Trait-Based Approaches to Plankton Ecology

Christopher A Klausmeier

Elena Litchman

Kellogg Biological Station Michigan State University

NPZ



Plankton Functional Groups





Continuum of Strategies



Continuum of Strategies



Trait-Based Approach

- 1. Ecologically relevant traits
- 2. Trade-offs between these traits
- 3. Mechanistic models of population interactions
- 4. Fitness
- 5. Source of novel phenotypes



N P N Si Fe N P



reproduction resource acquisition Si Fe Ν Ρ Ν N Ρ predator avoidance



1) Ecologically relevant traits

Ecological function



Nutrient Utilization Traits



Traits:

 μ_{∞} , growth rate at infinite quota Q_{min} , minimum internal nutrient content Q_{max} , maximum internal nutrient content V_{max} , maximum uptake rate of nutrient K, half-saturation constant for nutrient uptake

Light Utilization Traits



Traits:

 μ_{max} , maximum growth rate α , initial slope of the growth-irradiance curve I_{opt} , growth saturation irradiance

2) Trade-offs between traits

- Allocation of finite resources / time
- Physical / genetic constraints

3) Mechanistic models of population interactions

$$\frac{dP}{dt} = rP\left(1 - \frac{P}{K}\right) - f(P)Z \qquad \frac{\partial b}{\partial t} = \min(f_R(R), f_I(I))b - mb + D\frac{\partial^2 b}{\partial z^2} + \frac{\partial}{\partial z}\left(v\left(\frac{\partial g}{\partial z}\right)b\right)$$
$$\frac{\partial R}{\partial t} = ef(P)Z - mZ \qquad \frac{\partial R}{\partial t} = -\frac{b}{Y}\min(f_R(R), f_I(I)) + D\frac{\partial^2 R}{\partial z^2}$$
$$I(z) = I_{\rm in}e^{-\int_0^z (a_{\rm bg} + ab(Z))\,dZ}$$

- Spatial / temporal heterogeneity
- Age / size structure

4) Fitness

Growth rate of a rare species trying to invade a resident community (dominant eigenvalue, Floquet exponent, Lyapunov exponent)

(Metz, Nisbet & Geritz 1992)

5) Source of novel phenotypes

- Standing genetic variation
- Rare mutation
- Immigration
- Everything is everywhere

Linking traits and community structure

• Fitness = growth rate = g(E,traits)



Frequency-independent: maximize growth rate

Linking traits and community structure

 Interspecific interactions: species affect environment too: E(traits, abundances)



Frequency-dependent

Simplest case: resource competition

Minimize break-even nutrient concentration, *R** (Tilman 1982)

$$R^{*} = \frac{K\mu_{\infty}Q_{\min}m}{V_{\max}(\mu_{\infty}-m)-\mu_{\infty}Q_{\min}m}$$

 R^* decreases (competitive ability increases) when

 $\begin{array}{c} \mu_{\infty} \text{ (growth at max Q)} \\ V_{\text{max (max uptake rate)}} \end{array}$

•K (half-saturation constant)
•Q_{min (min quota)}
•M (mortality)

Ex 1: Optimal N:P Ratios



Ex 1: Optimal N:P Ratios

- Cell is made up of different types of machinery and factory walls
 - Uptake machinery, R_u per carbon
 - Assembly machinery, R_a per carbon
- Each component has its own N:P stoichiometry (N_x, P_x)
- Uptake machinery should be N-rich (proteins/ chloroplasts)
- Assembly machinery should be N- and P-rich (ribosomes)[Growth Rate Hypothesis]
- Trade-off between uptake and assembly machinery



Ex 1: Optimal N:P Ratios



General case

 $\frac{dN_i}{dt} = g(x_i; \vec{N}, \vec{x})N_i$

(Geritz et al. 1998 Evol Ecol)



(Geritz et al. 1998, Evol. Ecol)

General case





(Geritz et al. 1998, Evol. Ecol)



Pairwise invasibility plots (PIPs)



resident trait (Geritz et al. 1998, Evol. Ecol)

Eightfold classification



Eightfold classification



Eightfold classification





The Big Questions

- How do community structure (diversity, species traits) and ecosystem functions depend on abiotic environmental parameters?
- How will ecosystems reorganize in the face of human impacts?



environmental parameter
Ex 2: Diatom Size Evolution



(Litchman et al, 2009 PNAS)

Exponential growth and equilibrium



(Litchman et al, 2009 PNAS)





(Litchman et al, 2009 PNAS)

Other aquatic examples

- Follows et al. 2007 Science optimum temperature and irradiance in a global ocean model
- Bruggeman and Kooijman 2007 L&O light vs nutrient competitive ability in a seasonal 1D water column
- Clark et al. 2013 L&O cell size in a global ocean model

Trait-Based Approaches...

