, \bar{x}_{j}, V_{c})\right]$$
(C.17b)

In the adaptive dynamics context, the methods for performing evolutionary-branching and invasion analysis are well established (Metz et al., 1992; Geritz et al., 1998; Edwards et al., 2018; Klausmeier et al., 2020), and we assemble the community one species at a time until the community is uninvasible or use continuation to make bifurcation diagrams.

## The two-patch Lotka-Volterra model

For the two-patch model we consider two spatial patches with trait-density distributions  $v_1(x)$  and  $v_2(x)$ , with trait-space equations given by

$$\frac{\mathrm{d}v_1(x)}{\mathrm{d}t} = \int b_1(y)v_1(y)\mathcal{N}(y,x,M)\mathrm{d}y - \mu_1(x)v_1(x) - a(x,v_1)v_1(x) - dv_1(x) + dv_2(x), \quad \text{(C.18a)}$$

$$\frac{dv_2(x)}{dt} = \int b_2(y)v_2(y)\mathcal{N}(y,x,M)dy - \mu_2(x)v_2(x) - a(x,v_2)v_2(x) + dv_1(x) - dv_2(x), \quad (C.18b)$$

$$b_k(x) = r_0, \quad \mu_k(x) = \frac{(x - x_k^{\text{opt}})^2}{V_r},$$
 (C.18c)

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$$r_k(x) := b_k(x) - \mu_k(x) = r_0 - \frac{(x - x_k^{\text{opt}})^2}{V_r},$$
 (C.18d)

$$a(x,v_k) = \int \alpha(y,x)v_k(y)dy, \quad \alpha(y,x) = \exp\left(-\frac{(y-x)^2}{2V_c}\right). \tag{C.18e}$$

The two-patch model generalizes the unstructured model in that locally on each patch the same dynamics as in the unstructured model takes place, albeit with possibly different trait optima  $x_1^{\text{opt}}$  and  $x_2^{\text{opt}}$ . The patches are then connected by a symmetric and constant rate of dispersal d.

We can then get the moment equations for this model by plugging in the rates into our generic moment equations which yields

$$\frac{\mathrm{d}u_{i1}}{\mathrm{d}t} = \left[\hat{r}_1(\bar{x}_{i1}, V_{i1}) - \hat{a}(\bar{x}_{i1}, V_{i1}, \tilde{v}_1)\right] u_{i1} - du_{i1} + du_{i2},\tag{C.19a}$$

$$\frac{d\bar{x}_{i1}}{dt} = V_{i1} \left[ \frac{\partial \hat{r}_1}{\partial x} (\bar{x}_{i1}, V_{i1}) - \frac{\partial \hat{a}}{\partial x} (\bar{x}_{i1}, V_{i1}, \tilde{v}_1) \right] + \frac{u_{i2}}{u_{i1}} d(\bar{x}_{i2} - \bar{x}_{i1}), \tag{C.19b}$$

$$\frac{\mathrm{d}V_{i1}}{\mathrm{d}t} = V_{i1}^2 \left[ \frac{\partial^2 \hat{r}_1}{\partial x^2} (\bar{x}_{i1}, V_{i1}) - \frac{\partial^2 \hat{a}}{\partial x^2} (\bar{x}_{i1}, V_{i1}, \tilde{v}_1) \right] + \frac{u_{i2}}{u_{i1}} d(V_{i2} - V_{i1}) + \frac{u_{i2}}{u_{i1}} d(\bar{x}_{i2} - \bar{x}_{i1})^2$$

$$+\hat{b}_1(\bar{x}_{i1}, V_{i1})M$$
, (C.19c)

$$\frac{\mathrm{d}u_{i2}}{\mathrm{d}t} = \left[\hat{r}_2(\bar{x}_{i2}, V_{i2}) - \hat{a}(\bar{x}_{i2}, V_{i2}, \tilde{v}_2)\right] u_{i2} + du_{i1} - du_{i2}, \tag{C.19d}$$

$$\frac{d\bar{x}_{i2}}{dt} = V_{i2} \left[ \frac{\partial \hat{r}_2}{\partial x} (\bar{x}_{i2}, V_{i2}) - \frac{\partial \hat{a}}{\partial x} (\bar{x}_{i2}, V_{i2}, \tilde{v}_2) \right] + \frac{u_{i1}}{u_{i2}} d(\bar{x}_{i1} - \bar{x}_{i2}),$$
 (C.19e)

