

How self-regulation, the storage effect and their interaction contribute to coexistence in stochastic and seasonal environments

Coralie Picoche ^{1,*}, Frédéric Barraquand ^{1,2}

January 28, 2019

¹ University of Bordeaux, Integrative and Theoretical Ecology, LabEx COTE,
Bât. B2 - Allée Geoffroy St-Hilaire, 33615 Pessac, France

² CNRS, Institute of Mathematics of Bordeaux, 351 Cours de la Libération,
33405 Talence, France

* Corresponding author. Email: coralie.picoche@u-bordeaux.fr

Abstract

Explaining coexistence in species-rich communities of primary producers remains a challenge for ecologists because of the likely competition for shared resources. Following Hutchinson's seminal suggestion, many theoreticians have tried to create diversity through a fluctuating environment, which impairs or slows down competitive exclusion. There are now several fluctuating-environment models allowing coexistence, but they often produce only a dozen of coexisting species at best. Here, we investigate how to create even richer communities in fluctuating environments, using an empirically parameterized model. Building on the forced Lotka-Volterra model of Scranton and Vasseur (2016) inspired by phytoplankton communities, we have investigated the effect of two coexistence mechanisms, namely the storage effect and higher intra- than interspecific competition strengths (i.e., strong self-regulation). We tuned the competition ratio based on empirical analyses, in which self-regulation usually dominates interspecific interactions. Although a strong self-regulation maintained more species (50%) than the storage effect (25%), we show that none of the two coexistence mechanisms considered could, by itself, ensure the coexistence of all species present at the beginning of our simulations. Realistic seasonal environments only aggravated that picture, as they decreased persistence relative to a random environment. Our results suggest that combining different mechanisms for biodiversity maintenance into community models might be more fruitful than trying to find which mechanism explains best the observed diversity levels. We additionally highlight that while trait-biomass distributions provide some clues regarding coexistence mechanisms, they cannot indicate by themselves which coexistence mechanisms are at play.

Number of words: 242

Keywords: coexistence; seasonality; competition; phytoplankton; Lotka-Volterra; storage effect

1 Introduction

The continued maintenance of diversity in spite of widespread competition has long bewildered ecologists, especially for primary producers such as phytoplankton that share the same basic resources (Hutchinson, 1961). A solution for the ‘paradox of the plankton’ was proposed by Hutchinson: temporal variation of the environment. However, it has been shown later that inclusion of temporal variability *per se* in competition models is not sufficient for maintaining a realistic diversity (Chesson and Huntly, 1997; Fox, 2013). Additional mechanisms such as the storage effect (Chesson, 1994; Ellner et al, 2016) or a relative nonlinearity of competition (Armstrong and McGehee, 1980; Chesson, 2000; Descamps-Julien and Gonzalez, 2005; Fox, 2013) need to be introduced for diversity to maintain. Moreover, richness rarely exceeds a handful to a dozen of species in model competitive communities in fluctuating environments, except when external inputs such as immigration sustain diversity (Jabot and Lohier, 2016). To our knowledge, the effect of temporal variability on persistence in competition models has mostly been examined in theoretical communities of 2 to 3 species (e.g., Chesson and Huntly, 1997; Litchman and Klausmeier, 2001; Li and Chesson, 2016; Miller and Klausmeier, 2017).

One of the richest modeled communities that we identified is the model of Scranton and Vasseur (2016), which is based on temperature variation and different thermal optima for each species (Moisan et al, 2002). In this model, the synchronizing effect of the environment and the storage effect can maintain 12 phytoplankton-like species on average. Scranton and Vasseur (2016) described daily temperature as a random noise, i.e., independent and identically distributed Gaussian random variates over time. However, under most latitudes, seasonality drives part of the environmental variation: over short timescales, random temporal variations often only add noise to a largely deterministic seasonal trend (Scheffer et al, 1997; Boyce et al, 2017; Barraquand et al, 2018).

Seasonal forcing of parameters can strongly affect the dynamics of model communities by synchronizing species to the seasonal signal or even promoting oscillations with lower frequency (Rinaldi et al, 1993; Barabás et al, 2012; Miller and Klausmeier, 2017; Vesipa and Ridolfi, 2017). How seasonality affects coexistence, as opposed to a randomly fluctuating environment, is therefore

54 a key feature of this paper. Our present work can be seen as an attempt to blend Scranton and
55 Vasseur (2016)’s stochastic framework with the periodic environments of Barabás et al (2012), to
56 better represent the mixture of stochastic and deterministic environmental forces affecting phyto-
57 plankton community dynamics.

58 What other key features of field communities should be considered when modelling phyto-
59 plankton? Strong self-regulation, with intraspecific competition much stronger than interspecific
60 interactions, has been found to be widespread in terrestrial plant communities (Adler et al, 2018),
61 animal communities (Mutshinda et al, 2009), and more recently phytoplanktonic communities
62 (Barraquand et al, 2018). We will therefore insert those niche differences, manifesting as strong
63 self-regulation, into our models of phytoplankton competition. The interaction between environ-
64 ment variability and niche overlap was investigated by Abrams (1976) but his results did not extend
65 to communities more diverse than 4 species; our objective is therefore to see how those mechanisms
66 interact for species-rich communities.

67 Niche models have often been opposed to the neutral theory (Hubbell, 2001), where disper-
68 sal and drift can ensure a transient coexistence of many species, ~~though~~but several authors have
69 attempted to blend niche and neutral processes (Gravel et al, 2006; Scheffer and van Nes, 2006;
70 Carmel et al, 2017). An intriguing offshoot of these attempts is the concept of ‘clumpy coexistence’
71 (Scheffer and van Nes, 2006), whereby simultaneous influences of both niche and neutral processes
72 create several clumps of similar species along a single trait axis. Niche differences enable coexis-
73 tence of multiple clumps (Chesson, 2000) while within-clump coexistence occurs through neutral
74 processes. This ‘emergent neutrality’ within groups (Holt, 2006) has been proposed as a unifying
75 concept for niche and neutral theories (even though the neutrality of the original model has been
76 disputed due to hidden niches, Barabás et al, 2013). Since then, clumpy coexistence has been
77 shown to occur in theoretical models incorporating a temporally variable environment interacting
78 with a thermal preference trait axis (Scranton and Vasseur, 2016; Sakavara et al, 2018). The re-
79 lationship (or absence thereof) between biomass-trait distributions and coexistence mechanisms is
80 currently debated (D’Andrea and Ostling, 2016), although there are suggestions that clustering on
81 trait axes under competition may be a robust find (~~d’Andrea et al. 2018, 2019~~)(D’Andrea et al,

82 2018, 2019).

83 Here, we try to establish what are the relative contributions to coexistence of the storage effect
 84 vs strong self-regulation, in a phytoplankton-like theoretical community model with a large number
 85 of species. This led us to cross combinations of seasonality vs randomness in the forcing signal,
 86 presence of the storage effect or not, and intra- vs interspecific competition intensity, in order to
 87 disentangle the contributions of these factors to biodiversity maintenance and their potential inter-
 88 actions. Alongside the resulting species richness, we also report which biomass-trait distribution
 89 can be expected under a given combination of processes leading to coexistence.

90 2 Methods

91 *Models description*

92 The model described in Scranton and Vasseur (2016) is based on the Lotka-Volterra competition
 93 model. Fluctuations in the environment are introduced in the model by temperature-dependent
 94 intrinsic growth rates (see Eq. 1-2, all coefficients are defined in Table 1) so that species growth
 95 rates can be expressed as:

$$\frac{dN_i}{dt} = r_i(\tau)N_i \left(1 - \sum_{j=1}^S \alpha_{ij}N_j \right) - mN_i \quad (1)$$

$$r_i(\tau) = a_r(\tau_0)e^{E_r \frac{(\tau - \tau_0)}{k\tau\tau_0}} f_i(\tau) \quad (2)$$

$$\text{where } f_i(\tau) = \begin{cases} e^{-|\tau - \tau_i^{opt}|^3/b_i}, & \tau \leq \tau_i^{opt} \\ e^{-5|\tau - \tau_i^{opt}|^3/b_i}, & \tau > \tau_i^{opt} \end{cases} \quad (3)$$

$$\text{and } b_i \text{ is defined by numerically solving } \int r_i(\tau)d\tau = A \quad (4)$$

96 Model parameters are detailed in Table 1, and we set their values to match the features of
 97 phytoplankton communities as in Scranton and Vasseur's work (2016). The niche of each species is
 98 defined by its thermal optimum τ_i^{opt} . Thermal performance curves defined in Eq. 3 are parameter-

99 ized so that all species share the same niche area (Eq. 4), which sets a trade-off between maximum
100 growth rates and niche width.