- Are agnostic on level of adaptation
 - Species sorting (community assembly)
 - Microevolution
 - Physiological / behavioral
- Offer new perspectives on
 - Neutral vs. niche
 - Species coexistence

Robustness of Coexistence Mechanisms



(Geritz et al. 1998, Evol. Ecol)

Robustness of Coexistence Mechanisms



(Geritz et al. 1998, Evol. Ecol)

Robustness of Coexistence Mechanisms



⇒ Ecological coexistence does not imply evolutionary coexistence! (Geritz et al. 1998, Evol. Ecol)

Resource acquisition trade-off



(after Tilman 1982; Klausmeier et al. 2007)

Resource acquisition trade-off



(after Tilman 1982; Klausmeier et al. 2007)

Competition–predator resistance trade-off



(after Leibold 1996)

Competition–predator resistance trade-off



(after Leibold 1996)

Competition–predator resistance trade-off



- At equilibrium, only one species survives
- Trade-off: growth rate vs. equilibrium competitive ability



Seasonal Forcing





(Litchman & Klausmeier 2001 Am Nat)



(Kremer & Klausmeier in press J Theor Bio)



Mechanism 4) Light–nutrient tradeoff in poorly-mixed water column



Fitness in a Spatially Variable Environment

 $\frac{1}{n}\frac{\partial n}{\partial t} = g(x) + D\frac{\partial^2}{\partial z^2}$ $\lambda(x) = \text{dominant eigenvalue}$ $\text{of } \frac{1}{n}\frac{\partial n}{\partial t}$



Fitness in a Spatially Variable Environment

 $\frac{1}{n}\frac{\partial n}{\partial t} = g(x) + D\frac{\partial^2}{\partial z^2}$ $\lambda(x) = \text{dominant eigenvalue}$ $\text{of } \frac{1}{n}\frac{\partial n}{\partial t}$ $\frac{d\lambda}{dx} = 0 \Rightarrow \text{singular strategy}$



Fitness in a Spatially Variable Environment

 $\frac{1}{n}\frac{\partial n}{\partial t} = g(x) + D\frac{\partial^2}{\partial z^2}$ $\lambda(x)$ = dominant eigenvalue of $\frac{1}{n} \frac{\partial n}{\partial t}$ $\frac{d\lambda}{dx} = 0 \Rightarrow \text{singular strategy}$ $\frac{d\lambda}{dx} = \frac{\int \frac{\partial g}{\partial x} n^2}{\int n^2}$











-

Interplay between evolution and species sorting



Where σ is the "evolution rate"

(Kremer & Klausmeier in press J Theor Bio)



Time Series Examples: Branching Point **Evolution rate**

(Kremer & Klausmeier in press J Theor Bio)



Time Series Examples: Single Species ESS

Evolution rate large (1.0)

^{me} (Kremer & Klausmeier *in press* J Theor Bio)

Increased evolution rate prevents species coexistence



$$\begin{aligned} \frac{\partial N_i}{\partial t} &= g_i N_i + \frac{1}{2} V_i \frac{\partial^2 g_i}{\partial z^2} \Big|_{z=\bar{z}_i} N_i + D \frac{\partial^2 N_i}{\partial x^2} \\ &= \begin{bmatrix} \text{population} \\ \text{dynamics} \end{bmatrix} + \begin{bmatrix} \text{genetic} \\ \text{load} \end{bmatrix} + \begin{bmatrix} \text{dispersal} \end{bmatrix} \\ \frac{\partial \bar{z}_i}{\partial t} &= V_i \frac{\partial g_i}{\partial z} \Big|_{z=\bar{z}_i} + D \left(\frac{\partial^2 \bar{z}_i}{\partial x^2} + 2 \frac{\partial \log N_i}{\partial x} \frac{\partial \bar{z}_i}{\partial x} \right) \\ &= \begin{bmatrix} \text{directional} \\ \text{selection} \end{bmatrix} + \begin{bmatrix} \text{gene} \\ \text{flow} \end{bmatrix} \end{aligned}$$

(Case and Taper 2000)





space, x

(Norberg, Klausmeier, Urban, Vellend unpublished)



(Norberg, Klausmeier, Urban, Vellend unpublished)



(Norberg, Klausmeier, Urban, Vellend unpublished)

Scaling Up to Complex Communities

- 1. Food webs
- 2. Species abundance distributions

Traits in a Food Web Perspective


Traits in a Food Web Perspective



Nutrients

(With Helene Weigang & Ken Andersen)

Species Abundance Distributions (SADs)

- "Vector of the abundances of all species present in a community" (unlabeled)
- Intermediate-complexity description of diversity

