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

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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 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.

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27 Introduction

1
2 28 There has been a rich debate in theoretical ecology on how to reconcile niche and neutral
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4 29 perspectives on species coexistence (Gravel et al., 2006; Carmel et al., 2017). Under the neutral
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6 30 perspective, all species have equal birth and death rates and compete equally (since space is
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8 31 limited) whilst under the niche perspective, birth and death rates can vary between species
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10 32 and various mechanisms contribute to increasing intraspecific over interspecific competition
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12 33 (Hubbell, 2001). However, as it has been pointed out repeatedly, niche and neutral processes are
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14 34 not mutually exclusive: they may actually act together to produce observed species coexistence
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16 35 (Gravel et al., 2006; Mutshinda et al., 2009; Götzenberger et al., 2012).

18
19 36 An intriguing offshoot of the niche vs neutrality debate is the concept of ‘clumpy coexis-
20
21 37 tence’ (Scheffer and van Nes, 2006), whereby simultaneous influences of both niche and neutral
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23 38 processes create several clumps of similar species along a single trait axis. Classical stabiliz-
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25 39 ing niche differences (SNDs), such as a net intraspecific competition stronger than interspecific
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27 40 competition, enable coexistence of multiple clumps (Chesson, 2000), while within-clump coexis-
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29 41 tence occurs through neutral processes (Hubbell, 2001; Munoz and Huneman, 2016), as species
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31 42 that differ too little in their fitnesses cannot exclude themselves out on reasonable timeframes.
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33 43 Indeed, clumps on the trait axis eventually thin out in absence of immigration, but transient
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35 44 coexistence can last for extended periods of time. This ‘emergent neutrality’ within groups
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37 45 (Holt, 2006) has been proposed as a unifying concept for the niche and neutral theories. The
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39 46 findings of Scheffer and van Nes (2006) have been disputed due to hidden niches in the original
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41 47 model (Barabás et al., 2013). Hidden niches emerge through stronger intraspecific competition
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43 48 mediated by an additional predation-like term (Barabás et al., 2013). This makes coexistence
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45 49 in the Scheffer and van Nes model more similar to that of the classical Lotka-Volterra model
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47 50 (Barabás et al., 2016), so that coexistence within clumps is not exactly neutral. Still, the idea
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49 51 that niche and neutral assembly can mould communities stays potent (Haegeman and Loreau,
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51 52 2011; Vergnon et al., 2013). Since then, several studies have suggested that ‘clumpy coexis-
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53 54 tence’ can occur in theoretical models, most notably models incorporating temporal variation
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55 56 (Scranton and Vasseur, 2016; Sakavara et al., 2018). In these temporal-variation models, equal
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57 58 competitive strengths are combined with other mechanisms like the storage effect (or tempo-
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59 59 ral niche partitioning, that is an equivalent concept for forced Lotka-Volterra models, Barabás
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et al., 2012; Scranton and Vasseur, 2016). The storage effect increases the possibility of coexistence by making the interaction strength covary positively with a fluctuating environmental quality (see also Barabás et al., 2012).

Here, we build on the work of Scranton and Vasseur (2016) to investigate the possibility of coexistence through species response to fluctuating environments. Our enthusiasm for the Scranton and Vasseur (2016) model stems from our interest in phytoplankton communities, that inspired their thermal preference curves modeling intrinsic growth rates. However, Scranton and Vasseur (2016) described daily temperature as a random noise, i.e., independent and identically distributed Gaussian random variates over time. This appeared to us a key assumption to relax. Under most latitudes, temperature is indeed a seasonal signal, and seasonal forcing can strongly affect the dynamics of the community considered (Vesipa and Ridolfi, 2017). Hence, over short timescales, random temporal variations often only add noise to a largely deterministic seasonal trend. Our present work can therefore 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.

Because many phytoplankton species or genera respond in similar ways to temperature despite having different optimas (Moisan et al., 2002), we hypothesized that a large seasonal variation might not necessarily foster species coexistence. In fact, similar responses to seasonal fluctuations should lead to an increased synchrony of species abundances which, in turn, should theoretically mitigate the expected temporal partitioning. How seasonality affects coexistence (as opposed to a purely randomly fluctuating environment) is therefore a key feature of this paper. In particular, we contrast cases where the storage effect is present vs absent, which conveniently maps to two different parameterizations of the forced Lotka-Volterra model. Moreover, the overall diversity obtained at the end of the simulations with Scranton and Vasseur (2016)’s model was relatively low compared to what we usually observe in phytoplankton communities (several dozens to hundreds of species). We have therefore sought out which mechanisms would foster a truly species-rich community for extended periods of time.

In an empirical study combining phytoplankton community-level time series and multivariate autoregressive models (Barraquand et al., 2018), we found that despite a large influence of

the environment (including temperature, irradiance, and other factors), a strong intraspecific (or intragenus) competition, when compared to interspecific interaction coefficients, was most likely the key driver of species coexistence. In other words, strong self-regulation had a large role to play in maintaining species diversity in coastal phytoplankton (Barraquand et al., 2018). These high intraspecific interaction strengths mirror those found in a number of terrestrial plant communities (Adler et al., 2018) and in animal communities (Mutshinda et al., 2009).

Here, we therefore try to establish what are the relative contributions to coexistence of the storage effect vs strong self-regulation, in a phytoplankton-like theoretical community model. This led us to cross different combinations of seasonality in the forcing signal, presence of the storage effect or not, and intra- vs interspecific competition intensity, in order to disentangle the contributions of all these factors to biodiversity maintenance.

Methods

Model description

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

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

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

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

$$\text{and } b_i \text{ such as } \int r_i(\tau) d\tau = A \quad (4)$$

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

are parameterized so that all species share the same niche area (Eq. 4), which sets a trade-off between maximum 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)

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

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

Note that the upper limit for θ , $\sqrt{2}$, corresponds to a completely deterministic model which we do not explore here (but see Zhao (1991) proving bounded coexistence). We choose to 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 created 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 was 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 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.

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 $\kappa = 10$.

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 formulations of the model: with and 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.

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

$\frac{1}{N_i} \frac{dN_i}{dt} + m_i$	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 ($\kappa = 1$)	$r_i(\tau) \left(1 - \sum_{j=1}^S \alpha N_j \right)$	$r_i(\tau) - \sum_{j=1}^S \bar{r}_i \alpha N_j$

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 focused 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 was run for 5000 years in 1-day intervals. When the density of a species dropped below 10^{-6} , it was considered extinct. For each combination of parameters (type of environmental signal, storage effect and stabilizing niche differences), we ran 100 simulations.

All simulations were run with Matlab’s ode45 algorithm, an explicit 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.

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.

²<https://github.com/CoraliePicoche/Seasonality>, will be made public upon acceptance or at the reviewer’s request and stored in Zenodo

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 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.

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

Both a strong self-regulation and the storage effect markedly increased persistence. Without any of these coexistence mechanisms, only one species persisted at the end of the simulations. When only the storage effect was present, the number of extant species varied between 8 and 20 (14.8 ± 2.4) with random noise, or 2 and 6 (4.1 ± 0.7) with a seasonal signal. On the other hand, when only a strong self-regulation was present, the number of extant species nearly doubled, varying between 20 and 32 (27.5 ± 2.4), or 12 and 15 (13.3 ± 0.6), with a random or

