

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

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Abstract

Explaining coexistence in species-rich communities of primary producers remains a challenge for ecologists because of their 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. However, fluctuating-environment models often only produce a dozen of coexisting species at best. Here, we investigate how to create 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 intra/inter competition ratio based on empirical analyses, in which self-regulation 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 ensure the coexistence of all species alone. Realistic seasonal environments only aggravated that picture, as they decreased persistence relative to a random environment. However, strong self-regulation and the storage effect combined superadditively so that all species could persist with both mechanisms at work. Our results suggest that combining different coexistence mechanisms into community models might be more fruitful than trying to find which mechanism best explains diversity. We additionally highlight that while biomass-trait distributions provide some clues regarding coexistence mechanisms, they cannot indicate unequivocally which mechanisms are at play.

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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. By making the identity of the fittest species change over time, temporal variation could render competitive exclusion less likely, which was confirmed by early experiments (Sommer, 1984). 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; Jiang and Morin, 2007; Fox, 2013) need to be introduced for diversity to maintain. Moreover, richness rarely exceeds a handful to a dozen of species in modeled competitive communities in fluctuating environments, except when external inputs from immigration sustain diversity (e.g., Huisman et al, 2001; 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 can be found in 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 a key feature of this paper. Our present work can be seen as an attempt to blend Scranton and Vasseur (2016)’s stochastic framework with the periodic environments of Barabás et al (2012), to better represent the mixture of stochastic and deterministic environmental forces affecting phytoplankton community dynamics.

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

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

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

95 2 Methods

96 *Models*

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

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

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

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

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

101 Model parameters are detailed in Table 1, and we set their values to match the features
 102 of phytoplankton communities as in Scranton and Vasseur's work (2016). The niche of each
 103 species is defined by its thermal optimum τ_i^{opt} . Thermal performance curves defined in Eq. 3
 104 are parameterized so that all species share the same niche area (Eq. 4), which sets a trade-off
 105 between maximum growth rates and niche width.

106 The original environmental forcing is a normally distributed variable centered on 293 K

Table 1: Parameter definitions and values for the model described in Eqs. 1-4. Parameter values are not specified when they vary over time and/or with 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	Baseline strength of intraspecific competition	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)

107 (20 $^{\circ}\text{C}$), with a 5 K dispersion. Temperature varies from one day to the next, but is kept constant
 108 throughout the day. At and above the daily scale, temperature could therefore be considered
 109 as a white noise (Vasseur and Yodzis, 2004). However, from a mathematical viewpoint, the
 110 noise is slightly autocorrelated as the integration process goes below the daily time step. We
 111 therefore use the expression ‘random noise’ to describe this forcing, as opposed to the ‘seasonal
 112 noise’ described hereafter. To construct the seasonal noise, we add to the random forcing signal
 113 a lower-frequency component, using a sinusoidal function with a period of 365 days (Eq. 5).
 114 We tune the ratio of low-to-high frequency with the variable θ so as to keep the same energy
 115 content - i.e., equal total variance - in the forcing signal.

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

116 Note that the upper limit for θ , $\sqrt{2}$, corresponds to a completely deterministic model which
 117 we do not explore here (but see Zhao (1991) proving bounded coexistence). We choose to
 118 keep the stochasticity in the signal and to model a plausible temperature signal with $\theta = 1.3$

(illustrated in Fig. 1b) when considering a seasonal forcing of the dynamics.

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

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

Following Eq. 6, net competition remains unaffected by the environmental conditions, in contrast to intrinsic growth rates, while preserving the same average magnitude of competition as in Eq. 1.

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

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

where δ_{ij} is the Kronecker symbol, equal to 1 if $i = j$ and to 0 otherwise. The value of the parameter $\kappa = 10$ was chosen from analyses of phytoplanktonic data (Barraquand et al, 2018)¹. Hereafter, the expression “strong self-regulation” characterizes dynamics where the intraspecific competition strength is 10 times higher than the interspecific competition strength, as opposed to “equal competitive strengths” where intra- and interspecific competition strengths are equal.

