

1 **Environmental responses, not species interactions, determine synchrony of**
2 **dominant species in semiarid grasslands**

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8 **Running Head:** Drivers of species synchrony in grasslands

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Abstract

Temporal asynchrony among species helps diversity to stabilize ecosystem functioning, but identifying the mechanisms that determine synchrony remains a challenge. Here, we refine and test theory showing that synchrony depends on three factors: species responses to environmental variation, interspecific interactions, and demographic stochasticity. We then conduct simulation experiments with empirical population models to quantify the relative importance of these factors in five plant communities. We found that the average synchrony of per capita growth rates, which can range from 0 (perfect asynchrony) to 1 (perfect synchrony), was higher when environmental variation was present (0.62) rather than absent (0.43). Removing interspecific interactions and demographic stochasticity had small effects on synchrony. In these plant communities, where species interactions and demographic stochasticity have little influence, synchrony reflects the covariance in species responses to the environment.

Key words: synchrony, compensatory dynamics, environmental stochasticity, demographic stochasticity, interspecific competition, stability

INTRODUCTION

Ecosystems are being transformed by species extinctions (Cardinale et al. 2012), changes in community composition (Vellend et al. 2013, Dornelas et al. 2014), and anthropogenic environmental change (Vitousek et al. 1997), impacting the provisioning and stability of ecosystem services (Loreau et al. 2001, Hooper et al. 2005, Rockstrom et al. 2009). Experiments have provided compelling evidence that decreases in species richness will decrease productivity (Tilman et al. 2001) and the temporal stability of productivity (Tilman et al. 2006, Hector et al. 2010). The stabilizing effect of species richness stems from individual species responding in different ways to environmental fluctuations (environmental stochasticity), or fluctuating asynchronously because of random chance events (demographic stochasticity) (Isbell et al. 2009, Hector et al. 2010, de Mazancourt et al. 2013). Species richness affects synchrony because larger species pools are

more likely to contain species that respond dissimilarly to environmental conditions (Yachi and Loreau 1999), implying that species losses will reduce ecosystem stability. Even without species losses, abiotic homogenization can weaken compensatory dynamics and, in turn, decrease temporal stability of ecosystem functioning (Hautier et al. 2014). The link between synchrony and stability means that a mechanistic understanding of synchrony can help us predict the impacts of global change on ecosystem stability.

Theory identifies three main determinants of species synchrony: environmental stochasticity, demographic stochasticity, and interspecific interactions (Loreau and de Mazancourt 2008, 2013, Gonzalez and Loreau 2009). For example, in a community composed of large populations (no demographic stochasticity) with weak interspecific interactions, community-wide species synchrony should be determined by the covariance of species' responses to the environment (Loreau and de Mazancourt 2008). However, this prediction relies on a relatively simple population model and only holds under two assumptions: (i) species' responses to the environment are similar in magnitude and (ii) all species have similar growth rates. Whether such theoretical predictions hold in natural communities where species differences are unlikely to be symmetrical is unknown because few studies have explicitly tested theory on the drivers of species synchrony in natural communities (Mutshinda et al. 2009, Thibaut et al. 2012), and they did not consider demographic stochasticity.

In grasslands, most empirical studies have focused on whether species synchrony is primarily an outcome of species-specific responses to environmental conditions (Hautier et al. 2014) or competition (Gross et al. 2014). Even beyond grassland studies, whether competition or environmental responses drive compensatory dynamics remains controversial (reviewed in Gonzalez and Loreau 2009). In part, controversy remains because quantifying the relative strengths of each driver on the degree of synchrony from the covariance matrix of species abundances (e.g., Houlahan et al. 2007) is impossible. This is because an unbiased null expectation for synchrony does not exist (Loreau and de Mazancourt 2008) and observed synchrony can arise from non-unique combinations of factors (Ranta et al. 2008). For example, weak synchrony of population

71 abundances could reflect positive environmental correlations (synchronizing effect) offset by
72 strong competition (desynchronizing effect), or negative environmental correlations and weak
73 competition.