Table 1: Parameter definitions and values for the model described in Eqs. 1-4. Parameter values are not specified when they vary with time and/or the species considered.

Name	Definition	Value (unit)
S	Initial number of species	60 (NA)
N_i	Biomass density of the i^{th} species	(kg/area)
τ	Temperature	(K)
$r_i(\tau)$	Growth rate of species i as a function of temperature	$(\frac{\text{kg}}{\text{kg} \times \text{year}})$
α_{ij}	Strength of competition of species $j \rightarrow i$	0.001 (area/kg)
b_i	Normalization constant for the thermal decay rate	(K^3)
m	Mortality rate	$15(\frac{\text{kg}}{\text{kg} \times \text{year}})$
τ_0	Reference temperature	293 (K) / 20 ($^{\circ}\text{C}$)
$a_r(\tau_0)$	Growth rate at reference temperature	$386(\frac{\text{kg}}{\text{kg} \times \text{year}})$
E_r	Activation energy	0.467 (eV)
k	Boltzmann's constant	$8.6173324 \cdot 10^{-5} (\text{eV} \cdot \text{K}^{-1})$
$f_i(\tau)$	Fraction of the maximum rate achieved for the i^{th} species	(NA)
μ_τ	Mean temperature	293 (K)
σ_τ	Standard deviation for temperature	5 (K)
τ_{\min}	Minimum thermal optimum	288 (K)
τ_{\max}	Maximum thermal optimum	298 (K)
A	Niche breadth	$10^{3.1}(\frac{\text{kg}}{\text{kg} \times \text{year}})$
τ_i^{opt}	Thermal optimum for growth of the i^{th} species	(K)
θ	Scaling between random and seasonal noise	(0;1.3) (NA)
κ	Ratio of intra-to-interspecific competition strength	(1;10) (NA)

101 The original environmental forcing is a normally distributed variable centered on 293 K (20 $^{\circ}\text{C}$),
102 with a 5 K dispersion. Temperature varies from one day to the next, but is kept constant through-
103 out the day. At the monthly or annual temporal scale usually used in ecological studies, tempera-
104 ture could therefore be considered as a white noise (Vasseur and Yodzis, 2004). However, from a
105 mathematical viewpoint, the noise is slightly autocorrelated as the integration process goes below
106 the daily time step. We therefore use the expression ‘random noise’ to describe this forcing, as
107 opposed to the ‘seasonal noise’ described hereafter. To construct the seasonal noise, we add to the
108 random forcing signal a lower-frequency component, using a sinusoidal function with a period of
109 365 days (Eq. 5). We tune the ratio of low-to-high frequency with the variable θ so as to keep the
110 same energy content - i.e., equal total variance - in the forcing signal.

$$\tau(t) = \mu_\tau + \theta \sigma_\tau \sin(2\pi t) + \epsilon_t, \text{ where } \epsilon_t \sim \mathcal{N}\left(0, \sigma_\tau \sqrt{1 - \frac{\theta^2}{2}}\right) \quad (5)$$

111 Note that the upper limit for θ , $\sqrt{2}$, corresponds to a completely deterministic model which we
 112 do not explore here (but see Zhao (1991) proving bounded coexistence). We choose to keep the
 113 stochasticity in the signal and to model a plausible temperature signal with $\theta = 1.3$ (illustrated in
 114 Fig. 1b) when considering a seasonal forcing of the dynamics.

115 The formulation of the forced Lotka-Volterra model of Scranton and Vasseur (2016) implies
 116 a storage effect, as the net effect of competition exerted by species j on i is the product of the
 117 temperature-related growth rate $r_i(\tau)$ and the competitive strength α_{ij} exerted by species j multi-
 118 plied by its abundance N_j . Therefore, total net competition ($\sum_{j=1}^S r_i(\tau) \alpha_{ij} N_j$) covaries positively
 119 with the growth rate values $r_i(\tau)$, which defines the storage effect (Chesson, 1994; Fox, 2013; Ellner
 120 et al, 2016). To remove the assumption of an explicit storage effect, we created another version of
 121 the model using the mean value of a species' growth rate (\bar{r}_i) to weight the interaction coefficients
 122 (see Eq. 6). The mean growth rate value was computed by first generating the temperature time
 123 series and then averaging all r_i over the corresponding sequences of τ values.

$$\frac{dN_i}{dt} = N_i \left(r_i(\tau) - \sum_{j=1}^S \bar{r}_i \alpha_{ij} N_j \right) - m N_i \quad (6)$$

124 Following Eq. 6, net competition remains unaffected by the environmental conditions, in con-
 125 trast to intrinsic growth rates, while preserving the same average magnitude as in Eq. 1.

126 Strong self-regulation is ensured by the addition of the coefficient κ , which is the ratio of intra-
 127 to-interspecific competition strength. We can therefore re-write the interaction coefficients α_{ij} in
 128 Eq. 7

$$\alpha_{ij} = \alpha (1 + (\kappa - 1) \delta_{ij}) \quad (7)$$

129 where δ_{ij} is the Kronecker symbol, equal to 1 if $i = j$ and to 0 otherwise. The value of the
 130 parameter $\kappa = 10$ was chosen from analyses of phytoplanktonic data (Barraquand et al, 2018).
 131 Hereafter, the expression “strong self-regulation” characterizes dynamics where the intraspecific

132 competition strength is 10 times higher than the interspecific competition strength, as opposed to
 133 “equal competitive strengths” where intra- and interspecific competition strengths are equal.

134 In addition to two types of environmental forcings (random noise with $\theta = 0$, and seasonal
 135 noise with $\theta = 1.3$), we compare the results for four formulations of the model: with and without
 136 an explicit storage effect (Eq. 1 and Eq. 6, respectively); with strong self-regulation or equal intra-
 137 and inter-competition strength ($\kappa = 10$ or $\kappa = 1$, respectively). These are summed up in Table 2.

$\frac{1}{N_i} \frac{dN_i}{dt} + m_i$	Storage effect	No storage effect
Strong self-regulation ($\kappa = 10$)	$r_i(\tau) \left(1 - \sum_{j=1}^S \alpha (1 + 9\delta_{ij}) N_j \right)$	$r_i(\tau) - \sum_{j=1}^S \bar{r}_i \alpha (1 + 9\delta_{ij}) N_j$
Equal competitive strengths ($\kappa = 1$)	$r_i(\tau) \left(1 - \sum_{j=1}^S \alpha N_j \right)$	$r_i(\tau) - \sum_{j=1}^S \bar{r}_i \alpha N_j$

Table 2: Growth rate of species i in the four formulations of the model we present

138

139 Set-up

140 We replicate the ‘Species sorting’ experiment of Scranton and Vasseur (2016) so as to investigate
 141 how the structure of synthetic phytoplankton communities varies under the different scenarios we
 142 described above. We focused on the dynamics of a community initialized with 60 species with
 143 thermal optima uniformly spaced along the interval $[15^\circ\text{C}, 25^\circ\text{C}]$, and with the same initial density
 144 $\left(\frac{1}{\alpha S}\right)$. Each simulation was run for 5000 years in 1-day intervals. When the density of a species
 145 dropped below 10^{-6} , it was considered extinct. For each combination of parameters (type of
 146 environmental signal, storage effect and stabilizing niche differences), we ran 100 simulations.

147 All simulations were run with Matlab’s ode45 algorithm, an explicit Runge-Kutta (4,5) inte-
 148 gration scheme with an absolute error tolerance of 10^{-8} , and relative error tolerance of 10^{-3} . The
 149 code is available in a GitHub repository¹.

¹<https://github.com/CoraliePicoche/Seasonality>, will be made public upon acceptance or at the reviewer’s request and stored in Zenodo

3 Results

Typical dynamics of the community following Eq. 1 (the model of Scranton and Vasseur, 2016), with both a purely Gaussian noise (original choice of Scranton and Vasseur, 2016; Fig. 1a) and a seasonal noise described in Eq. 5 (our variant, Fig. 1b), are shown in Fig. 1c and d, respectively. A sinusoidal forcing produces the strongly seasonally structured dynamics that are typical of phytoplankton. Even though only 5 species can be seen in Fig. 1c, there were 14 species still present at the end of the simulation forced by a random noise, with large disparities in the range of their biomasses. A third of the species kept a biomass above 10 kg/area (setting area = 1 ha, with a depth of a few meters, produces a realistic standing biomasses; Reynolds, 2006) while 6 out of the 14 species biomasses remained below the unit. All persisting species in the random noise simulation were clustered within a 3.2°C-range of thermal optima (see the biomass distribution as a function of the thermal optimum in Electronic Supplementary Material, Fig. A1). No obvious temporal patterns (e.g., cycles) could be seen in the community forced by random noise. On the contrary, seasonal cycles were clear in the seasonally-forced case of Fig. 1d. Only 4 species coexisted at the end of the simulation with seasonal noise, gathered in two groups with large thermal optimum differences (5.7°C between the maximum thermal optimum of the first group and the minimum thermal optimum of the second group). When temperatures were high, the group with higher thermal optima reached its maximum biomass, then as temperature decreases through the season, these species leave room for the growth of the low-temperature group.