In addition to two types of environmental forcings (random noise with $\theta = 0$, and seasonal noise with $\theta = 1.3$), we compare the results for four versions of the original model: with and

¹The values of non-zero interspecific competition coefficients reported in Fig. 5 of Barraquand et al (2018) are somewhat higher than here (and κ lower, closer to 4) because the best-fitting model actually set to zero some intergroup competition coefficients; using a model where all α_{ij} are non-zero leads in contrast to $\kappa = 10$).

without an explicit storage effect (Eq. 1 and Eq. 6, respectively); with strong self-regulation or equal intra- 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 models

146

147 Set-up

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

All simulations are run with Matlab’s ode45 algorithm, an adaptive Runge-Kutta (4,5) integration scheme with an absolute error tolerance of 10^{-8} , and relative error tolerance of 10^{-3} . The code is available in a GitHub repository².

158 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

²<https://github.com/CoraliePicoche/Seasonality>

165 in the range of their biomasses. A third of the species kept a biomass above 10 kg/area (setting
 166 area = 1 ha, with a depth of a few meters, produces a realistic standing biomasses; Reynolds,
 167 2006) while 6 out of the 14 species biomasses remained below the unit. All persisting species
 168 in the random noise simulation were clustered within a 3.2°C-range of thermal optima (see
 169 the biomass distribution as a function of the thermal optimum in Electronic Supplementary
 170 Material, Fig. A1). No obvious temporal patterns (e.g., cycles) could be seen in the community
 171 forced by random noise. On the contrary, seasonal cycles were clear in the seasonally-forced
 172 case of Fig. 1d. Only 4 species coexisted at the end of the simulation with seasonal noise,
 173 gathered in two groups with large thermal optimum differences (5.7°C between the maximum
 174 thermal optimum of the first group and the minimum thermal optimum of the second group).
 175 When temperatures were high, the group with higher thermal optima reached its maximum
 176 biomass, then as temperature decreases through the season, these species leave room for the
 177 growth of the low-temperature group.

178 The decrease in persistence due to seasonality observed in Fig. 1 was confirmed in all our
 179 simulations (Fig. 2). In cases where final species richness varied from one simulation to another
 180 (namely, the two middle cases in Fig. 2: with storage effect but without strong self-regulation,
 181 or without storage effect but with strong self-regulation), seasonality reduced the number of
 182 extant species to, on average, 27% and 48% of their original values, respectively (Fig. 2). A
 183 seasonal signal therefore led to a much smaller average persistence. There was also less variance
 184 in persistence between seasonally forced simulations compared to random noise simulations.

185 Both a strong self-regulation and the storage effect markedly increased persistence. Without
 186 any of these coexistence mechanisms, only one species persisted at the end of the simulations.
 187 When only the storage effect was present, the number of extant species varied between 8
 188 and 20 (14.8 ± 2.4) with random noise, or 2 and 6 (4.1 ± 0.7) with a seasonal signal. On
 189 the other hand, when only a strong self-regulation was present, the number of extant species
 190 nearly doubled, varying between 20 and 32 (27.5 ± 2.4), or 12 and 15 (13.3 ± 0.6), with a
 191 random or a seasonal noise, respectively. Remarkably, when the storage effect and a strong
 192 self-regulation both affected the community dynamics, all species persisted in the community:
 193 the number of species coexisting with both mechanisms present is greater than the sum of
 194 the species coexisting with either mechanism alone. The two mechanisms therefore combine