$$\frac{\mathrm{d}V_{i2}}{\mathrm{d}t} = V_{i2}^2 \left[ \frac{\partial^2 \hat{r}_2}{\partial x^2} (\bar{x}_{i2}, V_{i2}) - \frac{\partial^2 \hat{a}}{\partial x^2} (\bar{x}_{i2}, V_{i2}, \tilde{v}_2) \right] + \frac{u_{i1}}{u_{i2}} d(V_{i1} - V_{i2}) + \frac{u_{i1}}{u_{i2}} d(\bar{x}_{i1} - \bar{x}_{i2})^2$$

$$+\hat{b}_2(\bar{x}_{i2}, V_{i2})M. \tag{C.19f}$$

Inserting the expressions for the population-level rates yields the equations in the main text (Eqs. 10).

40 Adaptive-dynamics version of the two-patch Lotka-Volterra model

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For the two-patch adaptive-dynamics model, we proceed in the same way as for the unstructured adaptive-dynamics model. We let  $u_{ik}$  be the density of species i on patch k and let  $\bar{x}_i$  be the trait value of species i. Note that in adaptive dynamics, since all individuals within a species are assumed to be identical the trait value for a species will be the same on both patches. We let the trait-density distribution  $v_k^{AD}(x)$  on patch k be given by

$$v_k^{AD}(x) = \sum_{i=1}^{S} u_{ik} \delta(x - \bar{x}_i).$$
 (C.20)

The expression for the selection gradient needs to take the spatial dynamics into account (see Wickman et al., 2017), and so the equations describing the density and trait dynamics are given by

$$\frac{\mathrm{d}u_{i1}}{\mathrm{d}t} = \left[\hat{r}_1^{\mathrm{AD}}(\bar{x}_i) - \hat{a}^{\mathrm{AD}}(\bar{x}_i, v_1^{\mathrm{AD}})\right] u_{i1} - du_{i1} + du_{i2} \tag{C.21a}$$

$$\frac{\mathrm{d}u_{i2}}{\mathrm{d}t} = \left[\hat{r}_2^{\mathrm{AD}}(\bar{x}_i) - \hat{a}^{\mathrm{AD}}(\bar{x}_i, v_2^{\mathrm{AD}})\right] u_{i2} + du_{i1} - du_{i2} \tag{C.21b}$$

$$\frac{\mathrm{d}\bar{x}_{i}}{\mathrm{d}t} = \epsilon^{\mathrm{evo}} \frac{1}{u_{i1}^{2} + u_{i2}^{2}} \left[ u_{i1}^{2} \left( \frac{\partial \hat{r}_{1}^{\mathrm{AD}}}{\partial x} (\bar{x}_{i}) - \frac{\partial \hat{a}^{\mathrm{AD}}}{\partial x} (\bar{x}_{i}, v_{1}^{\mathrm{AD}}) \right) + u_{i2}^{2} \left( \frac{\partial \hat{r}_{2}^{\mathrm{AD}}}{\partial x} (\bar{x}_{i}) - \frac{\partial \hat{a}^{\mathrm{AD}}}{\partial x} (\bar{x}_{i}, v_{2}^{\mathrm{AD}}) \right) \right]$$
(C.21c)

The community assembly then proceeds by solving the equations to equilibrium and checking for evolutionary branchings and invasions, see Wickman et al. (2017).

## Online Appendix D: A stage-structured resource-competition model

To further illustrate the application and utility of our methods, we present here an additional example of eco-evolutionary community assembly taking intraspecific variation into account. The Lotka-Volterra two-patch model we used to illustrate the generic equations in the main text was deliberately simple. First, it involved only a single trait. Second, the transition between classes (dispersal) was constant, and did not depend on traits. Third, the rate functions were simple enough for us to calculate the population-level rates analytically, and fourth, the model had no dependence on any external variables. However, such simplifications cannot always be made. To demonstrate such a case, we here adapt a model by De Roos et al. (2007) of a population subdivided into two stages, juveniles with trait-density distribution  $v_I$  and adults with trait-density distribution  $v_A$ , competing for two resources  $R_1$  and  $R_2$ . Both the maturation rate and the birth rate depend on how much resources the two stages acquire, as well as the traits associated with resource acquisition.