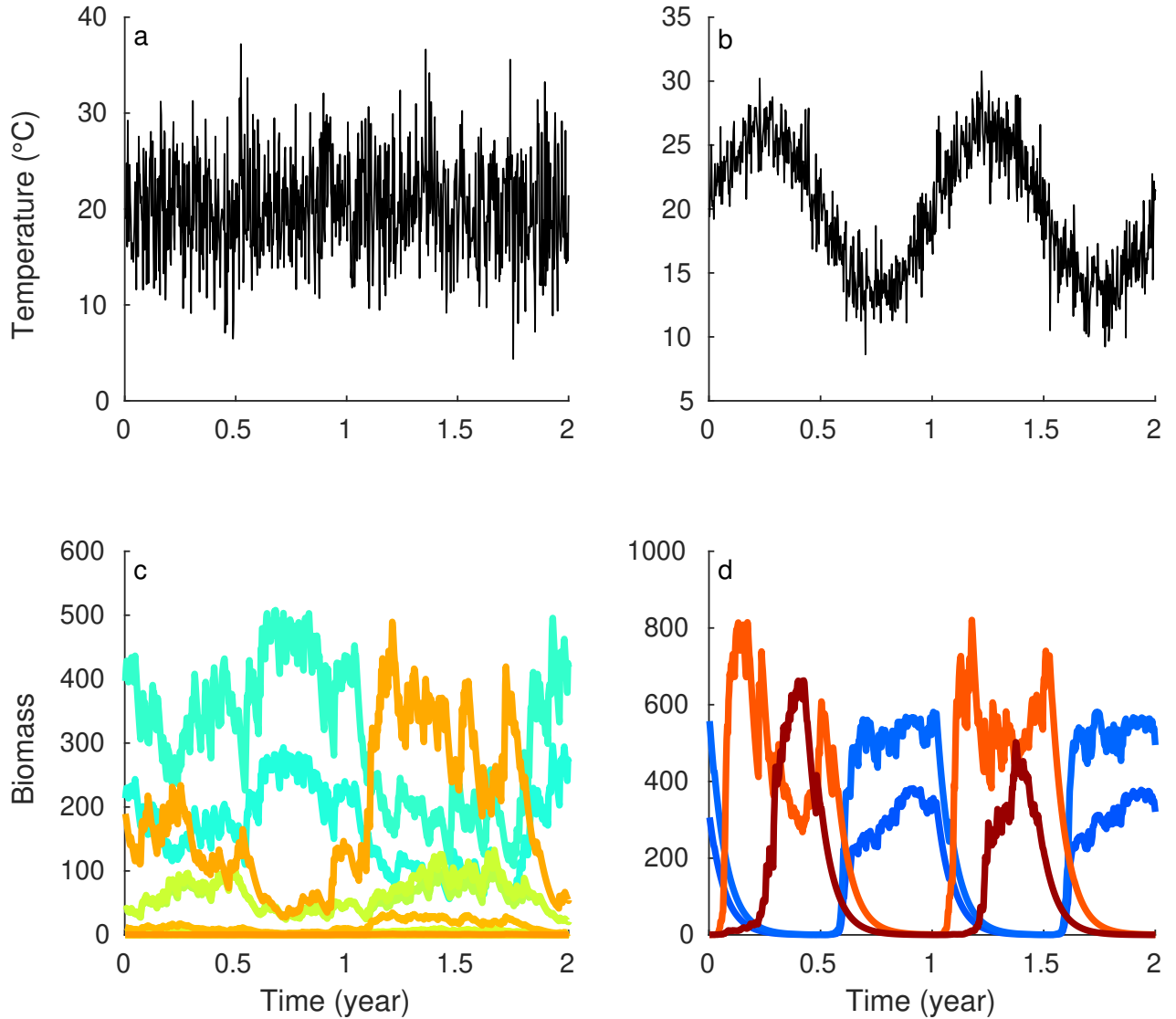


Figure 1: Time series of temperature (top; a-b) and extant species (bottom; c-d) for the 2 last years of a 5000-year simulation, with storage effect but no differences between intraspecific and interspecific competition strengths. The forcing temperature is either a random noise (a) or a seasonal noise (b), leading to community dynamics with more erratic fluctuations (c) vs seasonally structured fluctuations (d). Line colors of species biomasses correspond to their thermal optimum (from blue, corresponding to low thermal optimum, to red, corresponding to high thermal optimum).

169 The decrease in persistence due to seasonality observed in Fig. 1 was confirmed in all our
 170 simulations (Fig. 2). In cases where final species richness varied from one simulation to another
 171 (namely, the two middle cases in Fig. 2: with storage effect but without strong self-regulation, or
 172 without storage effect but with strong self-regulation), seasonality reduced the number of extant
 173 species to, on average, 27% and 48% of their original values, respectively (Fig. 2). A seasonal signal

174 therefore led to a much smaller average persistence. There was also less variance in persistence
175 between seasonally forced simulations compared to random noise simulations.

176 Both a strong self-regulation and the storage effect markedly increased persistence. Without
177 any of these coexistence mechanisms, only one species persisted at the end of the simulations.
178 When only the storage effect was present, the number of extant species varied between 8 and 20
179 (14.8 ± 2.4) with random noise, or 2 and 6 (4.1 ± 0.7) with a seasonal signal. On the other
180 hand, when only a strong self-regulation was present, the number of extant species nearly doubled,
181 varying between 20 and 32 (27.5 ± 2.4), or 12 and 15 (13.3 ± 0.6), with a random or a seasonal
182 noise, respectively. Remarkably, when the storage effect and a strong self-regulation both affected
183 the community dynamics, all species persisted in the community: the number of species coexisting
184 with both mechanisms present is therefore greater than the sum of the species coexisting with either
185 mechanism alone. The two mechanisms therefore combine superadditively, as their interaction has
186 a positive effect on the richness of the community.

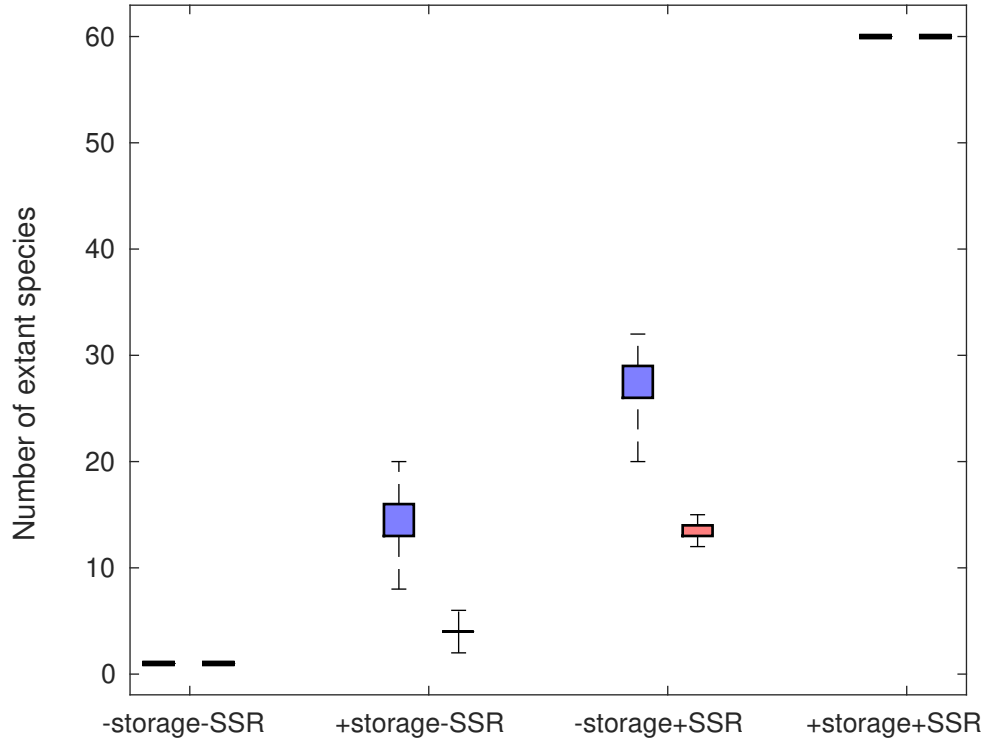


Figure 2: Number of species still present at the end of 100 simulations (5000 years each), initialized with 60 species, with a random forcing signal (blue) or a seasonal noise (red). The signs + or - storage refer to presence or absence of the storage effect, respectively; + / - SSR, presence or absence of Strong Self-Regulation, respectively. Community compositions are stable in the cases -storage-SSR and +storage+SSR, for which 1 or 60 species are still present at the end of all simulations, respectively. Due to low variance, the whiskers here represent min and max rather than 1.5 interquartile range.