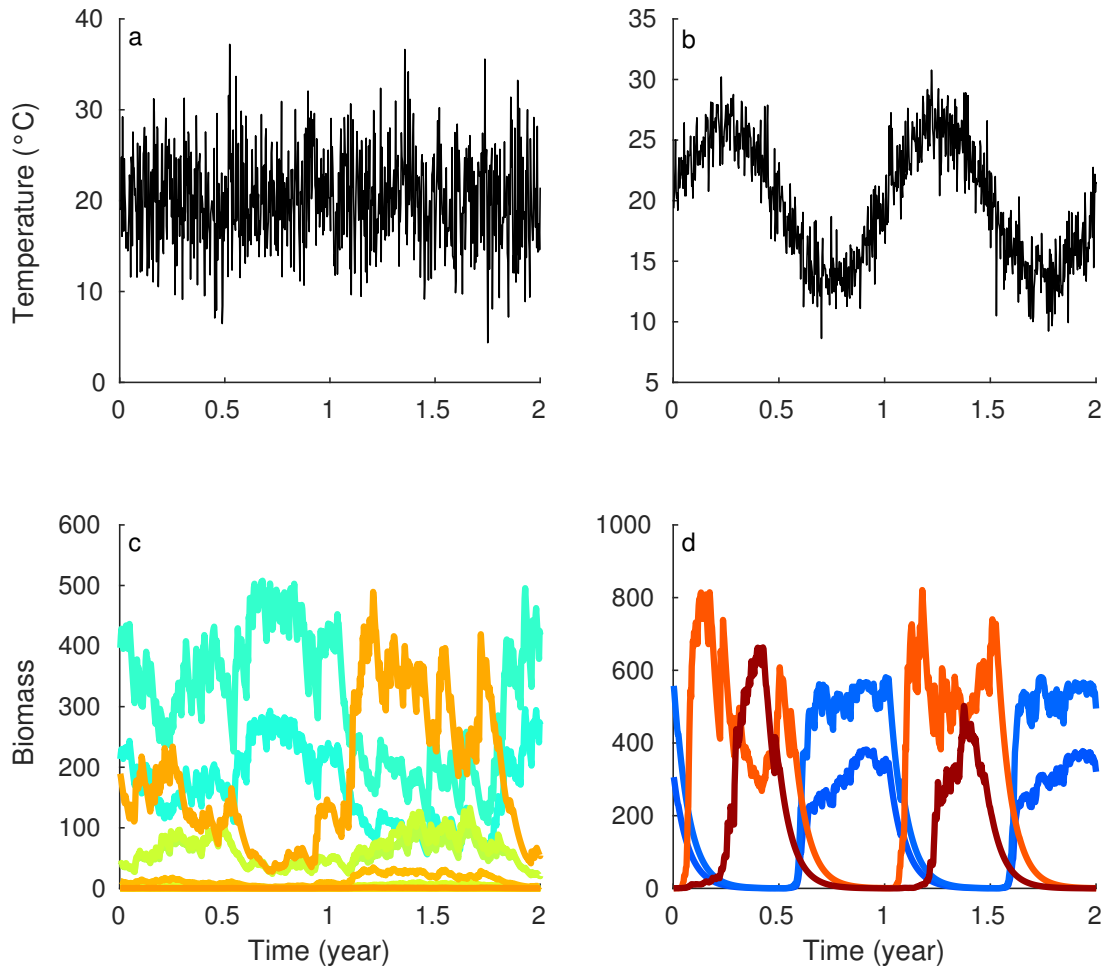


Figure 1: Time series of temperature (top; a-b) and extant species (bottom; c-d) for the 2 last years of a 5000-year simulation, with storage effect but no differences between intraspecific and interspecific competition strengths. The forcing temperature is either a random noise (a) or a seasonal noise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

a seasonal noise, respectively. Remarkably, when the storage effect and a strong self-regulation both affected the community dynamics, all species persisted in the community, while neither of these mechanisms was able to produce that result alone, for either random and seasonal noise.

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

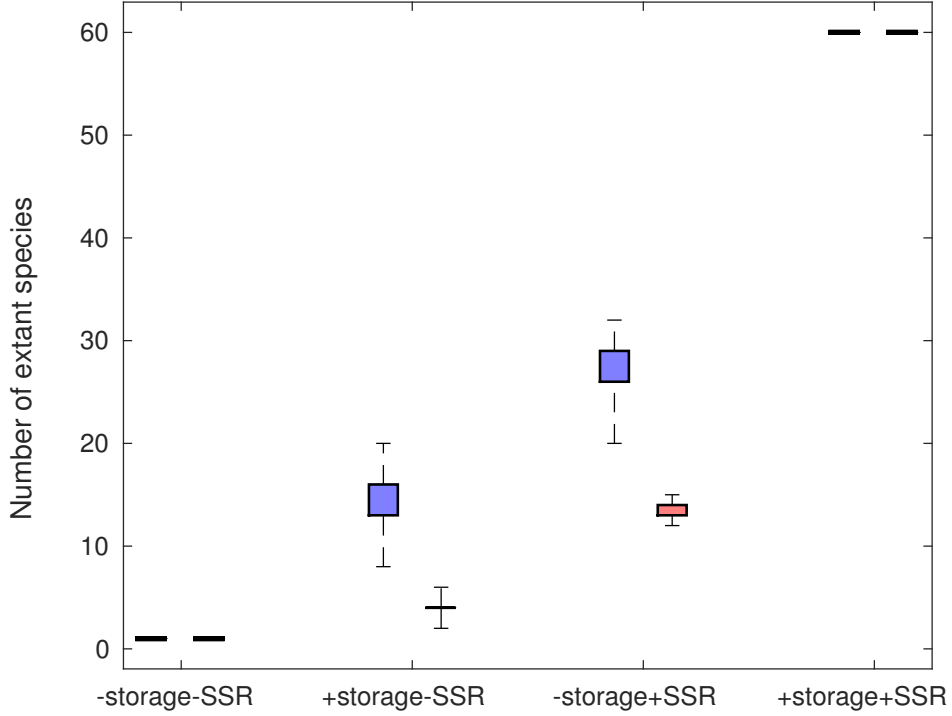


Figure 2: Number of species still present at the end of 100 simulations (5000 years each), initialized with 60 species, with a random forcing signal (blue) or a seasonal noise (red). The signs + or -storage refer to presence or absence of the storage effect, respectively; + / - SSR, presence or absence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

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 storage effect and strong self-regulation were present, the 60 initial species coexisted with small variations in biomasses for each species over the 100 simulations (mean CV=0.008 across simulations with either a random or a seasonal noise, Fig. 3b and d). The forcing signal modified only the distribution of biomasses resulting in contrasted community structures despite equal richness in both simulation types. With a random noise, the distribution was unimodal with a maximum biomass reached for the second highest long-term average