The trait-space equations read

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$$\frac{\mathrm{d}v_J(x,t)}{\mathrm{d}t} = \int r_A(y)v_A(y)\mathcal{N}(x,y,M)\mathrm{d}y + (r_J(x) - \mu_J(x))v_J(x) - \gamma(x)v_J(x), \tag{D.1a}$$

 $\frac{\mathrm{d}v_A(x,t)}{\mathrm{d}t} = \gamma(x)v_J(x) - \mu_A(x)v_A(x), \tag{D.1b}$ 

$$\frac{dR_1(t)}{dt} = \rho_1(K_1 - R_1) - \int r_{J1}(y)v_J(y)dy - \int r_{A1}(y)v_A(y)dy,$$
 (D.1c)

$$\frac{dR_2(t)}{dt} = \rho_2(K_2 - R_2) - \int r_{J2}(y)v_J(y)dy - \int r_{A2}(y)v_A(y)dy,$$
 (D.1d)

where the rate functions are given by

$$r_I(x) = q_I \frac{a_{I1}(x)R_1 + a_{I2}(x)R_2}{1 + a_{I1}(x)R_1 + a_{I2}(x)R_2},$$
(D.2a)

$$r_{Ij}(x) = q_I \frac{a_{Ij}(x)R_j}{1 + a_{I1}(x)R_1 + a_{I2}(x)R_2} \quad I \in \{J, A\}, j \in \{1, 2\},$$
 (D.2b)

$$\gamma = \frac{r_J(x) - \mu_J(x)}{1 - z^{1 - \mu_J(x)/r_J(x)}},$$
(D.2c)

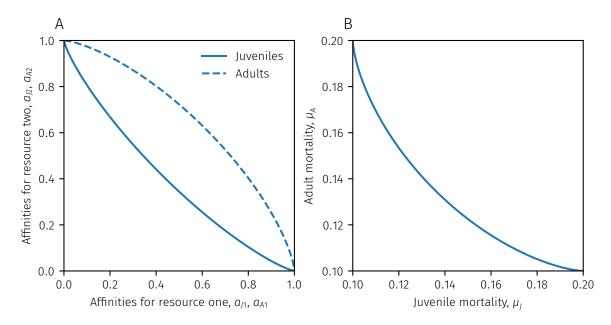
$$a_{J1}(x) = \left(\frac{e^x}{1 + e^x}\right)^{\alpha_J}, \qquad a_{J2} = \left(1 - \frac{e^x}{1 + e^x}\right)^{\alpha_J},$$
 (D.2d)

$$a_{A1}(x) = \left(\frac{e^x}{1 + e^x}\right)^{\alpha_A}, \qquad a_{A2} = \left(1 - \frac{e^x}{1 + e^x}\right)^{\alpha_A},$$
 (D.2e)

Here, the distributions  $v_J(x)$  and  $v_A(x)$  characterize the distributions of biomass density in trait space for juveniles and adults respectively. Both adults and juveniles consume the substitutable resources  $R_1$  and  $R_2$  with a type-II functional response at rates  $r_{Ij}$  for I = A, J, and j = 1, 2.

The adults use all of their intake of resources  $R_1$  and  $R_2$  to give birth to juveniles at a per capita rate of  $r_A = r_{A1} + r_{A2}$ , and suffer a mortality at a per capita rate of  $\mu_A$ . Juveniles grow at a per capita rate  $r_J = r_{J1} + r_{J2}$ , suffer a mortality rate of  $\mu_J$ , and transition into adults at a rate  $\gamma$  that depends both on juvenile growth and mortality (De Roos et al., 2007). In the absence of consumers, the resources are renewed chemostatically at rates  $\rho_j$  up to maximal supplies of  $K_j$  for resource j.

We let the trait vector  $x = (x_1, x_2) \in \mathbb{R}^2$ . The first trait  $x_1$  parameterizes trade-offs in resource affinities, so that juveniles experience a trade-off between their affinities  $a_{J1}$  and  $a_{J2}$  for  $R_1$  and  $R_2$  respectively, and adults experience a trade-off between their affinities  $a_{A1}$  and  $a_{A2}$ . While the same trait component  $x_1$  parameterizes the trade off in resource affinity for both juveniles and adults, we let the shapes differ so that the juveniles experience a specialist-favoring trade-off while adults experience a generalist-favoring trade-off (Fig. D.1A). Such differences could come about as foraging behavior changes between life stages. The second trait  $x_2$  parameterizes a trade-off between juvenile mortality  $\mu_J$  and adult mortality  $\mu_A$  (Fig. D.1B). Such trade-offs between juvenile and adult mortality could come about through, e.g., parental investment or risk taking on behalf of juveniles.