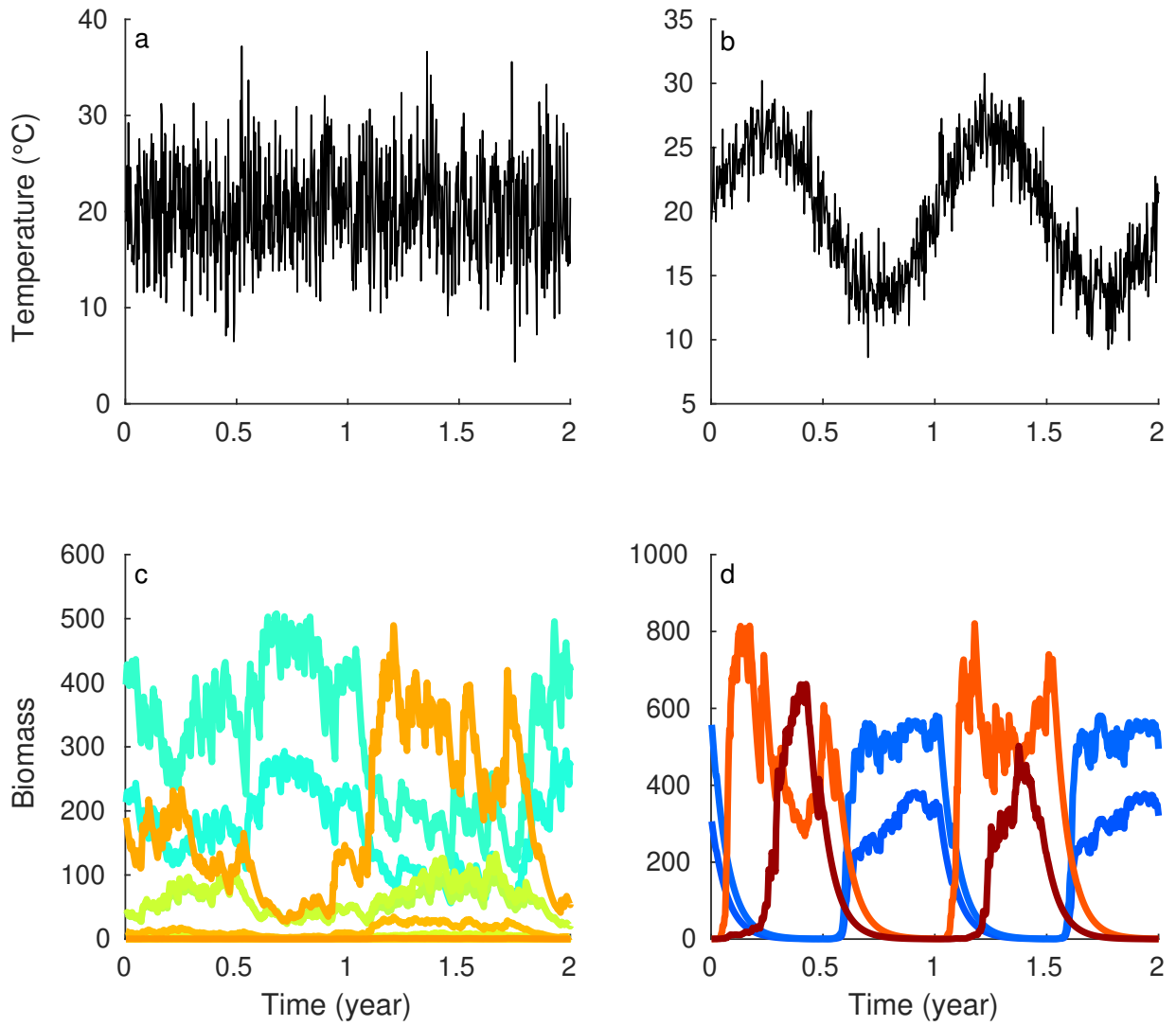


Figure 1: Time series of temperature (top; a-b) and extant species (bottom; c-d) for the 2 last years of a 5000-year simulation, with storage effect but no differences between intraspecific and interspecific competition strengths. The forcing temperature is either a random noise (a) or a seasonal noise (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).

superadditively, as their interaction has a positive effect on the richness of the community.