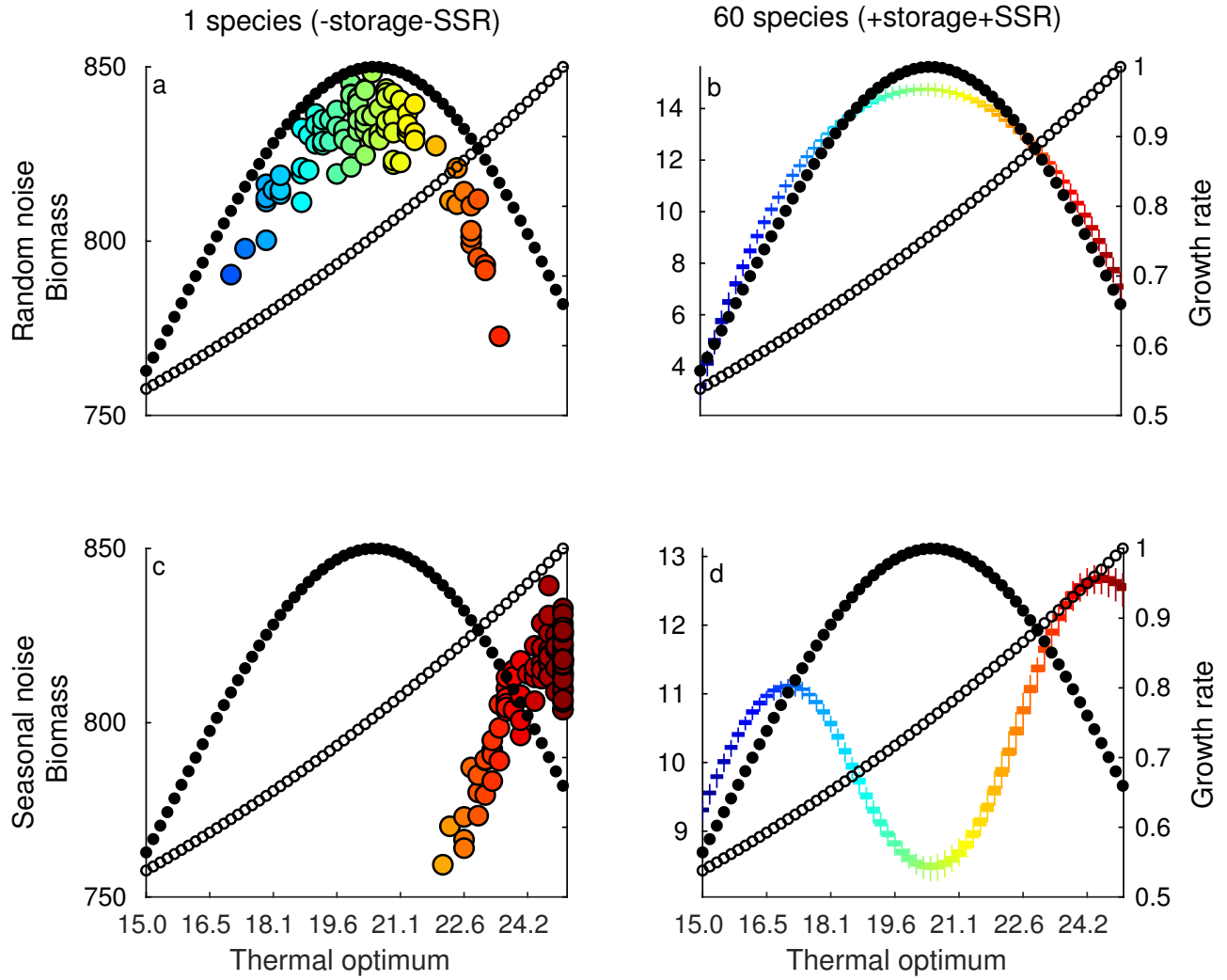


Figure 3: Mean biomass distribution over the last 200 years for 100 simulations, as a function of the species thermal optima. Here we consider the two stable-composition cases and two types of forcing signal. On the left column, simulations without storage effect nor strong self-regulation are presented.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

growth rate (corresponding to a thermal optimum of 20.2°C). On the contrary, a seasonal signal led to a bimodal distribution (centered on 17.0°C and 24.4°C), each corresponding to one season, with highest biomasses for higher thermal optima (Fig. 3d). The minimum biomass was reached for the highest long-term average growth rate at an intermediate temperature (20.4°C).

In cases where the richness of the community varied, the overall shape (multimodal vs unimodal) of the marginal distribution of extant species with respect to the trait axis were

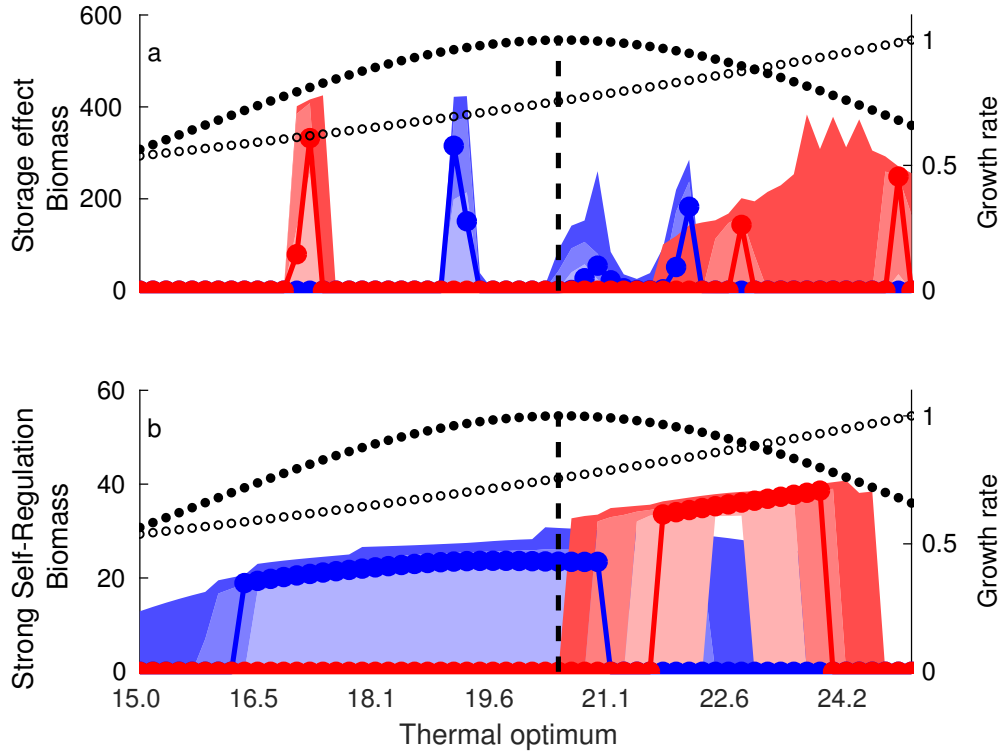


Figure 4: Mean biomass distribution over the last 200 years for 100 simulations, as a function of thermal optima, with storage effect and equal competitive strengths (a) and without storage effect, with strong self-regulation (b). The forcing signal is either a random (in blue) or a seasonal noise (in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

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 the 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.

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 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. We realized that convergence could be 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 for both technical and ecological reasons. From a technical standpoint, adding 10 000 years of numerical integration (or more) for the sake of reaching equilibrium would have been very challenging computationally, and comparison with the values reported by Scranton and Vasseur (2016) would have been compromised. From an ecological standpoint, waiting for full convergence when there are extremely long transients (Hastings et al., 2018) is also quite artificial: there is no reason to believe that very long transients (i.e., transients that maintains for thousands of years) have any less ecological reality than an attractor that is deemed stable. Speed of convergence is therefore an issue to judge whether transients should be considered or excluded, and a very long yet fixed time window for integration allows advantageously to compare all mechanisms.

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

Finally, our study is limited to communities whose species have fast population dynamics relative to the yearly timescale, like phytoplankton and likely other fast-living organisms, so that many generations can occur in a year. Different effects of seasonality may occur in species that have slower life histories or with generations that extend over multiple years (e.g., multiyear cycles and chaotic attractors, Rinaldi et al. 1993; Taylor et al. 2013; Tyson and Lutscher 2016). Persistence may be affected differently by seasonality in such cases with slower community dynamics.

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

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). Overall, while seasonality may be slightly better than no forcing at all in maintaining diversity if a storage effect is present, seasonal forcing of parameters does not improve coexistence when compared to white noise.

In addition to community diversity, the biomass-trait relationship also varied from one simulation to another. Some regularities did emerge across simulations though. The storage effect begot several clumps along the trait space (as observed by Scranton and Vasseur, 2016). The seasonality that we added to the temperature signal led to more 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 covers a fraction of the initial trait space. Therefore, the shape of the distribution was 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. The biomass-trait distributions therefore constitute clues to interpret community dynamics (D’Andrea and Ostling, 2016; Loranger et al., 2018), although we certainly recommend to interpret them with caution to avoid over-generalization. The identification of multiple

modes in biomass-trait relationships and SADs is relatively recent (Dornelas and Connolly,
 2008; Matthews et al., 2014) and is a rare pattern in theoretical models (McGill et al., 2007).
 Barabás et al. (2013) convincingly argued that multimodality could arise from the demographic
 stochasticity of a single model run (with either self-regulation or neutrality, but without the
 clumpy coexistence emerging from a storage effect). However, our results are based on many
 model runs, for which either the storage effect alone or a storage effect + strong self-regulation
 in a seasonal context consistently produced multimodal distributions, while simulations with-
 out the storage effect always led to a single cluster along the trait axis. Our suggestion for
 empirical studies is as follows: if only one spatial location is observed, caution in interpreting
 multiple clumps on the trait axis is of course required, as Barabás et al. (2013) highlighted.
 However, with several locations - or in a theoretical context - one could average across locations
 to reproduce similar graphs to the ones produced here. Clumps in the trait axis when averaged
 across model runs/locations are therefore a signature of a coexistence induced by the storage
 effect, for the cases that we considered in the article. Of course, other mechanisms that we did
 not include in our models may produce similar patterns (Rael et al., 2018) or obfuscate these
 patterns – typically strong self-regulation weakens the clustering on the trait axis. We therefore
 view clustering on the trait axis (when averaged over several samples) as an interesting clue
 suggesting to look for a storage effect, rather than any definite proof that the storage effect is
 at work.