**Figure D.1:** Trade-offs in the stage-structured model. (A) Trade-offs in resource affinities  $a_{J1}$  and  $a_{J2}$  for juveniles (solid line) and  $a_{A1}$  and  $a_{A2}$  for adults (dashed line). Juveniles experience a specialist-favoring trade-off, and adults experience a generalist-favoring trade-off. (B) Trade-off between juvenile and adult mortality. The trade-off between the mortalities is generalist-favoring.

Following our general procedure, to get our moment equations we now assume that the solutions to Eqs. D.1a–b are composed of a set of *S* normally distributed discrete peaks for both juveniles and adults, and approximate the solutions by

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$$v_J(x,t) \approx \tilde{v}_J(x,t) = \sum_{i=1}^S u_{Ji}(t) \mathcal{N}(x, \bar{x}_{Ji}(t), V_{Ji}(t)), \qquad (D.3a)$$

$$v_A(x,t) \approx \tilde{v}_A(x,t) = \sum_{i=1}^{S} u_{Ai}(t) \mathcal{N}(x, \bar{x}_{Ai}(t), V_{Ai}(t))$$
. (D.3b)

This means that each species i = 1, 2, ..., S is represented by six variables: the total densities of juveniles,  $u_{Ji}$ , and adults,  $u_{Ai}$ ; the mean trait vector for juveniles,  $\bar{x}_{Ji}$ , and adults  $,\bar{x}_{Ai}$ ; and the trait variance-covariance matrices for juveniles,  $V_{Ji}$ , and adults,  $V_{Ai}$ . To be able to write down our moment equations we must first deal with the population-level rate functions. For this example it is not possible to analytically calculate the population-level rates given by, for example,

$$\hat{\gamma}(x,W) = \int \gamma(y) \mathcal{N}(y,x,W) dy$$
 (D.4)

Instead, we Taylor-approximate the various rates to third order using the expressions derived in

Appendix A, section *Series solutions and Taylor approximations*, so that our various population-level rates and their derivatives will be given by

$$\hat{f}(x,W) \approx f(x) + \frac{1}{2}\nabla_x^2 f(x) : W, \qquad (D.5a)$$

$$\nabla_x \hat{f}(x, W) \approx \nabla_x f(x) + \nabla_x \left(\frac{1}{2} \nabla_x^2 f(x) : W\right),$$
 (D.5b)

$$\nabla_x^2 \hat{f}(x, W) \approx \nabla_x^2 f(x)$$
. (D.5c)

Here, ":" denotes the double-dot product, which for two square  $N \times N$  matrices A and B with entries  $A_{ij}$  and  $B_{ij}$  is given by  $A: B = \sum_{i=1}^{N} \sum_{j=1}^{N} A_{ij} B_{ij}$ . To make the moment equations more readable we will also omit the arguments of the rate functions below, and so we shall write for example

$$\hat{\gamma}_i := \hat{\gamma}(\bar{x}_{Ji}, V_{Ji}) + \frac{1}{2} \nabla_x^2 \gamma(\bar{x}_{Ji}) : V_{Ji},$$
 (D.6a)

$$\nabla_x \hat{\gamma}_i := \nabla_x \gamma(\bar{x}_{Ji}) + \left[ \nabla_x \left( \frac{1}{2} \nabla_x^2 \gamma(x) : V_{Ji} \right) \right]_{x = \bar{x}_{Ji}}, \tag{D.6b}$$

$$\nabla_x^2 \hat{\gamma}_i := \nabla_x^2 \gamma(\bar{x}_{Ji}), \tag{D.6c}$$

$$\hat{r}_{Ai} := r_A(\bar{x}_{Ai}) + \frac{1}{2} \nabla_x^2 r_A(\bar{x}_{Ai}) : V_{Ai}$$
(D.6d)

$$\nabla_x \hat{r}_{Ai} := \nabla_x r_A(\bar{x}_{Ai}) + \left[ \nabla_x \left( \frac{1}{2} \nabla_x^2 r_A(x) : V_{Ai} \right) \right]_{x = \bar{x}_{Ai}}, \tag{D.6e}$$

$$\nabla_x^2 \hat{r}_{Ai} := \nabla_x^2 r_A(\bar{x}_{Ai}), \tag{D.6f}$$

and so on.