The trait-biomass distribution of the community was affected by the type of forcing even when the richness of the community was stable (Fig. 3). Without storage effect nor strong self-regulation, there was only one species left at the end of the simulations. A random noise favored species with intermediate thermal optima: the final species had a thermal optimum between 18.9°C and 21.4°C (only a fourth of the initial range of thermal optima) for two simulations out of three and the maximum final biomasses over 100 simulations was reached in this range (Fig. 3a). This distribution may indicate a selection for the highest long-term growth rates, averaged

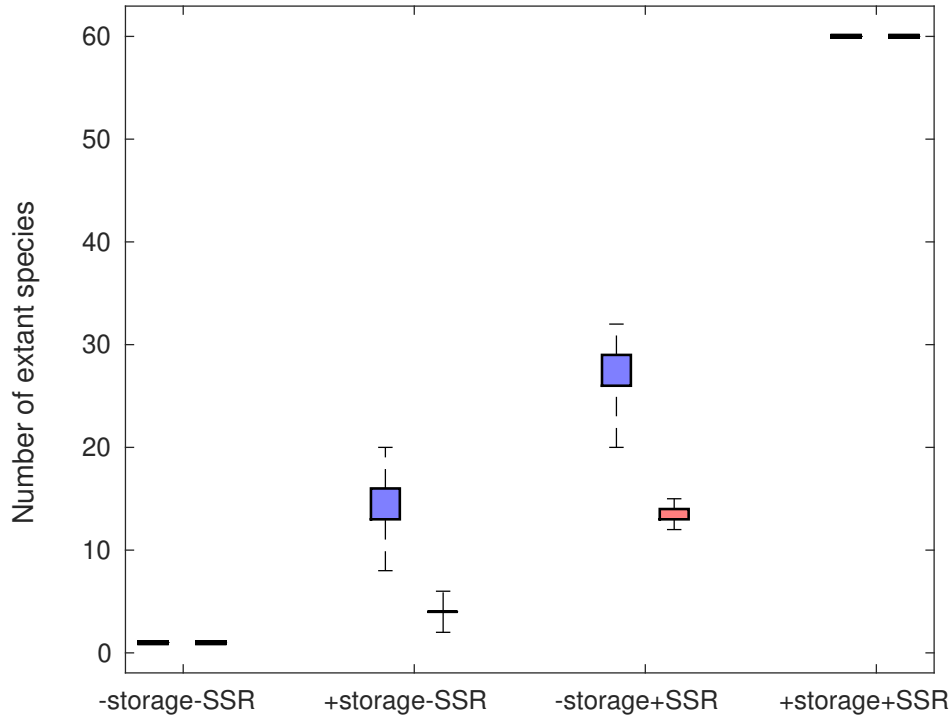


Figure 2: Number of species still present at the end of 100 simulations (5000 years each), initialized with 60 species, with a random (blue) or a seasonal forcing signal (red). The signs + or -storage refer to presence or absence of the storage effect, respectively; + / - SSR, presence or absence of 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.

over time (see scaled growth rates in Fig. 3). Seasonality with no coexistence mechanisms also led to a single final species but, in this case, the species always had a higher maximum growth rate (thermal optimum above 22°C). Species with a higher thermal optimum were more likely to persist and to reach a higher biomass at the end of the simulation. 38% of the simulations therefore ended with the species having the highest temperature optimum, 25°C. The shift in trait distribution towards higher maximum growth rates with a seasonal noise vs higher average growth rates with a random noise was consistent for all model types considered.

When both the storage effect and strong self-regulation were present, the 60 initial species coexist with almost no variation in their respective biomasses from one simulation to the next (mean CV across simulations is 0.008, averaged across species, Fig. 3b and d). The forcing signal modified only the distribution of biomasses, resulting in contrasted community structures despite equal richness. With a random noise, the distribution was unimodal. On the contrary, a seasonal signal led to a bimodal distribution (centered on 17.0°C and 24.4°C), each

216 corresponding to one season, with highest biomasses for higher thermal optima (Fig. 3d). The
 217 minimum biomass was reached for the highest long-term average growth rate at an intermediate
 218 temperature (20.4°C).