In our previous empirical study of coastal phytoplankton dynamics (Barraquand et al.,
 2018), we did not find any storage effect. This, however, does not mean that it could not be
 observed in other planktonic systems. Given the consequences of the storage effect for species
 richness and composition presented here, we are skeptical that the storage effect could by itself
 help explaining phytoplankton diversity. However, our results suggest that in phytoplankton-
 like seasonal environments, even though empirically-based self-regulation produce much more
 diversity than the storage effect when considered in isolation, the storage effect can help diver-
 sity maintenance when combined to other mechanisms. Indeed, the combination storage effect
 + strong self-regulation is non-additive: the cases were both self-regulation and the storage
 effect were present showed more diversity than generated by any mechanism on its own.

The above results suggest the very exciting idea that multiple coexistence mechanisms might

combine superadditively, thus helping us to better understand the astounding diversity of primary producers. This logic could, in principle, be extended to mechanisms that we have not considered here (e.g., spatial structure, specialized natural 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). 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 (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.

Acknowledgements

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References

- Adler PB, Ellner SP, Levine JM (2010) Coexistence of perennial plants: an embarrassment of niches. *Ecology letters* 13(8):1019–1029, DOI 10.1111/j.1461-0248.2010.01496.x
- Adler PB, Smull D, Beard KH, Choi RT, Furniss T, Kulmatiski A, Meiners JM, Tredennick AT, Veblen KE (2018) Competition and coexistence in plant communities: intraspecific competition is stronger than interspecific competition. *Ecology Letters* 21(9):1319–1329, DOI 10.1111/ele.13098
- Ashby B, Watkins E, Lourenço J, Gupta S, Foster KR (2017) Competing species leave many potential niches unfilled. *Nature Ecology & Evolution* 1(10):1495–1501, DOI 10.1038/s41559-017-0295-3
- Bagchi R, Gallery RE, Gripenberg S, Gurr SJ, Narayan L, Addis CE, Freckleton RP, Lewis OT (2014) Pathogens and insect herbivores drive rainforest plant diversity and composition. *Nature* 506(7486):85–88, DOI 10.1038/nature12911
- Barabás G, Meszéna G, Ostling A (2012) Community robustness and limiting similarity in periodic environments. *Theoretical Ecology* 5(2):265–282, DOI 10.1007/s12080-011-0127-z
- Barabás G, D’Andrea R, Rael R, Meszéna G, Ostling A (2013) Emergent neutrality or hidden niches? *Oikos* 122(11):1565–1572, DOI 10.1111/j.1600-0706.2013.00298.x
- Barabás G, Michalska-Smith MJ, Allesina S (2016) The Effect of Intra- and Interspecific Competition on Coexistence in Multispecies Communities. *The American Naturalist* 188(1):E1–E12, DOI 10.1086/686901
- Barabás G, Michalska-Smith MJ, Allesina S (2017) Self-regulation and the stability of

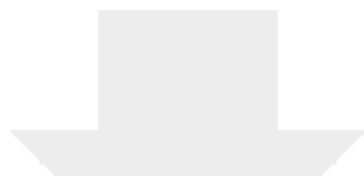
- large ecological networks. *Nature Ecology & Evolution* 1(12):1870–1875, DOI 10.1038/s41559-017-0357-6
- Barraquand F, Picoche C, Maurer D, Carassou L, Auby I (2018) Coastal phytoplankton community dynamics and coexistence driven by intragroup density-dependence, light and hydrodynamics. *Oikos* In press, DOI 10.1101/171264
- Bolker B, Pacala S (1999) Spatial Moment Equations for Plant Competition: Understanding Spatial Strategies and the Advantages of Short Dispersal. *The American Naturalist* 153(6):575–602, DOI 10.1086/303199
- Bolker BM (2003) Combining endogenous and exogenous spatial variability in analytical population models. *Theoretical Population Biology* 64(3):255–270, DOI 10.1016/S0040-5809(03)00090-X
- Carmel Y, Suprunenko YF, Kunin WE, Kent R, Belmaker J, Bar-Massada A, Cornell SJ (2017) Using exclusion rate to unify niche and neutral perspectives on coexistence. *Oikos* 126(10):1451–1458, DOI 10.1111/oik.04380
- Chesson P (1994) Multispecies Competition in Variable Environments. *Theoretical Population Biology* 45:227–276, DOI 10.1006/tpbi.1994.1013
- Chesson P (2000) Mechanisms of maintenance of species diversity. *Annual review of Ecology and Systematics* 31:343–366, DOI 10.1146/annurev.ecolsys.31.1.343
- Chesson P (2018) Updates on mechanisms of maintenance of species diversity. *Journal of Ecology* 106(5):1773–1794, DOI 10.1111/1365-2745.13035
- Chesson P, Huntly N (1997) The roles of harsh and fluctuating conditions in the dynamics of ecological communities. *The American Naturalist* 150(5):519–553, DOI 10.1086/286080
- Comita LS, Queenborough SA, Murphy SJ, Eck JL, Xu K, Krishnadas M, Beckman N, Zhu Y (2014) Testing predictions of the Janzen-Connell hypothesis: a meta-analysis of experimental evidence for distance- and density-dependent seed and seedling survival. *Journal of Ecology* 102(4):845–856, DOI 10.1111/1365-2745.12232

- 464 D’Andrea R, Ostling A (2016) Challenges in linking trait patterns to niche differentiation. *Oikos*
1 465 125(10):1369–1385, DOI 10.1111/oik.02979
2
3
4 466 Dornelas M, Connolly SR (2008) Multiple modes in a coral species abundance distribution.
5
6 467 *Ecology Letters* 11(10):1008–1016, DOI 10.1111/j.1461-0248.2008.01208.x
7
8
9 468 Ellner SP, Snyder RE, Adler PB (2016) How to quantify the temporal storage effect using
10
11 469 simulations instead of math. *Ecology Letters* 19(11):1333–1342, DOI 10.1111/ele.12672
12
13
14 470 Fox JW (2013) The intermediate disturbance hypothesis should be abandoned. *Trends in Ecol-*
15
16 471 *ogy & Evolution* 28(2):86–92, DOI 10.1016/j.tree.2012.08.014
17
18
19 472 Götzenberger L, de Bello F, Bråthen KA, Davison J, Dubuis A, Guisan A, Lepš J, Lindborg
20
21 473 R, Moora M, Pärtel M, Pellissier L, Pottier J, Vittoz P, Zobel K, Zobel M (2012) Ecological
22
23 474 assembly rules in plant communities-approaches, patterns and prospects. *Biological Reviews*
24
25 475 87(1):111–127, DOI 10.1111/j.1469-185X.2011.00187.x
26
27
28 476 Gravel D, Canham CD, Beaudet M, Messier C (2006) Reconciling niche and neutrality: the
29
30
31 477 continuum hypothesis: Reconciling niche and neutrality. *Ecology Letters* 9(4):399–409, DOI
32
33 478 10.1111/j.1461-0248.2006.00884.x
34
35
36 479 Haegeman B, Loreau M (2011) A mathematical synthesis of niche and neutral theories in
37
38 480 community ecology. *Journal of Theoretical Biology* 269(1):150–165, DOI 10.1016/j.jtbi.2010.
39
40 481 10.006
41
42
43 482 Hastings A, Abbott KC, Cuddington K, Francis T, Gellner G, Lai YC, Morozov A, Petrovskii S,
44
45 483 Scranton K, Zeeman ML (2018) Transient phenomena in ecology. *Science* 361(6406):eaat6412,
46
47 484 DOI 10.1126/science.aat6412
48
49
50 485 Haydon D (1994) Pivotal assumptions determining the relationship between stability and com-
51
52 486 plexity: an analytical synthesis of the stability-complexity debate. *The American Naturalist*
53
54 487 144(1):14–29, DOI 10.1086/285658
55
56
57 488 Holt R (2006) Emergent neutrality. *Trends in Ecology & Evolution* 21(10):531–533, DOI 10.
58
59 489 1016/j.tree.2006.08.003
60
61
62
63
64
65