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We can now derive the moment equations for the stage-structured model by plugging in the expressions for the trait-space equations for this model into our generic equations (Eq. A.28, Appendix A) yielding

$$\frac{\mathrm{d}u_{Ji}}{\mathrm{d}t} = \hat{g}_{Ji}u_{Ji} - \hat{\gamma}_i u_{Ji} + \hat{r}_{Ai}u_{Ai},\tag{D.7a}$$

$$\frac{\mathrm{d}\bar{x}_{Ji}}{\mathrm{d}t} = V_{Ji}(\nabla_x \hat{g}_{Ji} - \nabla_x \hat{\gamma}_i) + \frac{u_{Ai}}{u_{Ii}} \left( V_{Ai} \nabla_x \hat{r}_{Ai} + \hat{r}_{Ai} (\bar{x}_{Ai} - \bar{x}_{Ji}) \right) , \tag{D.7b}$$

$$\frac{\mathrm{d}V_{Ji}}{\mathrm{d}t} = V_{Ji}(\nabla_x^2 \hat{g}_{Ji} - \nabla_x^2 \hat{\gamma}_i)V_{Ji}$$

$$+ \frac{u_{Ai}}{u_{Ji}} \left( V_{Ai} \nabla_{x}^{2} \hat{r}_{Ai} V_{Ai} + \hat{r}_{Ai} \left( V_{Ai} - V_{Ji} \right) + \hat{r}_{Ai} M \right.$$

$$+ \hat{r}_{Ai} (\bar{x}_{Ai} - \bar{x}_{Ji}) (\bar{x}_{Ai} - \bar{x}_{Ji})^{T}$$

$$+ V_{Ai} \nabla_{x} \hat{r}_{Ai} (\bar{x}_{Ai} - \bar{x}_{Ji})^{T} + (\bar{x}_{Ai} - \bar{x}_{Ji}) (V_{Ai} \nabla_{x} \hat{r}_{Ai})^{T} \right), \qquad (D.7c)$$

$$\frac{\mathrm{d}u_{Ai}}{\mathrm{d}t} = \hat{\gamma}_i u_{Ji} - \hat{\mu}_{Ai} u_{Ai},\tag{D.7d}$$

$$\frac{\mathrm{d}\bar{x}_{Ai}}{\mathrm{d}t} = \frac{u_{Ji}}{u_{Ai}} \left( V_{Ji} \nabla_x \hat{\gamma}_i + \hat{\gamma}_i (\bar{x}_{Ji} - \bar{x}_{Ai}) \right) - V_{Ai} \nabla_x \hat{\mu}_{Ai}, \tag{D.7e}$$

$$\frac{\mathrm{d}V_{Ai}}{\mathrm{d}t} = \frac{u_{Ji}}{u_{Ai}} \left( V_{Ji} \nabla_x^2 \hat{\gamma}_i V_{Ji} + \hat{\gamma}_i (V_{Ji} - V_{Ai}) \right)$$

$$+ \hat{\gamma}_i (\bar{x}_{Ji} - \bar{x}_{Ai}) (\bar{x}_{Ji} - \bar{x}_{Ai})^T + V_{Ji} \nabla_x \hat{\gamma}_i (\bar{x}_{Ji} - \bar{x}_{Ai})^T + (\bar{x}_{Ji} - \bar{x}_{Ai}) (V_{Ji} \nabla_x \hat{\gamma}_i)^T$$

$$-V_A \nabla_x^2 \hat{\mu}_{Ai} V_A$$
, (D.7f)

$$\frac{\mathrm{d}R_1}{\mathrm{d}t} = \rho_1(K_1 - R_1) - \sum_{i=1}^{S} \hat{r}_{Ji1} u_{Ji} - \sum_{i=1}^{S} \hat{r}_{Ai1} u_{Ai},$$
 (D.7g)

$$\frac{\mathrm{d}R_2}{\mathrm{d}t} = \rho_2(K_2 - R_2) - \sum_{i=1}^{S} \hat{r}_{Ji2} u_{Ji} - \sum_{i=1}^{S} \hat{r}_{Ai2} u_{Ai}. \tag{D.7h}$$

Here, we let  $g_{Ji}$  be the net per capita growth of juveniles, i.e.,  $g_{Ji} = r_{Ji} - \mu_{Ji}$ . While somewhat involved, the various terms admit to ecological interpretation, and can be understood in the following way.