Three Ways to Look at SADs



Three Ways to Look at SADs

(b) Preston plot



Three Ways to Look at SADs



Table 2 Dozens of theories attempting to explain (and in most cases provide a mechanism to) the hollow curve SAD exist. This table briefly summarizes them and organizes them into related families. For a similar analysis performed a few years earlier see Marquet et al. (2003) Table 2 (continued)

Family	SAD	Comments	Family	SAD	Comments
Purely statistical	1. Logseries	Fisher <i>et al.</i> (1943) used a gamma distribution to describe the underlying 'true' abundance for purely empirical reasons, and then using the gamma random variable as the parameter of a Poisson distribution to describe the discrete samples that occur in finite real world samples gives a negative binomial distribution (which he then truncates the 0-abundance category and takes a limit). Boswell & Patil (1971)		 Stochastic single species Logistic-J 	Population dynamic models with stochastic noise can produce hollow curve SADs (Tuljapurkar 1990; Engen & Lande 1996a; Diserud & Engen 2000; Engen <i>et al.</i> 2002). Most of these models produce either a lognormal or a gamma distribution under quite general conditions on the population dynamics (Dennis & Patil 1984, 1988) Dewdney (2000) has developed a simulation of random encounters and random transfer of rescurses that produces what he colle the
	2. Negative binomial	Brian (1953) is one of the few people to use the seemingly obvious	Population dynamics	17 Noveral	logistic-J SAD.
	3. Gamma	negative binomial (usually 0-truncated) A variety of population dynamic models lead to a gamma distribution (Dennis & Patil 1984; Engen & Lande 1996a; Diserud & Engen 2000), which seems to fit some data well (Plotkin & Muller-Landau 2002)	(Neutral model subfamily)	18. Coolescent peutral	version of a random walk or drift) to produce SADs has excited much attention (Chave 2004; Alonso <i>et al.</i> 2006; McGill <i>et al.</i> 2006b). Bell (2000, 2001, 2003) and Hubbell (1979, 2001) have pushed this idea extensively recently, but it was shown much earlier by Caswell (1976) and Watterson (Watterson 1974) that with or without zero-sum dynamics neutral drift produces realistic SADs (Etienne <i>et al.</i> 2007a).
	4. Gamma-binomial or Gambin	Compounding the gamma with a binomial sampling process (cf. the Poisson compounded with the gamma to produce the logseries) gives a one parameter distribution where the single parameter seems to be			
Purely statistical (lognormal subfamily)	5. Lognormal I – Preston's	a good measure of the environmental complexity (Ugland <i>et al.</i> 2007) A discretized version of the lognormal (Preston 1948; Hubbell 2001) is		theory	2005) has shown that neutral population dynamics have some similarities to the branching processes described above.
	discrete, binned approximation	probably no longer justified given modern computing power	Niche partitioning	19. Geometric or niche preemption	Motomura (1932) used a model where each species takes a constant fraction of the remaining resources.
	6. Lognormal II – true continuos lognormal	The original lognormal (Galton 1879; McAlister 1879; Evans <i>et al.</i> 1993) which has received extensive application to ecology (Gray 1979; Dennis & Patil 1984, 1988; McGill 2003c)		20. Broken stick	MacArthur (1957, 1960) developed the opposite model where the niche space is broken up simultaneously and with random fractions and is known as the broken stick model. This model has the distinction of being one of the very few SAD models ever developed to have been strongly rejected by its inventor (MacArthur 1966; 'Let us hope these comments do not draw additional attention to what is now an obsolete approach to community ecology, which should be allowed to die a natural death.). Cohen (1968) showed that the same math of the
	7. Lognormal III – left truncated (veiled) lognormal	As in number 6, but with left truncation (Cohen 1949) to match Preston's idea of unveiling. Has rarely been used in practice (and which in fact usually does not fit the data as well as the untruncated version McGill 2003a)			
	8. Lognormal IV – Poisson lognormal	Mixes the lognormal with the Poisson (cf. the logseries which mixes the gamma and the Poisson; Bulmer 1974; Kempton & Taylor 1974).		04 C 1	broken stick could be produced by an exactly opposite set of biological assumptions from those of MacArthur.
		Requires an iterative likelihood method on a computer to fit which is often not available in standard statistical packages (Yin <i>et al.</i> 2005), and is sometimes confusingly called a truncated lognormal (Kempton &		21. Sugihara	Sughara (1980) crossed Motomura's (1952) and MacArthur's (1957) models by breaking the stick randomly but in sequential fashion. Nee <i>et al.</i> (1991) showed this produced realistic left skew.
	9. Lognormal V – Delta	Taylor 1974; Connolly <i>et al.</i> 2005). A mixture of the continuous lognormal and a Bernoulli variable to		22. Random fraction	Tokeshi (1993, 1996) has since developed a variety of niche apportionment models with various combinations of models 19–21.
Branching process	lognormal 10. Generalized Yule	allow zeros to occur with a probability P (Dennis & Patil 1984, 1988) Yule (1924) applied what is now known as the Galton-Watson branching process to model the number of species within a genus (which has a	Spatial distribution	23. Spatial stick breaking24. Continuum	Marquet <i>et al.</i> (2003) explored the consequences of adding spatial structure to niche breakage models. Several authors (Gauch & Whittaker 1972; Hengeveld <i>et al.</i> 1979) showed that the gravhylic cursing hell graved shape of shundares are a spatial structure.
		distribution similar to individuals within species). Kendall (1948b) and Simon (1955) generalized this work and used it as a model of population dynamics and abundance. Chu & Adami (1999) analysed this again in an ecological context, and Nee (2003) showed that this distribution provides extremely good fits to SADs.	or individuals		gradient or species range produces hollow curve SADs in local communities since at any one point most species are found in the tail of their bell-curve across species while a few species are found in the peak of their bell-curve (thereby flipping the emphasis from local interactions
	11. Zipf-Mandelbrot	Using a different type of branching process known as a scaling (or fractal) tree, Mandelbrot (1965) generalized Zipf's (1949) Law in linguistics to produce the Zipf-Mandelbrot distribution. This has been applied to SADs by several authors (Frontier 1985; Wilson 1991; Frontier 1994, 1985; Wilson 1991; Frontier 1994,		25. Fractal	 between species to regional spatial processes of individual species). McGill & Collins (2003) expanded this theory and provided empirical evidence that this mechanism is in fact explaining as much as 87% of the variation in local abundances. Harte <i>et al.</i> (1999) showed that starting only with an assumption that the
	12. Fractal branching model	Mouillot <i>et al.</i> (2000) introduce a fractal branching (tree-like) extension to the niche pre-emption model (#19)		distribution	distributions of individuals within a species were self-similar across spatial scale could lead to a realistic SAD. Although the initial formulation was found to not have a good fit to the data (Green et al. (2003)
Population dynamics	13. Lotka-Volterra	The generalized Lotka-Voltera models with random parameters can produce a hollow curve (Lewontin <i>et al.</i> 1978; Wilson <i>et al.</i> 2003).		26. Multifractal	Borda-de-Agua <i>et al.</i> (2002) extend the fractal distribution model to cover multifractals (fractal dimension changes with scale)
	14. rugnes	parameters (Hughes 1986) can produce hollow curves		Z/. HEAP	A newer model, also based on a different description of the distribution of individuals across space has been developed (Harte <i>et al.</i> 2005).