- 490 Hubbell SP (2001) The Unified Neutral Theory of Biodiversity and Biogeography (MPB-32).
 1 491 Princeton University Press
 2
 3
 4 492 Kawatsu K, Kondoh M (2018) Density-dependent interspecific interactions and the complexity–
 5 stability relationship. *Proc R Soc B* 285(1879):20180698, DOI 10.1098/rspb.2018.0698
 6 493
 7
 8
 9 494 Kokkoris GD, Jansen VAA, Loreau M, Troumbis AY (2002) Variability in interaction strength
 10 and implications for biodiversity. *Journal of Animal Ecology* 71(2):362–371, DOI 10.1046/j.
 11 495 1365-2656.2002.00604.x
 12
 13 496
 14
 15
 16 497 Kuang JJ, Chesson P (2009) Coexistence of annual plants: generalist seed predation weakens
 17 the storage effect. *Ecology* 90(1):170–182, DOI 10.1890/08-0207.1
 18 498
 19
 20
 21 499 Kuang JJ, Chesson P (2010) Interacting coexistence mechanisms in annual plant communi-
 22 ties: frequency-dependent predation and the storage effect. *Theoretical population biology*
 23 500 77(1):56–70, DOI 10.1016/j.tpb.2009.11.002
 24
 25 501
 26
 27
 28 502 Loranger J, Munoz F, Shipley B, Violle C (2018) What makes trait-abundance relationships
 29 when both environmental filtering and stochastic neutral dynamics are at play? *Oikos* DOI
 30 503 10.1111/oik.05398
 31
 32 504
 33
 34
 35 505 Matthews TJ, Borges PAV, Whittaker RJ (2014) Multimodal species abundance distributions:
 36 a deconstruction approach reveals the processes behind the pattern. *Oikos* 123(5):533–544,
 37 506 DOI 10.1111/j.1600-0706.2013.00829.x
 38
 39
 40 507
 41
 42
 43 508 McGill BJ, Etienne RS, Gray JS, Alonso D, Anderson MJ, Benecha HK, Dornelas M, Enquist
 44 BJ, Green JL, He F, Hurlbert AH, Magurran AE, Marquet PA, Maurer BA, Ostling A,
 45 509 Soykan CU, Ugland KI, White EP (2007) Species abundance distributions: moving beyond
 46 single prediction theories to integration within an ecological framework. *Ecology Letters*
 47 510 10(10):995–1015, DOI 10.1111/j.1461-0248.2007.01094.x
 48
 49 511
 50
 51 512
 52
 53
 54 513 Moisan JR, Moisan TA, Abbott MR (2002) Modelling the effect of temperature on the maximum
 55 growth rates of phytoplankton populations. *Ecological Modelling* 153(3):197–215, DOI 10.
 56 514 1016/S0304-3800(02)00008-X
 57
 58 515
 59
 60
 61
 62
 63
 64
 65

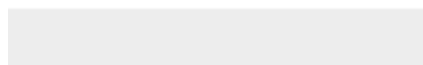
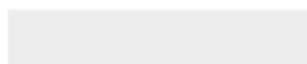
- 516 Mordecai EA (2015) Pathogen impacts on plant diversity in variable environments. *Oikos*
1 517 124(4):414–420, DOI 10.1111/oik.01328
2
3
4 518 Munoz F, Huneman P (2016) From the neutral theory to a comprehensive and multiscale
5
6 519 theory of ecological equivalence. *The Quarterly Review of Biology* 91(3):321–342, DOI 10.
7
8 520 1086/688098
9
10
11 521 Murrell DJ, Law R (2002) Heteromyopia and the spatial coexistence of similar competitors.
12
13 522 *Ecology Letters* 6(1):48–59, DOI 10.1046/j.1461-0248.2003.00397.x
14
15
16 523 Mutshinda CM, O’Hara RB, Woiwod IP (2009) What drives community dynamics? *Proceedings*
17
18 524 *of the Royal Society B: Biological Sciences* 276(1669):2923–2929, DOI 10.1098/rspb.2009.0523
19
20
21 525 Rael RC, D’Andrea R, Barabás G, Ostling A (2018) Emergent niche structuring leads to in-
22
23 526 creased differences from neutrality in species abundance distributions. *Ecology* 99(7):1633–
24
25 527 1643, DOI 10.1002/ecy.2238
26
27
28 528 Reynolds CS (2006) *The ecology of phytoplankton*. Cambridge University Press
29
30
31 529 Rinaldi S, Murator S, Kuznetsov Y (1993) Multiple attractors, catastrophes and chaos in sea-
32
33 530 sonally perturbed predator-prey communities. *Bulletin of Mathematical Biology* 55(1):15–35,
34
35 531 DOI 10.1007/BF02460293
36
37
38 532 Sakavara A, Tsirtsis G, Roelke DL, Mancy R, Spatharis S (2018) Lumpy species coexistence
39
40 533 arises robustly in fluctuating resource environments. *Proceedings of the National Academy*
41
42 534 *of Sciences* 115(4):738–743, DOI 10.1073/pnas.1705944115
43
44
45 535 Scheffer M, van Nes EH (2006) Self-organized similarity, the evolutionary emergence of groups
46
47 536 of similar species. *Proceedings of the National Academy of Sciences* 103(16):6230–6235, DOI
48
49 537 10.1073/pnas.0508024103
50
51
52
53 538 Scranton K, Vasseur DA (2016) Coexistence and emergent neutrality generate synchrony among
54
55 539 competitors in fluctuating environments. *Theoretical Ecology* 9(3):353–363, DOI 10.1007/
56
57 540 s12080-016-0294-z
58
59
60 541 Snyder RE (2008) When does environmental variation most influence species coexistence? *The-*
61
62 542 *oretical Ecology* 1(3):129–139, DOI 10.1007/s12080-008-0015-3
63
64
65

- 543 Stump SM (2017) Multispecies Coexistence without Diffuse Competition; or, Why Phylogenetic
1 544 Signal and Trait Clustering Weaken Coexistence. *The American Naturalist* 190(2):213–228,
2
3 545 DOI 10.1086/692470
4
5
6 546 Taylor RA, White A, Sherratt JA (2013) How do variations in seasonality affect population
7
8 547 cycles? *Proceedings of the Royal Society B: Biological Sciences* 280(1754), DOI 10.1098/
9
10 548 rspb.2012.2714
11
12
13 549 Tyson R, Lutscher F (2016) Seasonally Varying Predation Behavior and Climate Shifts Are
14
15 550 Predicted to Affect Predator-Prey Cycles. *The American Naturalist* 188(5):539–553, DOI
16
17 551 10.1086/688665
18
19
20 552 Vasseur DA, Yodzis P (2004) The Color Of Environmental Noise. *Ecology* 85(4):1146–1152,
21
22 553 DOI 10.1890/02-3122
23
24
25 554 Vergnon R, van Nes EH, Scheffer M (2013) Interpretation and predictions of the Emergent neu-
26
27 555 trality model: a reply to Barabás et al. *Oikos* 122(11):1573–1575, DOI 10.1111/j.1600-0706.
28
29
30 556 2013.00790.x
31
32
33 557 Vesipa R, Ridolfi L (2017) Impact of seasonal forcing on reactive ecological systems. *Journal of*
34
35 558 *Theoretical Biology* 419:23–35, DOI 10.1016/j.jtbi.2017.01.036
36
37
38 559 Winder M, Cloern JE (2010) The annual cycles of phytoplankton biomass. *Philosophi-*
39
40 560 *cal Transactions of the Royal Society B: Biological Sciences* 365(1555):3215–3226, DOI
41
42 561 10.1098/rstb.2010.0125
43
44
45 562 Wootton JT, Emmerson M (2005) Measurement of Interaction Strength in Nature. *Annual*
46
47 563 *Review of Ecology, Evolution, and Systematics* 36(1):419–444, DOI 10.1146/annurev.ecolsys.
48
49 564 36.091704.175535
50
51
52 565 Zhao XQ (1991) The qualitative analysis of n-species Lotka-Volterra periodic competition
53
54 566 systems. *Mathematical and Computer Modelling* 15(11):3–8, DOI 10.1016/0895-7177(91)
55
56 567 90100-L
57
58
59
60
61
62
63
64
65



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Dear Pr. Hastings,

We have edited our manuscript according to the constructive feedback of the reviewers, for which we are very grateful. You will find our answers to comments and the corresponding changes to the manuscript in bold after each reviewer comment.