The terms of Eq. D.7a describe in turn: net growth in mass of juveniles, the removal of juveniles that transition into adults, and the addition of mass due to birth by adults.

The changes to the mean trait vector of the juveniles  $\bar{x}_{Ji}$  (Eq. D.7b) are divided into two terms. The first, with a matrix factor  $V_{Ji}$ , describes how directional selection on the juvenile processes of net growth and transition to adulthood moves the mean trait of the juveniles. This is because juveniles with certain traits will have higher net growth than others, and this will push the mean trait of juveniles in the direction of the gradient  $\nabla_x \hat{g}_i$ . Conversely, some juveniles with certain traits will mature into adulthood more quickly than others, which removes them from the juveniles and thus moves the mean trait in the opposite direction of the gradient  $\nabla_x \hat{\gamma}_i$ . The

strength of both these effects depends on the how much variation  $V_{Ii}$  there is for a given species i. The second term, with a scalar factor  $u_{Ai}/u_{Ii}$  describes the influence of births from the adults on the mean trait of the juveniles. This is, in turn, composed of two terms. The first term,  $V_{Ai}\nabla_x\hat{r}_{Ai}$ , describes how directional selection in the birth rate of juveniles by adults contributes towards 1860 change of juvenile mean traits. This effect comes about since adults with different traits give birth at different rates, and more offspring will be produced along the direction of the gradient  $\nabla_x \hat{r}_{Ai}$ . This effect is stronger if the variation among the adults  $V_{Ai}$  is larger. The second term,  $\hat{r}_{Ai}(\bar{x}_{Ai}-\bar{x}_{Ji})$ , describes how the juvenile mean trait is pushed in the direction of the adult mean trait, homogenizing juvenile and adult mean traits. This is due to the fact that adults of species i will on average give birth to juveniles with trait  $\bar{x}_{iA}$ , and so, if there is a difference between 1866 juvenile and adult mean trait, the juvenile trait will become more similar to the adult mean trait over time. The overall factor  $u_{Ai}/u_{Ji}$  comes about through the fact that how much effect birth of juveniles by adults has on the juvenile mean trait depends on the mass ratio between the two 1869 stages. If there are few adults compared to juveniles, then the birth of new juveniles will have little effect on the mean trait of all the juveniles.

Equation D.7c describes the changes to the variance-covariance matrix of the juveniles over time. The first term,  $V_{Ji}(\nabla^2_x g_{Ji} - \nabla^2_x \gamma_i)V_{Ji}$ , describes the effects of stabilizing or disruptive selection of the net growth and transitions. Thus, for example, if the curvature of the net growth function,  $\nabla^2_x g_{Ji}$ , is negative around a mean trait component, this will reduce the variance of that trait component over time. There are then several terms with a factor  $u_{Ai}/u_{Ji}$ . The first term,  $V_{Ai}\nabla^2_x r_{Ai}V_{Ai}$ , reflects the effects of stabilizing or disruptive selection in the birth rates. The second term,  $\hat{r}_{Ai}(V_{Ai} - V_{Ji})$ , describes the homogenization of variance-covariance matrices between the stages, so that this term changes the juvenile variance-covariance to be more similar to that of the adults over time. The third term,  $\hat{r}_{Ai}M$ , describes the increase to juvenile trait variances due to mutations. Next, the term  $\hat{r}_{Ai}(\bar{x}_{Ai} - \bar{x}_{Ji})(\bar{x}_{Ai} - \bar{x}_{Ji})^T$  describes how variances are increased, and covariances changed over time due to differences in means between the juveniles and adults. This reflects that if the means of the adults are away from the means of the juveniles, then birthed

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juveniles will be away from the mean of the extant juveniles, and thus increase variance. The next two terms,  $V_{Ai}\nabla_x r_{Ai}(\bar{x}_{Ai} - \bar{x}_{Ji})^T + (\bar{x}_{Ai} - \bar{x}_{Ji})(V_{Ai}\nabla_x r_{Ai})^T$ , which are the transposes of one another, take into account the interaction of distance between the means of the stages and effects of directional selection in the birth rates.