187 The trait-biomass distribution of the community was affected by the type of forcing even
188 when the richness of the community was stable (Fig. 3). Without storage effect nor strong self-
189 regulation, there was only one species left at the end of the simulations. A random noise favored
190 species with intermediate thermal optima: the final species had a thermal optimum between 18.9°C
191 and 21.4°C (only a fourth of the initial range of thermal optima) for two simulations out of three
192 and the maximum final biomasses over 100 simulations was reached in this range (Fig. 3a). This
193 distribution may indicate a selection for the highest long-term growth rates, averaged over time (see
194 scaled growth rates in Fig. 3). Seasonality with no coexistence mechanisms also led to a single
195 final species but, in this case, the species always had a higher maximum growth rate (thermal
196 optimum above 22°C). Species with a higher thermal optimum were more likely to persist and to

197 reach a higher biomass at the end of the simulation. 38% of the simulations therefore ended with
198 the species having the highest temperature optimum, 25°C. The shift in trait distribution towards
199 higher maximum growth rates with a seasonal noise vs higher average growth rates with a random
200 noise was consistent for all model types considered.

201 When both storage effect and strong self-regulation were present, the 60 initial species coexisted
202 with small variations in biomasses for each species over the 100 simulations (mean CV=0.008
203 across simulations with either a random or a seasonal noise, Fig. 3b and d). The forcing signal
204 modified only the distribution of biomasses resulting in contrasted community structures despite
205 equal richness in both simulation types. With a random noise, the distribution was unimodal with
206 a maximum biomass reached for the second highest long-term average growth rate (corresponding
207 to a thermal optimum of 20.2°C). On the contrary, a seasonal signal led to a bimodal distribution
208 (centered on 17.0°C and 24.4°C), each corresponding to one season, with highest biomasses for
209 higher thermal optima (Fig. 3d). The minimum biomass was reached for the highest long-term
210 average growth rate at an intermediate temperature (20.4°C).

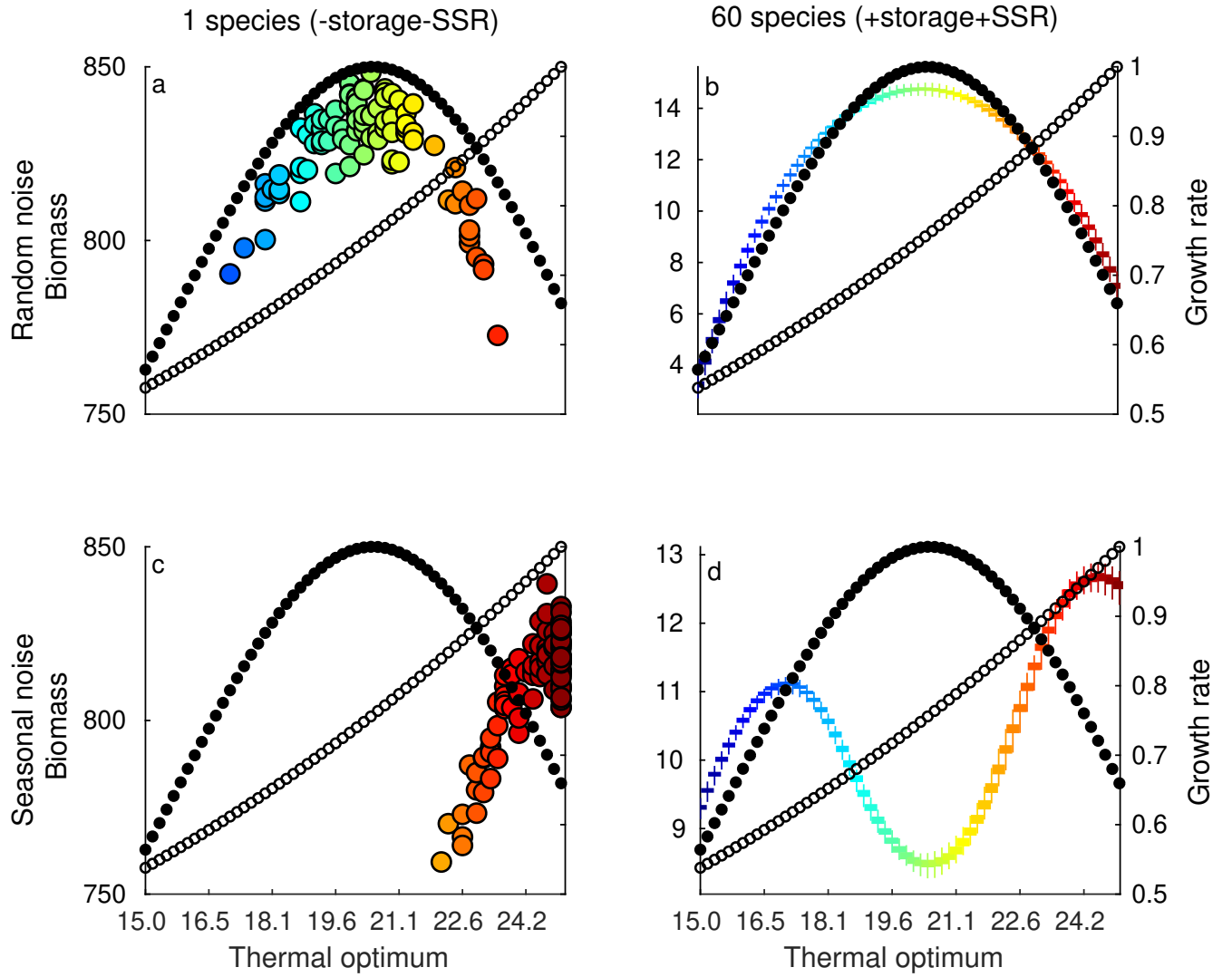


Figure 3: Mean biomass distribution over the last 200 years for 100 simulations, as a function of the species thermal optima. Here we consider the two stable-composition cases and two types of forcing signal. On the left column, simulations without storage effect nor strong self-regulation are presented. Only one species is present at the end of the simulations and its mean value is represented by one large colored circle per simulation. There can be several circles for the same species, corresponding to multiple simulations ending with this species alone. On the right column, simulations with storage effect and strong self-regulation are represented. All species are present at the end of the simulations and small boxplots present the variation in the temporal average of biomass with a given trait, for 100 simulations. The forcing signal is either a random (top) or a seasonal noise (bottom). Each species is identified by its thermal optimum through its color code. Scaled (divided by maximum) average and maximum growth rates are shown as small filled and open circles, respectively, and are indexed on the right y-axis.

211 In cases where the richness of the community varied, the overall shape (multimodal vs unimodal)
 212 of the marginal distribution of extant species with respect to the trait axis were similar for both
 213 types of environmental forcings (Fig. 4). By contrast, the type of coexistence mechanism generated

different shapes. Indeed, the storage effect (when acting alone) led to a multimodal biomass distribution with respect to thermal optima. We always observed 3 modes with a random noise and 3 modes in 95% of the seasonal simulations (Fig. 4a). With a random noise, extant species were grouped in rather similar clumps regarding species thermal optima (between 18.8°C and 22.2°C) whereas species tended to be further apart in the seasonal case, covering a total range of 7.7°C, with species grouping in the higher part of the thermal range, above 22°C. On the other hand, strong self-regulation led to a quasi-uniform biomass distribution (Fig. 4 b). Species in communities forced by a random noise stayed in the lower range of thermal optima (in 96% of the simulations, the highest thermal optimum was 22.4°C, see Fig. A2 in Electronic Supplementary Material) while they were filtered out in communities subjected to a seasonal fluctuation of their environment, for which species with thermal optima above 20.5°C persisted. As before (Fig. 3), seasonality promoted species with a higher maximum growth rate since the autocorrelated temperatures enabled them to achieve this highest growth rate for a longer period of time than a random noise would have.