Reviewers raised some issues regarding the focus that we chose for the manuscript, as well as the terminology employed. We edited the manuscript in response to both.

Regarding the focus, we have changed the title to “How self-regulation, the storage effect and their interaction contribute to coexistence in stochastic and seasonal environments”. This new title is, in our opinion, more representative of the paper: it explicitly refers to how seasonality influences coexistence, which is a central element of our work, and how coexistence mechanisms interact, which is also a key feature here. We have then sought to hold this focus throughout the manuscript.

Both reviewers noted that we were incorrect to equate “stabilizing niche differences” (SNDs) with cases in which intraspecific interaction coefficients are much larger than interspecific coefficients. Indeed, one could say as well that a storage effect induces stabilizing niche differences. We thank the reviewers for this remark, which will no doubt improve greatly the clarity of the manuscript, and we have corrected our wording to “strong self-regulation” (wherever we previously wrote SNDs).

In the same spirit of improving the readability of the manuscript, we changed the name of one of our variable, ρ , the ratio of intra-to-intergroup coefficient, to κ , to avoid any confusion with niche overlap in niche theory, which is usually denoted ρ as well.

We hope that you will find the updated manuscript improved, and that it may now be suitable for publication in Theoretical Ecology,

Sincerely,

Coralie Picoche & Frédéric Barraquand

**** Responses to reviewer comments are provided in bold below ***

COMMENTS FOR THE AUTHOR:

Reviewer #1: This ms appears to be about multiple things. On the one hand, it discusses the relative contributions of the storage effect and differences in within- and between-species competition coefficients. (I will avoid calling this stabilizing niche differences, for reasons explained below.) It further notes that these effects combine superadditively in this model. On the other hand, it's also a paper about how the abundances of the coexisting species are

distributed in trait space: in particular, whether or not we have a multi-modal distribution ("clumpy coexistence"). Or perhaps, like Scranton and Vasseur, it is less about the abundance distribution and more about how many species can be supported, the idea being that a bunch of very similar species can transiently (but lingeringly) coexist in each species clump.

What I find most useful about this ms is that it extends Scranton and Vasseur 2016 to consider noisy seasonal variation instead of white noise.

>> Extending the work of Scranton and Vasseur (2016) to seasonal environments was indeed our original motivation. The new title now explicitly mentions seasonality which is a main theme of the paper, and avoid to make any reference to stabilizing niche differences (see below for a disambiguation of the wording employed).

It is useful to know that a significant seasonal component can substantially reduce the number of coexisting species, at least if we're considering just a storage effect or just differences in between-/within-species competition. I'm not sure that uni- vs multi-modal distributions have a significance beyond that. The paper seems to focus on the shape of the distribution beyond the effect of the shape on the number of coexisting species, and it's not clear to me why this is important.

>> We agree with the referee that biomass-trait distributions can at times be misleading and should not be overinterpreted. We now make this clear at the end of the abstract (l. 21-23). But we believe that theoretical work should demonstrate if, and when, trait distributions are or are not indicative of coexistence mechanisms. Trait patterns are *de facto* being used to infer niche differentiation and environmental filtering (see refs in d'Andrea et al. 2016, Loranger et al. 2018); we therefore believe that it is useful to help accumulate knowledge on biomass-trait distributions.

Scranton and Vasseur (2016) reported multimodality in biomass-trait distributions. Since the models that we consider have been derived from theirs, we think that it is crucial to check if multimodality also arises with/without strong self-regulation and with/without seasonality. We certainly agree that such shapes are not sufficient on their own to form any conclusion as to the coexistence mechanism(s) - we think of these as "clues". We now make their limitations clearer in the discussion (l. 424 - 426).

It would be a pity, in our opinion, if we did not report these results that can enlighten debates on trait distributions while our models produce them as a by-product. But it is not the main focus of the paper - we only devote one paragraph to trait patterns in the discussion, for instance. The main focus is on coexistence mechanisms that allow species-rich species communities to maintain in noisy and seasonal environments.

I am not particularly excited by the result that multiple mechanisms may be contributing to coexistence in real systems --- we've been talking about that at least since Chesson started writing in the 1990s --- or that these mechanisms may combine nonadditively. It is, perhaps, a message that cannot be overemphasized, but I don't think it is

especially new.

>> We understand the reviewer's concern. However, it is one thing to know intuitively that a combination of mechanisms *could* sustain biodiversity and another to show that such combination *is* indeed important *in a species-rich context*.

We are aware of only a handful of references showing decisively non-additive effects of mechanisms (Kuang & Chesson 2009, Comita et al. 2014, Mordecai 2015) but we have not found any in species-rich contexts (dozens of species or more), that are the focus of the study. Reviewer #2 was interested by the non-additive effect of mechanisms and we tend to concur.

As we understand it, one's background reading has always a large impact on what one finds novel or not. If reviewer #1 has additional references to the ones we cite (especially older ones), that would be worth discussing in the context of non-additive effects, we will of course be glad to include and discuss those.

Comments:

1. II. 110--114: I found this a little confusing and ended up calculating the storage effect for both models so that I could understand --- not an option available to most readers. My confusion stemmed from the ambiguity of "competitive strength." I took this to mean the competition coefficients, α_{ij} , which do not in fact covary with r . What's going on is that if we define competition to be $\sum_{j=1}^S \alpha_{ij} N_j$ in model 1, then per capita growth depends on the product of the environment ($r_j(\tau)$) and competition, and this interaction produces a storage effect. In the second model, the environment and competition enter additively, so that there is no covariation. Maybe you need to say that the net effect of competition is given by that sum, and that in model 1, that sum is multiplied by the environmental response, $r_j(\tau)$, producing covariation between environment and competition.

>> This is a correct interpretation, which we now explain more clearly I. 140-146. To make sure there can be no confusion, we now use two terms: "competitive strength" refers to the coefficient α_{ij} and "net effect of competition" refers to the sum of products of the intrinsic growth rate, α_{ij} and the density of other species N_j .

2. I am grumpy about defining stabilizing niche differences as equivalent to the within-species competition coefficients being greater than the between-species competition coefficients. This is certainly one way to get stabilizing niche differences. But normally SND refers to any differences that increase the per capita growth rate of all species as invaders. Thus, the different temperature optima, which give rise to a storage effect in model 1, are also normally considered stabilizing niche differences.

>> Upon closer inspection of the literature, we found this remark to be perfectly accurate and we apologize for the confusion that we created.

We have been unfortunately influenced by the vocabulary used in different subfields: studies on the storage effect seem to use more often “stabilizing mechanisms” and studies using Lotka-Volterra models more often SNDs (e.g., Levine et al. 2017). We erroneously thought that SNDs were a subset of stabilizing mechanisms (while they are in fact one and the same thing). We have now corrected this mistake throughout the manuscript and have changed the terminology to “strong self-regulation”, or SSR, whenever intraspecific >> interspecific competition (e.g., l.154, l.213, etc., and Fig.2-4).

3. Results section: For this model, the storage effect alone was able to enable the coexistence of fewer species than competitive differences alone. That's worth knowing, but I would be hesitant to imply that this is a general result. I don't think the paper ever declares this to be universally true, but I would feel most comfortable if it were made clear that this result is contingent on this model.

>> We completely agree that the result is contingent upon the model. Now mentioned explicitly in the discussion l. 361-368. We did, however, our best to inform the model by estimates coming from empirical work (see l. 355-359).

4. ll. 181--183: "On the contrary, seasonality tended to favor..." All of this is still without the storage effect, correct? I'm pretty sure that's the case, but I had to read the paragraph multiple times.