The terms in the equations for the adults are mostly analogous to those for the juveniles, with the difference that the maturation function  $\gamma$  now plays the role that the birth rate function  $r_A$  did for the juveniles, as this is the function that determines the rate of transition from the juvenile to the adult stage. Additionally, as we can see in the trait-space equations (Eqs. D.1), we assume that a juvenile with trait x matures into an adult with the same trait x, and thus no mutation term enters into the equations for adult variance-covariance. Finally, we approximate the integrals in trait space in the resource equations (Eqs. D.1c–d) in the same way as we do for the other rates by Taylor-expanding to third order.

Using these equations we let the population go through our evolutionary assembly process (Fig. D.2A). The traits  $x_1$  and  $x_2$  parameterize the trade-offs in resource affinities and mortalities respectively. However, as the traits that actually matter for the ecology are the affinities and mortalities themselves, we depict this assembly process in the derived trait space of  $(a_{I1} - a_{I2}) \times (\mu_I - \mu_A)$  for I = J, A to get a better understanding of how the expressed traits that impact the ecology change. The final community of one moderate  $R_1$  specialist and one moderate  $R_2$  specialist comes about through the conflicting trade-offs for juveniles and adults. The specialist-favoring trade-off in resource affinity for the juveniles engenders selective pressure towards specialization into two species, but the generalist-favoring trade-off for the adults will eventually counter balance this disruptive force, and the community will settle on substantial, but not complete, specialization for both species. The differences between juveniles and adults in their resource affinities seen in Fig. D.2A stem mostly from their their different trade-offs; the mean traits  $\bar{x}_J$  and  $\bar{x}_A$  differ little within the same species. The distributions in  $x_1 \times x_2$  space can be seen in Fig. D.3, where we also compare the numerical moment solutions for the ecoevolutionarily stable two-species community to numerical solutions of the trait-space equations.

Solving the trait-space equations Eq. D.1 for this system with these given parameters would require an unfeasible numerical resolution in trait space. However, since the mutation variance-covariance matrix is very small, without covariance, and with the same variances, we can approximate the birth/mutation integral with a diffusion term in the following way (Kimura, 1965; Débarre et al., 2013):

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$$\int r_A(y)v_A(y)\mathcal{N}(x,y,M)\mathrm{d}y \approx r_A(x)v_A(x) + \frac{M_{11}}{2}\Delta_x(r_A(x)v_A(x)), \tag{D.8}$$

where  $\Delta_x = \frac{\partial^2}{\partial x_1^2} + \frac{\partial^2}{\partial x_2^2}$  is the Laplacian in trait space. We discretize two-dimensional trait space into an equispaced grid of  $256 \times 256$  points with  $x_1, x_2 \in [-4, 4]$ , and approximate the Laplacian with a central-difference approximation. We then used the DifferentialEquations.jl library (Rackauckas and Nie 2017) in Julia (Bezanson et al. 2017) to solve the semi-discretized ordinary differential equations to equilibrium. Both trait-space equations and moment equations were solved to equilibrium.

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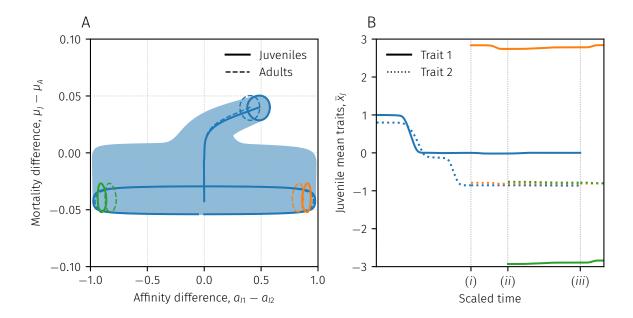