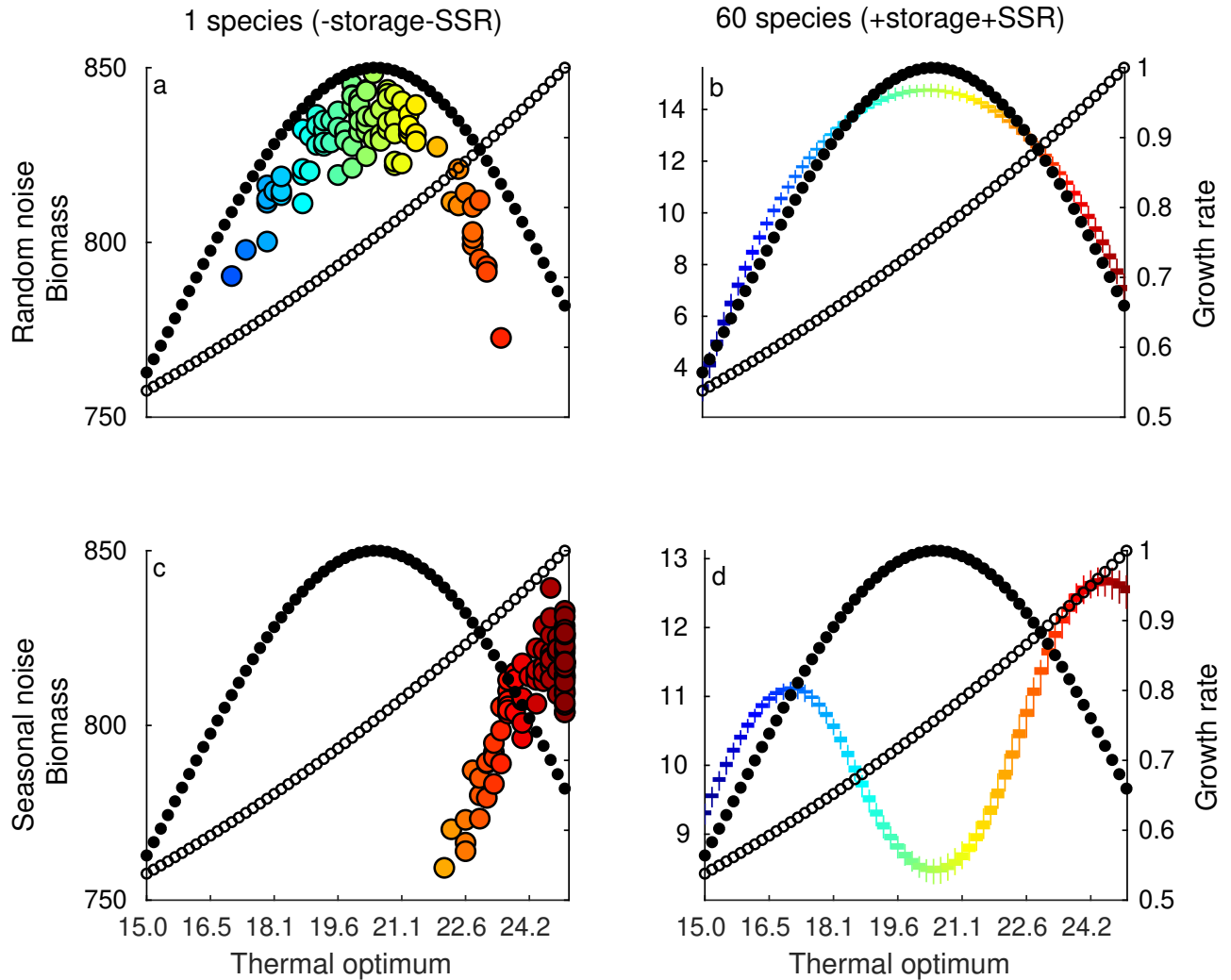


Figure 3: Mean biomass distribution over the last 200 years for 100 simulations, as a function of the species thermal optima. Here we consider the two stable-composition cases and two types of forcing signal. On the left column, simulations without storage effect nor strong self-regulation are presented. 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.