>> Indeed, the paragraph (l. 225 to 240) describes the effect of the random and seasonal noise without any of the coexistence mechanisms. We now repeat that we are considering a case with no coexistence mechanism (l.225-226 and l.232-233).

5. l. 182: "Species with a higher thermal optimum are more likely to persist and to reach a higher biomass..." Any intuition about why this is true?

>> The shift to higher values of the average thermal optimum when the community is forced by a seasonal noise can be found for all four models that we considered. The autocorrelation in the seasonal noise allows species with a higher thermal optimum, and, thus, a higher maximum growth rate, to maintain a high productivity for longer contiguous periods of time than a random noise would, as is now explained l. 269-272.

6. 284: "Of course, other mechanisms that we did not include in our models may produce similar patterns." This is important to note. I think it's also important to note that a different model with the same mechanisms might produce different results. How confident are you that a storage effect will always produce clustering on the trait axis in the presence of seasonality? Can you explicitly state your intuitions for why this should be so?

>> We stated in the earlier sentence that “Clumps in the trait axis when averaged across model runs/locations are therefore a signature of the storage effect for the cases that we considered in this article”.

We therefore already note implicitly that a different model could produce different results. We do not know for sure that the finding is general, which is why we stay prudent in the latter sentence (modified from the first submission version):

“We therefore view clustering on the trait axis (when averaged over several samples) as an interesting clue suggesting to look for a storage effect, rather than any definite proof that the storage effect is at work.” (l.424-426)

Here we only say that clustering could be seen as a clue of the storage effect, not that a storage effect would always lead to clusters.

As to why trait clusters exist in the first place: the storage effect essentially models niches in time, with some species being better for some of the environmental variable values. When this mechanism dominates, we therefore expect that the traits of the remaining species will exhibit contrasted values.

Minor comments:

1. Table 1: b_i and $f_i(\tau)$ appear to be missing values.

>> These values change with the considered species and timestep. This is now clarified in the caption of the Table 1.

2. Fig. 3: It would be really helpful to add row labels to this figure: "White noise" for the top row and "Seasonal" for the bottom row.

>> We have added row labels. Following a remark of reviewer #2, “white noise” has been modified to “random noise” (it is not exactly white in the sense of a stochastic differential equation).

3. Fig. 4: Again, row labels would make this clearer: "Storage effect only" for the top and "Competitive differences only" for the bottom.

>> We have changed the labels to “storage effect” and “strong self-regulation”, thank you for this suggestion.

Reviewer #2: The manuscript looks at coexistence in a forced Lotka-Volterra model with two potential coexistence mechanisms: the storage effect and classical frequency dependence operating on shorter timescales than the temporal fluctuations. The Authors find that both mechanisms can individually support some coexistence, but their combination can support more than the sum of the two. Additionally, the forcing signal was made to be both random noise and a noisy sinusoidal forcing, with random noise able to support more species when only one coexistence mechanism was acting.

Overall, I enjoyed reading the manuscript. Below I have some technical suggestions, as well as a few comments on interpreting the results.

First, if I understand correctly, the Authors' white noise isn't really white, and it shouldn't be. I was trying to reproduce their results, and could only do so if the value of tau was kept constant for the duration of one day at a time. Is that what was done?

>> Indeed, that is exactly what was done, to keep the comparison to Scranton and Vasseur (2016) possible.

In that case, since the random jumps in temperature are interspersed by 1-day-long periods of constant temperature, the noise must be somewhat autocorrelated and therefore red.

This is all well, since a stochastic differential equation can only be defined consistently if the white noise term appears linearly on its right hand side - which it doesn't in the manuscript. A "nonlinear SDE" is a non-entity; see, e.g., Simo Särkkä's book "Applied Stochastic Differential Equations" (p. 34) for a discussion. Therefore, having the slightly autocorrelated noise is perfectly fine and even necessary. I would emphasize that temperature was kept constant throughout a day, and would drop the terminology of white noise in the manuscript. Instead, I would just call it "random noise".

>> We completely agree with this remark and thank you for pointing it out.

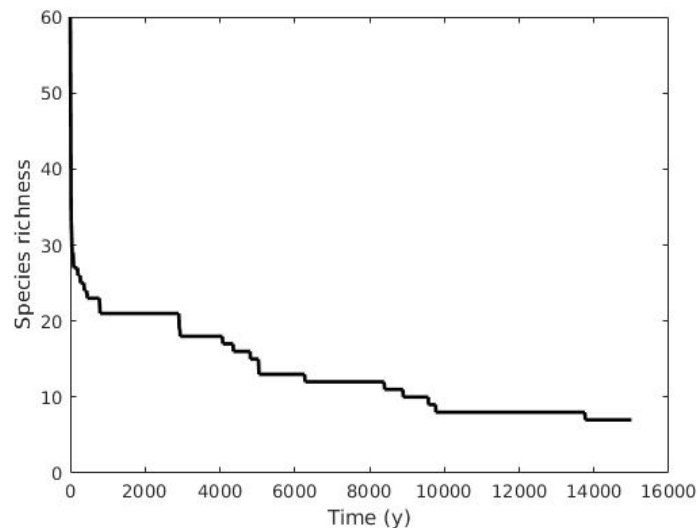
A probabilist colleague once brought to our attention that precisely for that reason, SDEs are in fact a very small part of all random dynamical systems (sensu e.g. Arnold, L. (2013). *Random dynamical systems*. Springer).

We have therefore chosen to use the 'random noise' wording throughout the manuscript. We also define this noise more thoroughly I. 123-129 - explaining that it is not entirely white, but can be considered so at the monthly or annual scale.

Second, I am not convinced the model was run long enough for species richness to stabilize. At least, when I was running it for 15000 instead of 5000 years, the richness against time curve still didn't quite settle down in the pure storage + random noise scenario. This means that Figure 2 probably overestimates species richnesses.

>> This is true that convergence is not fully reached at $t = 5000$ and we now include these details in the Discussion (I. 295-314). However, we do not believe that waiting for convergence would necessarily be meaningful here.

This work originally started as a replication of Scranton and Vasseur (2016)'s results. It was for us a pre-requisite to adding seasonality (we firmly believe that repeatability is paramount for progress in quantitative ecology). Replicating Scranton and Vasseur's model, we realised that even there convergence was not always reached (see in the Figure below the temporal course of the species richness, for a randomly forced community with a storage effect - that is the model of Scranton and Vasseur).



While we considered waiting for convergence, the last transients can be really long, in the sense that exclusion can take an added >10 000 years.

While mathematically speaking the community is not stabilized, we then thought about the biological meaning of waiting an additional 10 000 years and it seemed like a very artificial thing to do. A phytoplankton-like community (the biological target) would necessarily evolve or change in such an amount of time, which would require to add variability to all traits, not only the growth rates. This would lead to another model and we would lose the connection of our models to the one of Scranton and Vasseur (2016). There were also computational difficulties associated to such an increase in simulation length, both in terms of computation duration and memory use.

Thus we decided to keep the 5000 years used by Scranton and Vasseur, which at least allows for a clear-cut comparison. We now explain plainly in the Discussion (I.303-314) that this methodological choice was done to allow for (1) comparison between modelling studies and (2) ecological consistency -- after all, if a model produces robust transient dynamical behaviour between 5000 and 15000 years (i.e., not a short-term transient), perhaps this transient is as important as the asymptotic behaviour (see for similar arguments Hastings et al. Science 2018, now cited as well).

There is a simple way of speeding up convergence, and as an added benefit also making sure that the results are not an artifact of parameter fine-tuning: I would make the m values slightly different across species. What I have done is set m_i equal to 15 plus a uniform random variable, drawn either from $[-0.1, 0.1]$ or $[-1, 1]$. In both cases, at least for the parameterizations and scenarios I looked at, the species richnesses converged at the same final values. This is useful, since the change in richness is then presumably not due to altering the dynamical behavior through the m_i , but to more rapid convergence stemming from resolving the fine-tuning. I encourage the Authors to do the same, and to check for

convergence (e.g., by checking whether species richness has been constant for 100 years, say) instead of integrating for a fixed time interval.