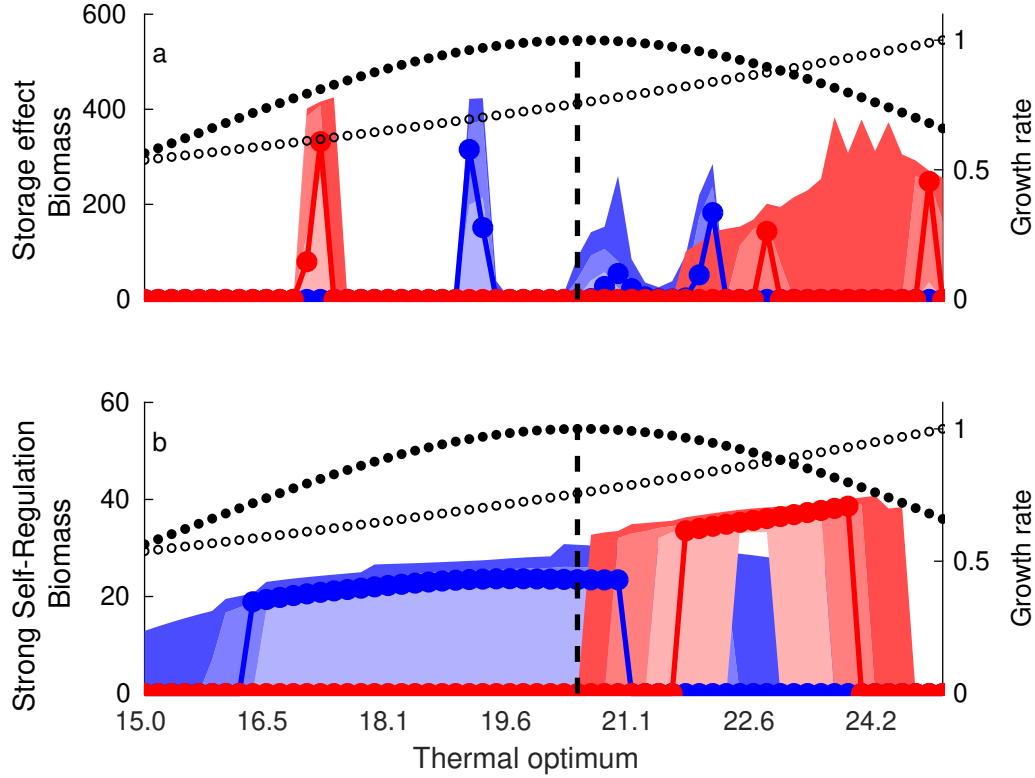


Figure 4: Mean biomass distribution over the last 200 years for 100 simulations, as a function of thermal optima, with storage effect and equal competitive strengths (a) and without storage effect, with strong self-regulation (b). The forcing signal is either a random (in blue) or a seasonal noise (in red). Shades of the same color correspond to the 50th, 90th and 100th percentiles of the distributions while colored lines correspond to one representative simulation. Scaled (divided by maximum) average (whose maximum is indicated by the dashed line) and maximum growth rates are shown as filled and open and circles, respectively, and indexed on the right y-axis.

4 Discussion

We have simulated competitive Lotka-Volterra dynamics forced by a fluctuating environment (e.g., temperature fluctuations) under a range of scenarios allowing more or less coexistence. Two coexistence mechanisms, the storage effect and strong self-regulation (i.e., intraspecific competition much stronger than interspecific competition), could be either present or absent, which led to four scenarios. These four scenarios were crossed with two possibilities for the forcing signal, a random noise (mostly white) and a stochastic yet seasonal signal, both with equal temporal variance.

Our investigation therefore built on the model of Scranton and Vasseur (2016), which included a random forcing and a storage effect, but considered seven additional combinations of mechanisms. This was motivated by our wish to include two observed features of phytoplankton dynamics: seasonal cycles (Winder and Cloern, 2010) and strong self-regulation (Chesson, 2000; Adler et al, 2010; Barraquand et al, 2018). Many mechanisms can lead to intraspecific competition being stronger than interspecific competition: nonlinearities in the functional forms of competition or mutualism that contribute to increasing self-regulation (Kawatsu and Kondoh, 2018), or predation as well as parasitism (see e.g., the generalist predators in Haydon, 1994). Strong self-regulation seems nonetheless an ubiquitous feature in competition networks of primary producers (Adler et al, 2018), and perhaps even more general networks (Barabás et al, 2017).

Before discussing the ecological interpretation of our results, we first recall some technical assumptions made in this study. All our simulations lasted for a fixed duration (5000 timesteps) as in Scranton and Vasseur (2016). ~~This means that~~ While short- and medium-term transients (a few years to hundreds of years) are completely negligible at the end of the time series, ~~but~~ very long transients can remain in this class of models (Hastings et al, 2018): ~~these are not mere artefacts but instead traduce the fact that some processes (e.g., exclusion of a species) can be really slow.~~ We realized that convergence ~~could be~~ was incomplete after 5000 years in some cases (e.g., random noise + storage effect + equal competitive strength). Such simulations would take up to 15 000 years to converge and the rate of convergence would slow over time, as can also be observed for similar models (Scheffer and van Nes, 2006). ~~We kept a fixed time integration window rather than waiting for convergence. From a technical standpoint, adding 10 000 years of numerical integration (or more) for the sake of reaching equilibrium is more challenging computationally, and~~ We could have considered longer time intervals, but comparison with the values reported by Scranton and Vasseur (2016) would then have been compromised. Another way to shorten the transients, suggested by a referee (GB), would be to vary the mortality parameter. This worked, and did not alter the conclusions (see Appendix B in Electronic Supplementary Material). Unfortunately, added variability also shifts the model further away from neutral dynamics, which renders comparisons difficult. ~~We checked this for robustness's sake and This did not alter the conclusions (see Appendix~~

262 ~~B in Electronic Supplementary Material).~~ WeAll things considered, we therefore kept the 5000-year
263 time window for integration.

264 Another strong assumption pertains to competition coefficients. To allow for comparison with
265 Scranton and Vasseur (2016), we did not introduce variability in intraspecific competition strength
266 or interspecific competition strength. By contrast, data-based coefficients vary between species
267 (Barraquand et al, 2018), with a majority of weak interactions (as suggested in Wootton and
268 Emmerson, 2005) and more variance in intraspecific coefficients. Stump (2017) recently considered
269 the potential effects of competition coefficient variability (also called non-diffuse competition), as
270 did Kokkoris et al (2002); more variance in interspecific competition strength is usually detrimental
271 to coexistence (see Stump (2017) for a classification of the various effects). Setting the competition
272 coefficients using a multidimensional trait-based framework, like that of Ashby et al (2017), would
273 provide a natural development to the work presented here; it is in our opinion difficult to speculate
274 on those variance effects because both intra- and interspecific competition coefficient variances may
275 matter to community persistence.

276 Finally, our study is limited to communities whose species have fast population dynamics rela-
277 tive to the yearly timescale, like phytoplankton and likely other fast-living organisms, so that many
278 generations can occur in a year. Persistence in community with slower dynamics may be affected
279 differently by seasonality (Miller and Klausmeier, 2017). This especially true for species with gen-
280 erations that extend over multiple years. In models where trophic interactions are implemented,
281 seasonality has been shown to promote ~~(e.g.,~~ multiyear cycles and the existence of chaotic attrac-
282 tors; (Rinaldi et al, 1993; Taylor et al, 2013; Tyson and Lutscher, 2016). ~~Inter-annual variability,~~
283 ~~as opposed to intra-annual seasonality, can also emerge in the presence of an additional trophic~~
284 ~~level.~~ These rich dynamics of consumers may feed back into the lower trophic levels: Dakos et al
285 (2009) present a planktonic community with seasonally-entrained chaotic dynamics which may be
286 partly due to zooplanktonic predation. Predation probably entails additional niche differences,
287 possibly with an emerging self-regulation created by predation processes (Chesson, 2018), but it
288 seems unlikely that we would be able to generate such dynamics with the models presented in this
289 article. Additional nonlinearities would be needed.