219 In cases where the richness of the community varied, the overall shape (multimodal vs
 220 unimodal) of the marginal distribution of extant species with respect to the trait axis were
 221 similar for both 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 c,d), 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.

4 Discussion

We have simulated competitive Lotka-Volterra dynamics forced by a fluctuating temperature 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 signal 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; Boyce et al, 2017) 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,

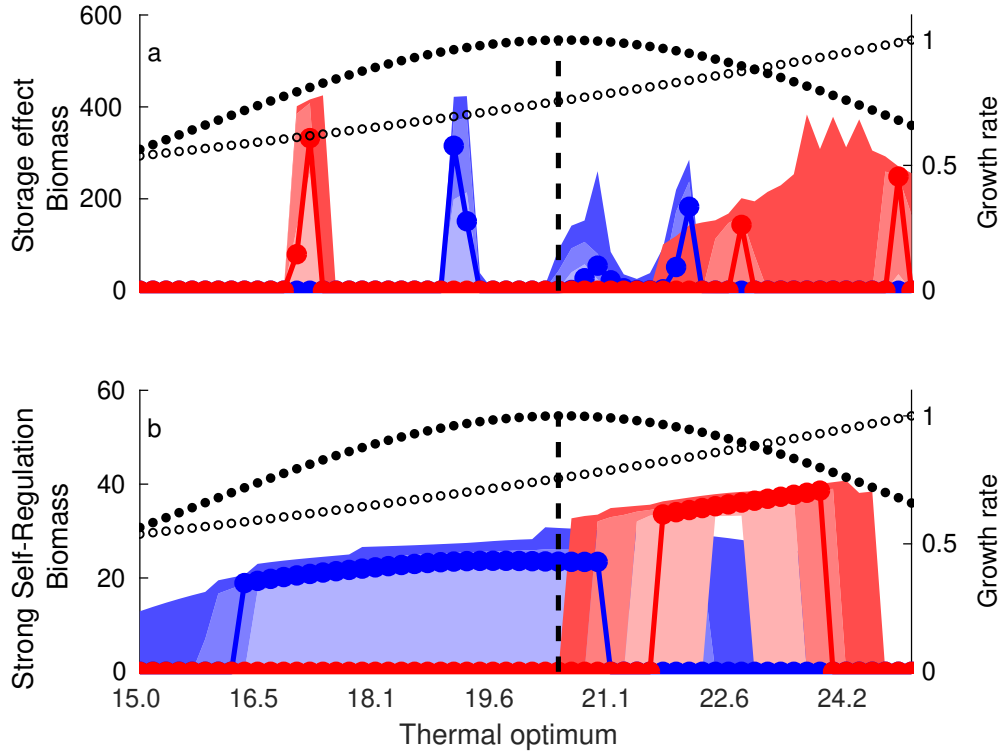


Figure 4: Mean biomass distribution over the last 200 years for 100 simulations, as a function of thermal optima, (a) with storage effect and equal competitive strengths and (b) without storage effect, with strong self-regulation. The forcing signal is either a random (in blue) or a seasonal noise (in 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 and maximum growth rates are shown as filled and open circles, respectively, and indexed on the right y-axis. The maximum average growth rate is indicated by the dashed line.

1994). Strong self-regulation seems 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). While short- and medium-term transients (a few years to hundreds of years) are completely negligible at the end of the time series, very long transients can remain in this class of models (Scheffer and van Nes, 2006; 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 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.

262 We could have considered longer time intervals, but comparison with the values reported by
263 Scranton and Vasseur (2016) would then have been compromised. Another way to shorten
264 the transients, suggested by a referee (GB), is to vary the mortality parameter. This did not
265 alter the conclusions (see Appendix B in Electronic Supplementary Material). Unfortunately,
266 added variability also shifts the model further away from neutral dynamics (when intra and
267 interspecific competition strengths are equal), which renders comparisons difficult. All things
268 considered, we therefore kept the 5000-year time window for integration.

