Ubiquitous abundance decay in the rare biosphere of marine plankton

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Rencontre de la chaire MMB, March 12, 2020

Marine plankton communities in a dynamic seascape



SeaWiFS ocean color data: Chlorophyll concentration

Plankton diversity and physical forcings





Life-Forms of Phytoplankton As Survival Alternatives in An Unstable Environment Ramon Margalef, Oceanologica Acta (1978)

Mesoscale variability of plankton communities



Fluid dynamical niches of phytoplankton types D'Ovidio, De Monte et al. PNAS 2010

Marine biogeography



Ecological Geography of the Sea Alan Longhurst, Academic Press (1998)

Macroecological patterns of diversity





Kasner et al., PLoS One (2011)

Spatio-temporal variability of marine plankton



DARWIN model MIT (Mick Follows)

Patterns of diversity of marine plankton





Tara oceans: Global-scale sampling with uniform protocol



Barcodes: V9 of 18S rRNA gene

388 samples of plankton communities in 121 different locations in the world ocean, covering 8 oceanic regions 4 organisms' size classes: pico-nano (0.8-5 μm), nano (5-20 μm), micro (20-180 μm), meso (108-2000 μm) Different methods of sequence clustering/taxonomic resolution: Swarms and OTUs (UCLUST 95% and 97%) Physico-chemical (temperature, salinity, nutrients, etc.) and biological (Chl, ocean colour, diversity, etc.) context

- > ~150.000 different OTUs identified, few thousands per sample
- > 388 samples in 121 locations

De Vargas, Audic, Henry, et al. Eukaryotic plankton diversity in the sunlit global ocean Science 2015



Cell (2019)



Community composition differs from site to site (average Jaccard index <0.15) OTUs display biogeographical patterns



Optical Molecular 80 40 Latitude 0 -40 2 3 0 Shannon index ---- FC | <20 μm ---- 16S | 0.22–3 μm ---- 18S | 0.8-2000 μm — LM | 20–180 μm ---- Imaging | >200 μm ---- 18S | 20-180 μm — Imaging | >300 μm — Imaging | >680 μm

F. Ibarbalz, L. Zinger, IBENS, Paris
+ more from Paris, Villefranche-sur-Mer, Roscoff,
Zürich, Ohio, Kyoto, Naples, Maine

Latitudinal Diversity Gradients







De Vargas, Audic, Henry, et al. Science 2015

Carradec et al. Nature Comm 2018

Measuring community diversity

Ecological community characterized by:

K species of abundance (n_1, \ldots, n_K)



 $N = \sum n_i$ organisms

Diversity indicators: Species richness K Shannon Index $H = \sum n_i \log n_i$

Measuring community diversity: SAD

Ecological community characterized by:

K species of abundance (n_1, \ldots, n_K)

 $N = \sum n_i$ organisms



Fit with theoretical models to determine the qualitative shape of the distribution

Empirical vs theoretical SADs

Theoretical models based on mechanistic or statistical hypotheses predict different functional forms for the abundance distributions. The most commonly used are (Poisson) lognormal and log-series.

Fitting empirical distributions has led to inconclusive results as to the underlying mechanisms.

Problems with model-fitting:

1. different hypotheses give rise to the same distributions

2. there are parameter values for which different distributions are indistinguishable

3. based on the hypothesis that all members of the community obey the same ecological process

Community decomposition



Endemic and 'visitor' species obey different distributions

Magurran & Henderson, Nature (2003)



Huge number of rare species Regular abundance decay for rare species Variability of abundant species

Adaptive algorithm for community decomposition

Aim: identify the largest community component that is well fitted by a family of distributions.

- **1**. Set an abundance threshold τ for abundances (take only $10^2 < n_i \le \tau$)
- **2.** Maximize the likelihood τ to fit the data below the threshold $% \tau$ and compute p-value
- **3.** Loop on τ and choose the largest value of τ for which the data represent a random realization of the fitting distribution (p-value ≥ 0.1)

- \rightarrow Identification of **abundant** and **non-abundant** OTUs
- → Quantitative comparison of best-fit parameters among samples