>> This is an interesting suggestion and we are very grateful for your thoroughness. For the reasons mentioned above (comparison to SV16 and ecological interpretation), we would prefer to keep a fixed time interval.

Moreover, changing mortality would also affect the ‘emergent neutrality’ (sensu Holt) as species would get more dissimilar, i.e., they would then differ in more ways than just their thermal niche and the niches implied by strong self-regulation. We would then have no reason to get several species coexisting in the same trait clump, for instance - changing the mortalities immediately induces new niche differences.

Third, a small comment on terminology. The Authors distinguish between "stabilizing niche differences" (SND) and the storage effect. Within the Chessonian terminology however, the storage effect also counts as an SND (anything does which can boost the long-term invasion growth rate of all species simultaneously). Instead, I would call the Authors' SNDs "classical frequency-dependent stabilization" or something along those lines.

>> As you can see in our response to reviewer 1, we realize that we were wrong to call high intraspecific competition SNDs (we’ve been misled by the fact that many articles with Lotka-Volterra models use SNDs to designate high intraspecific competition while storage effects paper usually refer to stabilizing “mechanisms”). We have changed to “strong self-regulation”, and define precisely the wording I. 159-162.

Fourth, I wanted to make sure that the interpretation of competition coefficients was correct. Usually, what can be directly measured in an experiment is the reduction in per capita growth rates. But the α and ρ terms here measure the reduction in intrinsic rates, as per Eq. (1). Is this correct, and does this indeed map onto the values obtained by Barraquand et al. (2018)? I'm just making sure.

>> This is correct. But these two concepts map: if $\alpha_{ii} = 10 \cdot \alpha_{ij}$ then $r_i(\tau) \alpha_{ii} = 10 \cdot r_i(\tau) \alpha_{ij}$. We therefore think there is no problem here.

Moreover, $\rho = 10$ is taken as an order of magnitude rather than an exact value. We do not pretend that in real data the value is always 10. In fact, the model in Barraquand et al. (2018) is a discrete-time model on the logarithmic scale (Gompertz), because this model fitted best the plankton data. This it is not exactly the same model, but we think that the order of magnitude (10 rather than 1 or 100) will hold. Based on plant data, Adler et al. (2018) identified ρ to be closer to 4 or 5. We have done a few simulations with $\rho = 4$ and it did not change the results qualitatively, but we believe that $\rho = 10$ is closer to plankton communities. We now mention all this in the Discussion (I. 362-368). ¹ There are other caveats regarding the comparison

¹ The notation ρ has been changed to κ to avoid confusion with the usual niche overlap measure.

between our models and empirical data. For example, we assume in the theoretical models that all intra- or inter-specific interaction coefficients are alike with each category, i.e., we discard the intra- or inter-specific coefficient variances that exist in the empirical data (now fully acknowledged and discussed I. 317-328). The choices that we have made therefore reflect a compromise between being able to compare our results to the theoretical work of SV16 (assuming equal coefficients) and connecting to our empirical work.

Fifth, the presence of frequency-dependence (the $\rho = 10$ case) means there must be differences between species providing larger intra- than interspecific competition. We do not know what these differences are, because it is all encoded phenomenologically, through the competition coefficients. But they must be there, and must be unrelated to temperature optima (indeed, even if two species by accident had the exact same temperature optimum, intraspecific competition would still be ten times greater than interspecific between them). This should be taken into account when interpreting the coexistence of "similar" species with $\rho = 10$: these species are not really similar, it's just that the differences between them aren't being modeled explicitly. See our article (Barabás et al. 2013 Oikos) for more details.

>> Overall we agree and have corrected the wording accordingly: “the diversity within clumps of similar values of thermal optima was considerably decreased” (I.371-372). The use of the word “similar” was influenced by our knowledge of phytoplankton - many diatoms are similar in terms of resource requirements and abiotic drivers. Phytoplankton ecologists usually dub them “similar species” but we completely agree that they have different shapes and life-histories (which, we suspect, is instrumental to their coexistence and producing such weak interspecific competition).

A few minor comments:

- I would stick to using kilograms, years, electronvolts, and Kelvins consistently. So in Eq. (5) I would not divide the argument of the sine function by 365, and in line 131 I would express the temperature interval in Kelvins.

>> We have indeed changed Eq. (5) and kept the same units, except for the use of the Kelvins. We remain consistent with the already published paper of Scranton and Vasseur for their use of Kelvins and Celsius. Celsius are easier to interpret (for a sizeable fraction of the planet at least).

- Eq. (6): How was the mean r_i obtained? Was it calculated by first generating the full time-series for τ , and then taking the temporal average? Or by some other method? Please explain.

>> This is exactly what we did. This is now explained I. 148-150.

- Lines 247-248: With $\rho=10$, there is no neutral kind of diversity in any sense of the word, since by default $\text{intra} > 10 \times \text{inter}$, precluding neutrality (see also my comment above).

>> Yes, we agree. We have now removed “neutral” (l.371-373) as it could be misinterpreted, even with the quotation marks (we meant within-clump diversity, which consists in species with similar coefficient values related to temperature, but we agree that self-regulation implies other niches differences).

- In general, pitching the article in terms of reconciling niche and neutral perspectives is a bit misleading. The Authors' model does not have any neutrality, and their result of the superadditive influence of various mechanisms is interesting in its own right. I would focus more on this superadditivity as the main thrust.

>> We have changed the title to better represent the focus of the article, hinting at the superadditivity of coexistence mechanisms (which we find indeed quite interesting). Our Introduction mentions studies that have sought to reconcile niche and neutral perspectives, but we do not write anywhere that we try such reconciliation ourselves.

We only contextualize how this idea of “clumpy coexistence” (connected to the biomass-trait distribution) came to be in the Introduction, which requires to talk about “emergent neutrality”. This is, in our view, needed to introduce properly Scranton and Vasseur’s 2016 model and discuss the meaning of biomass-trait distributions later on. We have therefore re-written a bit the Introduction to introduce the concept of clumpy coexistence and the work of SV16, starting l. 38 and ending l. 65.

References used in this response

1. Adler, P. B. et al. Competition and coexistence in plant communities: intraspecific competition is stronger than interspecific competition. *Ecology Letters* (2018). doi:10.1111/ele.13098
2. Arnold, L. *Random dynamical systems*. Springer. (2013)
3. Barraquand, F. , Picoche, C. , Maurer, D. , Carassou, L. and Auby, I. Coastal phytoplankton community dynamics and coexistence driven by intragroup density-dependence, light and hydrodynamics . *Oikos* (2018). doi:10.1111/oik.05361
4. Comita, L. S. et al. Testing predictions of the Janzen-Connell hypothesis: a meta-analysis of experimental evidence for distance- and density-dependent seed and seedling survival. *Journal of Ecology* 102, 845–856 (2014).
5. D’Andrea, R. & Ostling, A. Challenges in linking trait patterns to niche differentiation. *Oikos* 125, 1369–1385 (2016).
6. Hastings, A. et al. Transient phenomena in ecology. *Science* 361(6406), (2018).
7. Holt, R. Emergent neutrality. *Trends in Ecology & Evolution* 21, 531–533 (2006).
8. Kuang, J. J. & Chesson, P. Coexistence of annual plants: generalist seed predation weakens the storage effect. *Ecology* 90, 170–182 (2009).
9. Levine, J. M., Bascompte, J., Adler, P. B. & Allesina, S. Beyond pairwise mechanisms of species coexistence in complex communities. *Nature* 546, 56–64 (2017).
10. Loranger, J., Munoz, F., Shipley, B. & Violle, C. What makes trait–abundance relationships when both environmental filtering and stochastic neutral dynamics are at play? *Oikos* (2018). doi:10.1111/oik.05398
11. Mordecai, E. A. Pathogen impacts on plant diversity in variable environments. *Oikos* 124, 414–420 (2015).
12. Scranton, K. & Vasseur, D. A. Coexistence and emergent neutrality generate synchrony among competitors in fluctuating environments. *Theoretical Ecology* (2016). doi:10.1007/s12080-016-0294-z