290 With these assumptions in mind, we have found that first, temporally forced Lotka-Volterra
 291 dynamics cannot sustain any diversity with our phytoplankton-based set of parameters, unless the
 292 structure is geared to include either a storage effect or a strong self-regulation. Although this
 293 absence of diversity-enhancing effect of “pure” environmental variation has already been stated by
 294 other authors (Chesson and Huntly, 1997; Barabás et al, 2012; Fox, 2013; Scranton and Vasseur,
 295 2016), this is not always intuitive (Fox, 2013), so we feel compelled to stress it once more: temporal
 296 variation in growth rate alone cannot help coexistence within competitive communities. A nice
 297 point made by Scranton and Vasseur (2016) was that a built-in storage effect in a forced Lotka-
 298 Volterra model, parameterized for phytoplankton communities, could lead to a reasonable degree
 299 of coexistence. Our investigation reproduced these results, using the random noise considered by
 300 Scranton and Vasseur (2016). However, an arguably more lifelike noisy and seasonal temperature
 301 forcing considerably lessened the richness of the community after 5000 years, decreasing from
 302 15 to 4 species on average. Even imagining that groups represented here are genera or classes
 303 rather than species, this is a fairly low diversity for a phytoplankton-like community (see e.g.,
 304 Chapter 1 in Reynolds, 2006). This suggests that the storage effect may not, on its own, be
 305 sufficient to maintain species-rich communities (e.g., dozens to hundreds of species). We have
 306 therefore sought out whether a stronger self-regulation could maintain a higher diversity, using
 307 field-based intra- vs intergroup (species or genera) competition strength ratio (Barraquand et al,
 308 2018), where the intragroup density-dependence was estimated 10 times stronger. Implementing
 309 such strong self-regulation, in the forced Lotka-Volterra models that we considered, produced a
 310 higher level of diversity than the storage effect (almost double). Of course, the result is somehow
 311 contingent upon the strength of self-regulation. Our estimates are a little stronger than what was
 312 found in perennial plants (Adler et al, 2010), where interspecific competition was suggested 4 or 5
 313 times stronger than intraspecific. Still, the widespread effects of natural enemies in phytoplankton
 314 (zooplankton, parasites) may contribute to increase the strength of self-regulation (Barraquand
 315 et al, 2018; Chesson, 2018) relative to other systems, hence we believe that 10 times stronger
 316 intraspecific competition constitutes a reasonable order of magnitude.

317 However, such strong self-regulation was still insufficient to maintain the whole community

diversity (60 species) by itself, especially when the seasonal forcing (always decreasing species richness) was considered. The diversity within clumps of similar values of thermal optima was considerably decreased once seasonality was implemented. This diversity reduction occurs because within a season, the signal autocorrelation gives long, contiguous time intervals to the best competitor to exclude its less adapted competitors. This makes the results likely to hold not only for seasonal environments, but more generally for autocorrelated ones above the daily scale, i.e., “red” noise. In contrast, the random noise scenario – which can be considered white noise above the daily temporal scales – generates large temperature shifts more frequently, and thereby forbids such competitive exclusion. In a seasonal setting, a species with the highest long-term (arithmetically) averaged growth rate may not be the best competitor, and can disappear as a result of a strong competition from both low- and high-temperature tolerant species. This holds with or without a storage effect.

Our results may appear at odds with recent proposals that seasonal forcing in itself would help maintain diversity (Sakavara et al, 2018). However, we compared the effect of seasonal forcing to that of other forcing signals while controlling for total variance. Thus, the contrast between our results and those of Sakavara et al (2018) may be due to the role of forcing variance over time—(we compare scenarios under a constant total variance, much like what is done when examining the effect of noise color on population and community dynamics (Ruokolainen et al, 2009)). Overall Thinking in terms of signal spectrum, while seasonality may maintain slightly more diversity than no forcing at all if a storage effect is present, the reddening of the environmental noise due to such seasonality does not necessarily improve reduces coexistence. This increase in autocorrelation, despite keeping the same strength in the forcing signal, can either increase or decrease biomass fluctuations and synchrony, depending on species intrinsic growth rates, which can in turn destabilize a community (Ruokolainen et al, 2009).—This result may be contingent upon the correlated positive responses of the species growth rate to increases in the environmental variable (Ruokolainen et al, 2009, and references therein).

In addition to community diversity, the biomass-trait relationship also varied from one simulation to another. Some regularities did emerge across simulations though. The biomass-trait relationship

346 was affected more marginally by the type of forcing signal. The storage effect alone begot several
 347 clumps along the trait space (as observed by Scranton and Vasseur, 2016). The seasonality that
 348 we added to the temperature signal led to more distant clumps on the trait axis, with less species
 349 per clump. Conversely, strong self-regulatory mechanisms alone led to relatively uniform biomass
 350 distributions, with species forming a single large cluster, which covers a fraction of the initial trait
 351 space. Therefore, the shape of the distribution was mostly affected by the coexistence mechanism
 352 at work while the average trait value was modified by the type of environmental forcing, even
 353 though the mean value of the environmental signal did not change. However, when both strong-
 354 self regulation and the storage effect were at play, the biomass-trait distribution could either be
 355 unimodal or multimodal depending on the type of noise (random or seasonal, respectively) driving
 356 the community dynamics. This implies that the mere observation of multimodality in a thermal
 357 preference trait-biomass distribution is not a proof of a storage effect, or conversely, the proof of
 358 the influence of a seasonal environment. The biomass-trait distributions constitute clues to inter-
 359 pret community dynamics (D’Andrea and Ostling, 2016; Loranger et al, 2018) but they seem to
 360 provide no clear-cut answers. The identification of multiple modes in these distributions is also a
 361 relatively recent feature in models and data (Segura et al, 2013; D’Andrea et al, 2018, 2019) and,
 362 so we recommend to interpret them with caution to avoid over-generalization. Barabás et al (2013)
 363 convincingly argued that multimodality could arise from the demographic stochasticity of a single
 364 model run (with either self-regulation or neutrality, but without the clumpy coexistence emerging
 365 from a storage effect). However, our results are based on many model runs, for which either the
 366 storage effect alone or a storage effect + strong self-regulation in a seasonal context consistently
 367 produced multimodal distributions, while simulations without the storage effect always led to a
 368 single cluster along the trait axis. Our suggestion for empirical studies is as follows: if only one
 369 spatial location is observed, caution in interpreting multiple clumps on the trait axis is of course
 370 required, as Barabás et al (2013) highlighted. However, with several locations - or in a theoretical
 371 context - one could average across locations. Clumps in the thermal preference trait axis when
 372 averaged across model runs/locations may therefore be a “storage effect clue”, for the cases that we
 373 considered in the article. Of course, other mechanisms that we did not include in our models may

374 produce similar clustered patterns (Rael et al, 2018) or obfuscate ~~these patterns~~ clusters altogether
 375 ~~—~~: typically, strong self-regulation weakens the clustering on the trait axis. Moreover, one should
 376 note that the occurrence of clustering is very sensitive to the shape of the competition kernel:
 377 small differences in shape can shift the distribution towards either clustered or uniform (Pigolotti
 378 et al, 2010). ~~Moreover,~~ Finally, we recall that we focus on a trait (thermal optimum) which clearly
 379 interacts with the environment: clustering may emerge on another trait axis, such as size, which
 380 typically affects the competition coefficient, without having any relationship to the storage effect
 381 (Segura et al, 2011, 2013; D’Andrea et al, 2018, 2019). We therefore view clustering on the thermal
 382 preference trait axis as an interesting clue suggesting to look for a storage effect, rather than any
 383 definite proof that the storage effect is at work.

384 In our previous empirical study of ~~coastal~~ phytoplankton dynamics (Barraquand et al, 2018),
 385 we did not find any storage effect. This, ~~however,~~ does not mean that it could not be observed
 386 in other planktonic systems: we studied a coastal ecosystem and focused a specific fraction of
 387 phytoplankton: relatively large diatoms and dinoflagellates. However, ~~g~~Given the consequences of
 388 the storage effect for species richness and composition presented here, we are skeptical that the
 389 storage effect could, by itself, ~~help explaining~~ fully explain phytoplankton diversity at any location.
 390 ~~However,~~ ~~o~~Our results suggest that in phytoplankton-like seasonal environments, ~~even though~~
 391 empirically-tuned self-regulation produces much more diversity than the storage effect, when both
 392 are considered in isolation. ~~T~~The storage effect ~~can~~ may therefore help phytoplankton diversity
 393 maintenance, but only when combined to other mechanisms. ~~Indeed,~~ This is all the more likely
 394 that in our models, the combination storage effect + strong self-regulation is non-additive: the
 395 cases where both self-regulation and the storage effect were present showed more diversity than
 396 generated by any mechanism on its own.