269 Another strong assumption pertains to competition coefficients. To allow for comparison
270 with Scranton and Vasseur (2016), we did not introduce variability in intraspecific competi-
271 tion strength or interspecific competition strength. By contrast, data-based coefficients vary
272 between species (Barraquand et al, 2018), with a majority of weak interactions (as suggested in
273 Wootton and Emmerson, 2005) and more variance in intraspecific coefficients. Stump (2017)
274 recently considered the potential effects of competition coefficient variability (also called non-
275 diffuse competition), as did Kokkoris et al (2002); more variance in interspecific competition
276 strength is usually detrimental to coexistence for an equal amount of self-regulation (see Stump
277 (2017) for a classification of the various effects). Setting the competition coefficients using a
278 multidimensional trait-based framework, like that of Ashby et al (2017), would provide a natural
279 development to the work presented here; it is in our opinion difficult to speculate on those vari-
280 ance effects because both intra- and interspecific competition coefficient variances may matter
281 to community persistence.

282 Finally, our study is limited to communities whose species have fast population dynamics
283 relative to the yearly timescale, like phytoplankton and likely other fast-living organisms, so
284 that many generations can occur in a year. Persistence in community with slower dynamics may
285 be affected differently by seasonality (Miller and Klausmeier, 2017). This especially true for
286 species with generations that extend over multiple years. In models where trophic interactions
287 are implemented, seasonality has been shown to promote multiyear cycles and the existence of
288 chaotic attractors (Rinaldi et al, 1993; Taylor et al, 2013; Tyson and Lutscher, 2016). These rich
289 dynamics of consumers may feed back into the lower trophic levels: Dakos et al (2009) present
290 a planktonic community with seasonally-entrained chaotic dynamics which may be partly due
291 to zooplanktonic predation. Predation probably entails additional niche differences, possibly

292 with an emerging self-regulation created by predation processes (Chesson, 2018), but it seems
293 unlikely that we would be able to generate such dynamics with the models presented in this
294 article. Additional nonlinearities would be needed to create intrinsically variable and chaotic
295 dynamics.

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

322 Chesson, 2018) relative to other systems, hence we believe that 10 times stronger intraspecific
323 competition constitutes a reasonable order of magnitude.

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

337 Our results may appear at odds with recent proposals that seasonal forcing in itself would
338 help maintain diversity (Sakavara et al, 2018). However, we compared the effect of seasonal
339 forcing to that of other forcing signals while controlling for total variance. Thus, the contrast
340 between our results and those of Sakavara et al (2018) may be due to the role of forcing variance
341 over time: we compare scenarios under a constant total variance, much like what is done when
342 examining the effect of noise color on population and community dynamics (Jiang and Morin,
343 2007; Ruokolainen et al, 2009). Thinking in terms of signal spectrum, while seasonality may
344 maintain slightly more diversity than no forcing at all if a storage effect is present, the reddening
345 of the environmental noise due to such seasonality reduces coexistence. This result may be
346 contingent upon the correlated positive responses of the species growth rate to increases in the
347 environmental variable (Ruokolainen et al, 2009, and references therein).

348 The biomass-trait relationship was affected more marginally by the type of forcing signal.
349 The storage effect alone begot several clumps along the trait space (as observed by Scranton
350 and Vasseur, 2016). The seasonality that we added to the temperature signal led to more
351 distant clumps on the trait axis, with less species per clump. Conversely, strong self-regulatory

mechanisms alone led to relatively uniform biomass distributions, with species forming a single large cluster, which covered a fraction of the initial trait space. Therefore, the shape of the distribution was mostly affected by the coexistence mechanism at work while the average trait value was modified by the type of environmental forcing, even though the mean value of the environmental signal did not change. However, when both strong-self regulation and the storage effect were at play, the biomass-trait distribution could either be unimodal or multimodal depending on the type of noise driving the community dynamics (random or seasonal, respectively). This implies that the mere observation of multimodality in a thermal preference trait-biomass distribution is not a proof of a storage effect, or conversely, the proof of the influence of a seasonal environment.