Neutral, density-dependent model for community assembly

Birth & death rates $\begin{cases} a \\ a \end{cases}$

$$\begin{cases} b_n = b \ n + \chi \\ d_n = d \ n + \mu \end{cases}$$

Negative binomial beta distribution:

$$\langle \phi_n \rangle = \theta \frac{\Gamma(n+\alpha)\Gamma(1+\beta)}{\Gamma(\alpha)\Gamma(n+\beta+1)} e^{-rn}$$
 $\alpha = \frac{\chi}{b}$ $\beta = \frac{\mu}{d}$ $r = \frac{b}{d}$

Engen 1978, He 2005 Ser-Giacomi et al. 2018

Neutral, density-dependent model for community assembly

Birth & death rates $\left\{ \begin{array}{c} c \\ c \end{array} \right\}$

$$\begin{cases} b_n = b \ n + \chi \\ d_n = d \ n + \mu \end{cases}$$

Negative binomial beta distribution:

$$\langle \phi_n \rangle = \theta \frac{\Gamma(n+\alpha)\Gamma(1+\beta)}{\Gamma(\alpha)\Gamma(n+\beta+1)} e^{-rn} \qquad \alpha = \frac{\chi}{b} \qquad \beta = \frac{\mu}{d} \qquad r = \frac{b}{d}$$

 $\sim e^{-rn} n^{-\lambda} \qquad \qquad \lambda = 1 - \alpha + \beta$

Engen 1978, He 2005 Ser-Giacomi et al. 2018

Fit to empirical distributions



Ser-Giacomi et al. 2018



Spatial variation of best-fit parameters



Variation of best-fit parameters of the same amplitude as contextual parameters, but no systematic co-variation.

➡ Ubiquitous distribution of rare species

Non-abundant OTUs and biogeography



Spatial information on community diversity is concentrated in the 1% most abundant species



Non-abundant OTUs:

Local balance of linear birth and death

Strong correlation of density/dispersal-dependent corrections

Equivalence of non-abundant species

Plankton species differ substantially in their local growth rates ('fitness')

Abundant species are directly engaged in competition, and shape biogeography

Non-abundant species are likely non-growing, locally non-adapted, sharing ecological histories with similar spatio-temporal statistics → 'effective' neutrality

Is a neutral model the best to describe plankton communities?

Effective neutrality in a niche model

Matthieu Baron, ENS Physics, Paris Giulio Biroli, ENS Physics, Paris

Microbial seed bank



Nature Reviews | Microbiology 9, 119-130 (2011)

Microbial seed banks: the ecological and evolutionary implications of dormancy Jay T. Lennon & Stuart E. Jones

Temporal intermittency



UNIVERSAL POWER LAWS GOVERN INTERMITTENT RARITY IN COMMUNITIES OF INTERACTING SPECIES

REGIS FERRIERE^{1,2,4} AND BERNARD CAZELLES^{1,3}

Ecology, 80(5), 1999, pp. 1505–1521 © 1999 by the Ecological Society of America



Power law rank-abundance models for marine phage communities

Karl Heinz Hoffmann¹, Beltran Rodriguez-Brito^{2,3}, Mya Breitbart⁴, David Bangor^{2,3}, Florent Angly², Ben Felts³, James Nulton³, Forest Rohwer^{2,5} & Peter Salamon³

FEMS Microbiol Lett 273 (2007) 224-228

Model for ecosystem dynamics

Generalized Lotka-Volterra equations:

$$\frac{dN_i}{dt} = \lambda + N_i(1 - N_i) - \sum_{j=1}^{S} \alpha_{ij} N_i N_j$$

- 1. Species have a logistic growth
- 2. Species interact (their growth depends on the density of other species)
- 3. Immigration

The interaction parameters are randomly chosen from a Gaussian distribution of average μ and standard deviation σ

Phase diagram for weak interactions



The chaotic regime produces SADs with a power law of exponent 1

Roy et al. Numerical implementation of dynamical mean field theory for disordered systems: application to the Lotka-Volterra model of ecosystems Journal of Physics A: Mathematical and Theoretical (2019)

Open questions

Is plankton different from other microbial communities? *Lucie Zinger, IBENS*

To what extent plankton species are 'equivalent'? Giulio Biroli, Dept. of Physics, ENS

What is the role of ocean transport? Francesco d'Ovidio, LOCEAN; Mick Follows, MIT

What are the best descriptors of diversity in plankton communities? Arne Traulsen, MPI Evolutionary Biology, Plön, Germany

Looking for a post-doc to work at the Max Planck Institute of Evolutionary Biology, Plön, Germany