397 The above results suggest the very exciting idea that multiple coexistence mechanisms might
 398 combine superadditively to determine the richness of the community, thus helping us to better
 399 understand the astounding diversity of primary producers. This logic could, in principle, be ex-
 400 tended to mechanisms that we have not considered here (e.g., spatial structure, specialized natural
 401 enemies, that could be as important here for plankton as they are for tropical trees, see Bagchi

et al, 2014; Comita et al, 2014; Barraquand et al, 2018). The effect of interacting mechanisms can be measured either on community diversity, as we did here, or on processes rates directly, e.g. the invasion growth rates. Using the latter metric, previous research has however demonstrated that generalist seed predation could weaken the storage effect (Kuang and Chesson, 2009, 2010) thus different mechanisms might not always combine superadditively as we found here. That said, superadditivity has been found in some cases, i.e., pathogens could enhance the storage effect and broaden the conditions in which species could coexist (Mordecai, 2015). Better explaining plant or microbial diversity would then not be about selecting the best unique mechanism susceptible to explain the observed diversity, but rather better combining those mechanisms together. This may obviously be an annoyance for those who like to sharpen Occam’s razor, but it clearly holds opportunities for theoreticians wishing to investigate synergies between coexistence mechanisms in highly diverse communities. Aside from the synergies between predator diversity-enhancing effects, strong self-regulation through various means and storage effects (on the temporal axis), one obvious follow-up of this research would be interactions with spatial structure. Spatial structure occurs both endogeneously, through spatially restricted movements and interactions, and exogeneously, through spatial variation in environmental covariates (Bolker, 2003). Numerous studies (e.g., Bolker and Pacala, 1999; Murrell and Law, 2002) have shown that spatially restricted movements and interactions - very small-scale spatial structure - can help coexistence, which we believe would be especially important for phytoplankton since many species form colonies (Reynolds, 2006; see discussion in Barraquand et al, 2018). Moreover, although temperature is usually relatively spatially homogeneous over space, other drivers (e.g., rainfall, pH in terrestrial ecosystems; salinity in aquatic ones) may exhibit spatial variation which is a main factor for coexistence (Snyder, 2008). The odds that different (resource) niches, natural enemies, spatial limits to competition and temporal niche partitioning all interact to promote the very high-dimensional coexistence observed in the field seem much higher than for any of those mechanisms alone. Whether the diversity-enhancing effects of these mechanisms combine subadditively (as in Kuang and Chesson, 2010) or superadditively like here is therefore worthy of further research.

429 Acknowledgements

430 We thank Alix Sauve for thoughtful comments and some bibliographic references. We are very
431 grateful to György Barabás and an anonymous referee for their constructive feedback. This study
432 was supported by the French ANR through LabEx COTE (ANR-10-LABX-45).

433 References

- 434 Abrams PA (1976) Niche overlap and environmental variability. *Mathematical Biosciences*
435 28(3):357–372, doi:10.1016/0025-5564(76)90133-4
- 436 Adler PB, Ellner SP, Levine JM (2010) Coexistence of perennial plants: an embarrassment of
437 niches. *Ecology letters* 13(8):1019–1029, doi:10.1111/j.1461-0248.2010.01496.x
- 438 Adler PB, Smull D, Beard KH, Choi RT, Furniss T, Kulmatiski A, Meiners JM, Tredennick AT, Ve-
439 blen KE (2018) Competition and coexistence in plant communities: intraspecific competition is
440 stronger than interspecific competition. *Ecology Letters* 21(9):1319–1329, doi:10.1111/ele.13098
- 441 Armstrong R, McGehee R (1980) Competitive Exclusion. *American Naturalist* 115(2):151–170
- 442 Ashby B, Watkins E, Lourenço J, Gupta S, Foster KR (2017) Competing species leave many
443 potential niches unfilled. *Nature Ecology & Evolution* 1(10):1495–1501, doi:10.1038/s41559-017-
444 0295-3
- 445 Bagchi R, Gallery RE, Gripenberg S, Gurr SJ, Narayan L, Addis CE, Freckleton RP, Lewis OT
446 (2014) Pathogens and insect herbivores drive rainforest plant diversity and composition. *Nature*
447 506(7486):85–88, doi:10.1038/nature12911
- 448 Barabás G, Mészéna G, Ostling A (2012) Community robustness and limiting similarity in periodic
449 environments. *Theoretical Ecology* 5(2):265–282, doi:10.1007/s12080-011-0127-z
- 450 Barabás G, D’Andrea R, Rael R, Mészéna G, Ostling A (2013) Emergent neutrality or hidden
451 niches? *Oikos* 122(11):1565–1572, doi:10.1111/j.1600-0706.2013.00298.x

452 Barabás G, Michalska-Smith MJ, Allesina S (2017) Self-regulation and the stability of large eco-
453 logical networks. *Nature Ecology & Evolution* 1(12):1870–1875, doi:10.1038/s41559-017-0357-6

454 Barraquand F, Picoche C, Maurer D, Carassou L, Auby I (2018) Coastal phytoplankton community
455 dynamics and coexistence driven by intragroup density-dependence, light and hydrodynamics.
456 *Oikos* In press, doi:10.1111/171264

457 Bolker B, Pacala S (1999) Spatial Moment Equations for Plant Competition: Understanding Spa-
458 tial Strategies and the Advantages of Short Dispersal. *The American Naturalist* 153(6):575–602,
459 doi:10.1086/303199

460 Bolker BM (2003) Combining endogenous and exogenous spatial variability in analytical population
461 models. *Theoretical Population Biology* 64(3):255–270, doi:10.1016/S0040-5809(03)00090-X

462 Boyce DG, Petrie B, Frank KT, Worm B, Leggett WC (2017) Environmental structuring of marine
463 plankton phenology. *Nature Ecology & Evolution* doi:10.1038/s41559-017-0287-3

464 Carmel Y, Suprunenko YF, Kunin WE, Kent R, Belmaker J, Bar-Massada A, Cornell SJ (2017)
465 Using exclusion rate to unify niche and neutral perspectives on coexistence. *Oikos* 126(10):1451–
466 1458, doi:10.1111/oik.04380

467 Chesson P (1994) Multispecies Competition in Variable Environments. *Theoretical Population*
468 *Biology* 45:227–276, doi:10.1006/tpbi.1994.1013

469 Chesson P (2000) Mechanisms of maintenance of species diversity. *Annual review of Ecology and*
470 *Systematics* 31:343–366, doi:10.1146/annurev.ecolsys.31.1.343

471 Chesson P (2018) Updates on mechanisms of maintenance of species diversity. *Journal of Ecology*
472 106(5):1773–1794, doi:10.1111/1365-2745.13035

473 Chesson P, Huntly N (1997) The roles of harsh and fluctuating conditions in the dynamics of
474 ecological communities. *The American Naturalist* 150(5):519–553, doi:10.1086/286080

475 Comita LS, Queenborough SA, Murphy SJ, Eck JL, Xu K, Krishnadas M, Beckman N, Zhu Y
476 (2014) Testing predictions of the Janzen-Connell hypothesis: a meta-analysis of experimental

477 evidence for distance- and density-dependent seed and seedling survival. *Journal of Ecology*
478 102(4):845–856, doi:10.1111/1365-2745.12232

479 Dakos V, Beninca E, van Nes EH, Philippart CJM, Scheffer M, Huisman J (2009) Interannual
480 variability in species composition explained as seasonally entrained chaos. *Proceedings of the*
481 *Royal Society B: Biological Sciences* 276(1669):2871–2880

482 D’Andrea R, Ostling A (2016) Challenges in linking trait patterns to niche differentiation. *Oikos*
483 125(10):1369–1385, doi:10.1111/oik.02979

484 D’Andrea R, Ostling A, O’Dwyer J (2018) Translucent windows: how uncertainty in competitive
485 interactions impacts detection of community pattern. *Ecology Letters* 21(6):826–835

486 D’Andrea R, Riolo M, Ostling A (2019) Generalizing clusters of similar species as a signature of
487 coexistence under competition. *PLOS Computational Biology* 15(1):e1006688

488 Descamps-Julien B, Gonzalez A (2005) Stable coexistence in a fluctuating environment: an exper-
489 imental demonstration. *Ecology* 86(10):2815–2824

490 Ellner SP, Snyder RE, Adler PB (2016) How to quantify the temporal storage effect using simula-
491 tions instead of math. *Ecology Letters* 19(11):1333–1342, doi:10.1111/ele.12672

492 Fox JW (2013) The intermediate disturbance hypothesis should be abandoned. *Trends in Ecology*
493 *& Evolution* 28(2):86–92, doi:10.1016/j.tree.2012.08.014