Some SAD Theories

- Purely statistical
 - Log series (Fisher)
 - Lognormal (Preston)
- Niche partitioning
 - Broken stick (MacArthur, Sugihara)
- Population dynamics
 - Neutral theory (Hubbell)

- Selection
- Drift
- Speciation
- Dispersal

Trait-Based Community Ecology in a Metacommunity Context

$$\frac{dN_i}{dt} = g(x_i; \vec{N}, \vec{x})N_i + i(x_i)$$
$$= \begin{bmatrix} \text{population} \\ \text{dynamics} \end{bmatrix} + \begin{bmatrix} \text{immigration} \end{bmatrix}$$

At Equilibrium

$$\widehat{N}(x) = \frac{i(x)}{-g(x)} = \frac{i(x)}{e(x)} = \frac{\left[\text{immigration}\right]}{\left[\text{exclusion}\right]}$$

$$\log \widehat{N}(x) = \log i(x) - \log e(x)$$

Model 1: Lotka-Volterra Competition (1 Niche)

$$g(x_i) = r(x_i) - \sum_j r(x_j) N_j$$



Model 1: Lotka-Volterra Competition (1 Niche)



Continuous Approximation



Continuous Approximation



























Model 2: Resource Competition (1 Niche)

$$g(x_i) = b(x_i)R - d$$



Model 2: Resource Competition (1 Niche)



Model 3: Lotka-Volterra Competition (1+ Niches)

$$g(x_i) = r(x_i) - \sum_i \alpha(x_i - x_j) N_j$$




















Back to Finite Species



Back to Finite Species



Conclusions

- Selection + immigration yields many realistic and complex SADs
- Increased immigration supports more rare species
- "Classic SADs" are not the only possibilities
- Multiple factors (local and regional) determine a species' abundance
- Complex patterns may be hard to detect in real communities
- Often bimodal: core / satellite species

"Because the ecosystem structure and function are, by design, emergent and not tightly prescribed, this modeling approach is ideally suited for studies of the relations between marine ecosystems, evolution, biogeochemical cycles, and past and future climate change."

- Follows et al. 2007

Acknowledgments

- NSF DEB & BioOc
- NCEAS
- James S McDonnell Foundation

Immigration Experiment



(Patrick 1967 PNAS)