The identification of multiple modes in biomass-trait distributions is relatively recent (Segura et al, 2013; Loranger et al, 2018; D’Andrea et al, 2018, 2019), so we recommend to interpret them with caution to avoid over-generalization. Barabás et al (2013) convincingly argued that multimodality could arise from the demographic stochasticity of a single model run. However, with several locations - or in a theoretical context as done here - one could average across locations. There are additional reasons to be cautious: the occurrence of clustering is very sensitive to the shape of the competition kernel; small differences in shape can shift the distribution towards either clustered or uniform (Pigolotti et al, 2010). We therefore view clustering on the thermal preference trait axis as an interesting clue suggesting to look for a storage effect, rather than any definite proof that the storage effect is at work. Finally, we recall that we focus on a trait (thermal optimum) which clearly interacts with the environment: clustering may emerge on another trait axis, such as size, which typically affects the competition coefficient, without having any relationship to the storage effect (Segura et al, 2011, 2013; D’Andrea et al, 2018, 2019).

In our previous empirical study of phytoplankton dynamics (Barraquand et al, 2018), we did not find any storage effect. This does not mean that it could not be observed in other planktonic systems: we studied a coastal ecosystem and focused a specific fraction of phytoplankton: relatively large diatoms and dinoflagellates. However, given the consequences of the storage effect for species richness and composition presented here, we are skeptical that the storage effect could, by itself, fully explain phytoplankton diversity at any location. Our results suggest that

382 in phytoplankton-like seasonal environments, empirically-tuned self-regulation produces much
383 more diversity than the storage effect, when both are considered in isolation. The storage effect
384 may therefore help phytoplankton diversity maintenance, but only when combined to other
385 mechanisms. This is all the more likely that in our models, the combination storage effect
386 + strong self-regulation is non-additive: the cases where both self-regulation and the storage
387 effect were present showed more diversity than generated by any mechanism on its own.

388 The above results suggest the very exciting idea that multiple coexistence mechanisms might
389 combine superadditively to determine the richness of the community, thus helping us to better
390 understand the astounding diversity of primary producers. This logic could, in principle, be
391 extended to mechanisms that we have not considered here (e.g., spatial structure, specialized
392 natural enemies, that could be as important here for plankton as they are for tropical trees, see
393 Bagchi et al, 2014; Comita et al, 2014; Barraquand et al, 2018). Superadditivity, i.e. the posi-
394 tive effect of interactions between mechanisms can be measured either on community diversity,
395 as we did here, or on the invasion growth rates (Ellner et al, 2019). Using the latter metric,
396 previous research has however demonstrated that generalist seed predation could weaken the
397 storage effect (Kuang and Chesson, 2009, 2010) thus different mechanisms might not always
398 combine superadditively as we found here. That said, superadditivity has been found in some
399 cases, i.e., pathogens could enhance the storage effect and broaden the conditions in which
400 species could coexist (Mordecai, 2015). Better explaining plant or microbial diversity would
401 then not be about selecting the best unique mechanism susceptible to explain the observed
402 diversity, but rather better combining those mechanisms together. This may obviously be
403 an annoyance for those who like to sharpen Occam’s razor, but it clearly holds opportunities
404 for theoreticians wishing to investigate synergies between coexistence mechanisms in highly
405 diverse communities. Aside from the synergies between predator diversity-enhancing effects,
406 strong self-regulation through various means and the storage effect (on the temporal axis), one
407 obvious follow-up of this research would be interactions with spatial structure. Spatial struc-
408 ture occurs both endogeneously, through spatially restricted movements and interactions, and
409 exogeneously, through spatial variation in environmental covariates (Bolker, 2003). Numer-
410 ous studies (e.g., Bolker and Pacala, 1999; Murrell and Law, 2002) have shown that spatially
411 restricted movements and interactions - very small-scale spatial structure - can help coexis-

tence, 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.

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