494 Gravel D, Canham CD, Beaudet M, Messier C (2006) Reconciling niche and neutrality:
495 the continuum hypothesis: Reconciling niche and neutrality. *Ecology Letters* 9(4):399–409,
496 doi:10.1111/j.1461-0248.2006.00884.x

497 Hastings A, Abbott KC, Cuddington K, Francis T, Gellner G, Lai YC, Morozov A, Petrovskii S,
498 Scranton K, Zeeman ML (2018) Transient phenomena in ecology. *Science* 361(6406):eaat6412,
499 doi:10.1126/science.aat6412

500 Haydon D (1994) Pivotal assumptions determining the relationship between stability and com-
501 plexity: an analytical synthesis of the stability-complexity debate. *The American Naturalist*
502 144(1):14–29, doi:10.1086/285658

503 Holt R (2006) Emergent neutrality. *Trends in Ecology & Evolution* 21(10):531–533,
504 doi:10.1016/j.tree.2006.08.003

505 Hubbell SP (2001) *The Unified Neutral Theory of Biodiversity and Biogeography* (MPB-32).
506 Princeton University Press

507 Hutchinson GE (1961) The paradox of the plankton. *The American Naturalist* 95(882):137–145

508 Jabot F, Lohier T (2016) Non-random correlation of species dynamics in tropical tree communities.
509 *Oikos* 125(12):1733–1742, doi:10.1111/oik.03103

510 Kawatsu K, Kondoh M (2018) Density-dependent interspecific interactions and the complexity–
511 stability relationship. *Proc R Soc B* 285(1879):20180698, doi:10.1098/rspb.2018.0698

512 Kokkoris GD, Jansen VAA, Loreau M, Troumbis AY (2002) Variability in interaction strength
513 and implications for biodiversity. *Journal of Animal Ecology* 71(2):362–371, doi:10.1046/j.1365-
514 2656.2002.00604.x

515 Kuang JJ, Chesson P (2009) Coexistence of annual plants: generalist seed predation weakens the
516 storage effect. *Ecology* 90(1):170–182, doi:10.1890/08-0207.1

517 Kuang JJ, Chesson P (2010) Interacting coexistence mechanisms in annual plant communities:
518 frequency-dependent predation and the storage effect. *Theoretical population biology* 77(1):56–
519 70, doi:10.1016/j.tpb.2009.11.002

520 Li L, Chesson P (2016) The Effects of Dynamical Rates on Species Coexistence in a Variable
521 Environment: The Paradox of the Plankton Revisited. *The American Naturalist* 188(2):E46–
522 E58

523 Litchman E, Klausmeier CA (2001) Competition of phytoplankton under fluctuating light. *The*
524 *American Naturalist* 157(2):170–187

525 Loranger J, Munoz F, Shipley B, Violle C (2018) What makes trait-abundance relationships
526 when both environmental filtering and stochastic neutral dynamics are at play? *Oikos*
527 doi:10.1111/oik.05398

528 Miller ET, Klausmeier CA (2017) Evolutionary stability of coexistence due to the storage effect in
529 a two-season model. *Theoretical Ecology* 10(1):91–103, doi:10.1007/s12080-016-0314-z

530 Moisan JR, Moisan TA, Abbott MR (2002) Modelling the effect of temperature on the
531 maximum growth rates of phytoplankton populations. *Ecological Modelling* 153(3):197–215,
532 doi:10.1016/S0304-3800(02)00008-X

533 Mordecai EA (2015) Pathogen impacts on plant diversity in variable environments. *Oikos*
534 124(4):414–420, doi:10.1111/oik.01328

535 Murrell DJ, Law R (2002) Heteromyopia and the spatial coexistence of similar competitors. *Ecology*
536 Letters 6(1):48–59, doi:10.1046/j.1461-0248.2003.00397.x

537 Mutshinda CM, O’Hara RB, Woiwod IP (2009) What drives community dynamics? *Proceedings*
538 of the Royal Society B: Biological Sciences 276(1669):2923–2929, doi:10.1098/rspb.2009.0523

539 Pigolotti S, López C, Hernández-García E, Andersen K (2010) How Gaussian competition leads
540 to lumpy or uniform species distributions. *Theoretical Ecology* 3(2):89–96

541 Rael RC, D’Andrea R, Barabás G, Ostling A (2018) Emergent niche structuring leads to in-
542 creased differences from neutrality in species abundance distributions. *Ecology* 99(7):1633–1643,
543 doi:10.1002/ecy.2238

544 Reynolds CS (2006) *The ecology of phytoplankton*. Cambridge University Press

545 Rinaldi S, Murator S, Kuznetsov Y (1993) Multiple attractors, catastrophes and chaos in sea-
546 sonally perturbed predator-prey communities. *Bulletin of Mathematical Biology* 55(1):15–35,
547 doi:10.1007/BF02460293

548 Ruokolainen L, Lindén A, Kaitala V, Fowler M (2009) Ecological and evolutionary dynamics under
549 coloured environmental variation. *Trends in Ecology & Evolution* 24(10):555–563

550 Sakavara A, Tsirtsis G, Roelke DL, Mancy R, Spatharis S (2018) Lumpy species coexistence arises
551 robustly in fluctuating resource environments. *Proceedings of the National Academy of Sciences*
552 115(4):738–743, doi:10.1073/pnas.1705944115

553 Scheffer M, van Nes EH (2006) Self-organized similarity, the evolutionary emergence of groups
554 of similar species. *Proceedings of the National Academy of Sciences* 103(16):6230–6235,
555 doi:10.1073/pnas.0508024103

556 Scheffer M, Rinaldi S, Kuznetsov Y, van Nes E (1997) Seasonal Dynamics of *Daphnia* and Algae
557 Explained as a Periodically Forced Predator-Prey System. *Oikos* 80(3):519

558 Scranton K, Vasseur DA (2016) Coexistence and emergent neutrality generate synchrony among
559 competitors in fluctuating environments. *Theoretical Ecology* 9(3):353–363, doi:10.1007/s12080-
560 016-0294-z

561 Segura AM, Calliari D, Kruk C, Conde D, Bonilla S, Fort H (2011) Emergent neutrality drives
562 phytoplankton species coexistence. *Proceedings of the Royal Society B: Biological Sciences*
563 278(1716):2355–2361

564 Segura AM, Kruk C, Calliari D, García-Rodríguez F, Conde D, Widdicombe CE, Fort H (2013)
565 Competition Drives Clumpy Species Coexistence in Estuarine Phytoplankton. *Scientific Reports*
566 3:1037

567 Snyder RE (2008) When does environmental variation most influence species coexistence? *Theo-*
568 *retical Ecology* 1(3):129–139, doi:10.1007/s12080-008-0015-3

569 Stump SM (2017) Multispecies Coexistence without Diffuse Competition; or, Why Phylogenetic
570 Signal and Trait Clustering Weaken Coexistence. *The American Naturalist* 190(2):213–228,
571 doi:10.1086/692470

572 Taylor RA, White A, Sherratt JA (2013) How do variations in seasonality affect population cycles?
573 *Proceedings of the Royal Society B: Biological Sciences* 280(1754), doi:10.1098/rspb.2012.2714

- 574 Tyson R, Lutscher F (2016) Seasonally Varying Predation Behavior and Climate Shifts
575 Are Predicted to Affect Predator-Prey Cycles. *The American Naturalist* 188(5):539–553,
576 doi:10.1086/688665
- 577 Vasseur DA, Yodzis P (2004) The Color Of Environmental Noise. *Ecology* 85(4):1146–1152,
578 doi:10.1890/02-3122
- 579 Vesipa R, Ridolfi L (2017) Impact of seasonal forcing on reactive ecological systems. *Journal of*
580 *Theoretical Biology* 419:23–35, doi:10.1016/j.jtbi.2017.01.036
- 581 Winder M, Cloern JE (2010) The annual cycles of phytoplankton biomass. *Philosophical*
582 *Transactions of the Royal Society B: Biological Sciences* 365(1555):3215–3226,
583 doi:10.1098/rstb.2010.0125
- 584 Wootton JT, Emmerson M (2005) Measurement of Interaction Strength in Na-
585 ture. *Annual Review of Ecology, Evolution, and Systematics* 36(1):419–444,
586 doi:10.1146/annurev.ecolsys.36.091704.175535
- 587 Zhao XQ (1991) The qualitative analysis of n-species Lotka-Volterra periodic competition systems.
588 *Mathematical and Computer Modelling* 15(11):3–8, doi:10.1016/0895-7177(91)90100-L