Figure D.2: Community assembly in the stage-structured example. (A) Depiction of the assembly process and final eco-evolutionary equilibrium in the derived trait space  $(a_{I1} - a_{I2}) \times (\mu_J - \mu_A)$  for I = J, A. The eco-evolutionary process is started towards the top-right corner, where the evolutionary paths of the mean derived traits  $a_{I1} - a_{I2}$  and  $\mu_J - \mu_A$  are depicted as a solid blue line for juveniles and broken blue line for adults. The 95% transformed confidence ellipse for the juveniles is depicted at each time-point around the means in lighter color. The evolutionary process continues until the system reaches a one-species equilibrium. The 95% transformed confidence ellipses are shown as a solid blue ellipse (juvenile) and dashed blue ellipse (adult). This one-species equilibrium is subsequently invaded by two specialist species, and the final two-species equilibrium is depicted in orange and green. (B) Evolution and assembly of juvenile mean traits over time. Trait 1 (solid line) governs the resource-affinity trade-off and trait 2 (dotted line) governs the juvenile-adult mortality trade-off. The process starts with one species reaching an eco-evolutionary equilibrium, but is invaded by species two (orange) at (i). The two-species community subsequently reaches an eco-evolutionary equilibrium, which is in turn invaded by a third species (green) at (ii). With two specialists to compete with, the generalist species (blue) cannot persist and goes extinct at (iii). The new two-species community then evolves to a new equilibrium which is stable to further invasion, and the assembly process is complete. Time has been rescaled non-uniformly to illustrate the process.



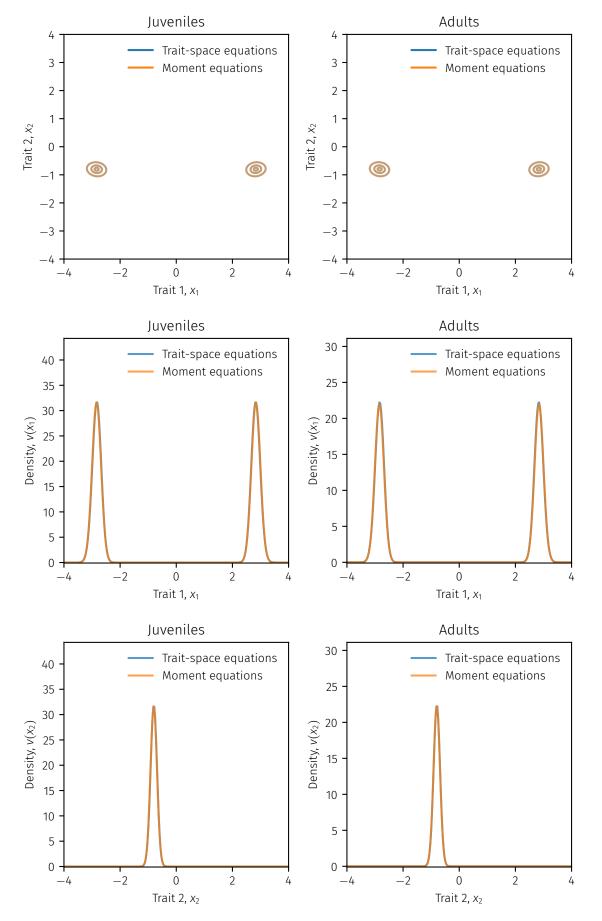


Figure D.3: Comparison of trait-space equations and moment equations for the stage-structured model. Top row shows contour lines for the trait-space and moment equation solutions at eco-evolutionary equilibrium. The contour lines are very nearly on top of each other. The bottom four panels show slices in the  $x_1$  and  $x_2$  directions, where both slices are made across the global density maximum of the trait-space solution. The curves are very nearly on top of each other.

Symbol	Description	Value	
$ ho_1$	Resource 1 renewal rate	1.0	
$ ho_2$	Resource 2 renewal rate	1.0	
$K_1$	Resource 1 supply	1.0	
$K_2$	Resource 2 supply	1.0	
$q_J$	Juvenile conversion efficiency	1.0	
$q_A$	Adult conversion efficiency	1.0	
z	Juvenile to adult size ratio	0.3	
$\mu_{0J}$	Juvenile base mortality	0.1	
$\mu_{0A}$	Adult base mortality	0.1	
$\alpha_J$	Juvenile resource trade-off shape parameter	1.3	
$\alpha_A$	Adult resource trade-off shape parameter	0.7	
$\alpha_{\mu}$	Juvenile-adult mortality trade-off shape parameter	1.5	
M	Mutation variance-covariance matrix	$10^{-5} \begin{bmatrix} 1.0 & 0.0 \\ 0.0 & 1.0 \end{bmatrix}$	

Table D.1: Parameter values used for numerical solutions of the stage-structured example.

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