74 The best way to quantify the effects of environmental stochasticity, demographic stochastic-
75 ity, and interspecific interactions is to remove them one-by-one, and in combination. In principle,
76 this could be done in an extremely controlled laboratory setting, but empirically-based models
77 of interacting populations, fit with data sets from natural communities, offer a practical alterna-
78 tive. For example, Mutshinda et al. (2009) fit a dynamic population model to several community
79 time series of insect and bird abundances. They used a statistical technique to decompose tem-
80 poral variation into competition and environmental components, and found that positively cor-
81 related environmental responses among species determined community dynamics. Thibaut et al.
82 (2012) used a similar approach for reef fish and came to a similar conclusion: environmental re-
83 sponses determine synchrony. While a major step forward, Mutshinda et al.'s (2009) and Thibaut
84 et al.'s (2012) modeling technique relied on abundance data that may or may not reliably capture
85 competitive interactions that occur at the individual level. Furthermore, although both studies
86 quantified the relative importance of environmental stochasticity and interspecific interactions to
87 explain the observed variation of species synchrony, they did not use the model to quantify how
88 much synchrony would change when each factor is removed.

89 Here, we use multi-species population models fit to long-term demographic data from five
90 semi-arid plant communities to test theory on the drivers of species synchrony. Our objectives are
91 to (1) derive and test theoretical predictions of species synchrony and (2) determine the relative
92 influence of environmental stochasticity, demographic stochasticity, and interspecific interactions
93 on species synchrony in natural plant communities. To achieve these objectives, we first refine
94 theory that has been used to predict the effects of species richness on ecosystem stability (de
95 Mazancourt et al. 2013) and species synchrony (Loreau and de Mazancourt 2008) to generate
96 predictions of community-wide species synchrony under two limiting cases derived from the
97 dynamics of individual species in monoculture. We then confront our theoretical predictions with

simulations from the empirically-based population models. Second, we use the multi-species population models to perform simulation experiments that isolate the effects of environmental stochasticity, demographic stochasticity, and interspecific interactions on community-wide species synchrony. Given that our population models capture the essential features of community dynamics important to synchrony (density-dependence, and demographic and environmental stochasticity), and that these models successfully reproduce observed community dynamics (Chu and Adler 2015), perturbing the models can reveal the processes that determine species synchrony in our focal grassland communities.

THEORETICAL MODEL

The model

While existing theory has identified [environmental responses, demographic stochasticity, and species interactions as the drivers of the temporal synchrony of species' per capita growth rates, and thus abundances](#), we do not have a simple expression to predict synchrony in a particular community with all factors operating simultaneously. However, we can derive analytical predictions for species synchrony under special limiting cases. The limiting case predictions we derive serve as baselines to help us interpret results from empirically-based simulations (described below). We focus on synchrony of per capita growth rates, rather than abundances, because growth rates represent the instantaneous response of species to the environment and competition, and are less susceptible to the legacy effects of drift and disturbance (Loreau and de Mazancourt 2008). We present equivalent results for synchrony of species abundances in the Appendix S1, and show that they lead to the same overall conclusions as synchrony of per capita growth rates. Following Loreau and de Mazancourt (2008) and de Mazancourt et al. (2013), we define population growth, ignoring observation error, as

$$r_i(t) = \ln N_i(t+1) - \ln N_i(t) \quad (1)$$

$$= r_{mi} \left[1 - \frac{N_i(t) + \sum_{j \neq i} \alpha_{ij} N_j(t)}{K_i} + \sigma_{ei} u_{ei}(t) + \frac{\sigma_{di} u_{di}(t)}{\sqrt{N_i(t)}} \right] \quad (2)$$

121 where $N_i(t)$ is the biomass of species i in year t , and $r_i(t)$ is its population growth rate in year t .
 122 r_{mi} is species i 's intrinsic rate of increase, K_i is its carrying capacity, and α_{ij} is the interspecific
 123 competition coefficient representing the effect of species j on species i . Environmental stochas-
 124 ticity is incorporated as $\sigma_{ei} u_{ei}(t)$, where σ_{ei}^2 is the **temporal variance of environmental conditions**.
 125 **Species-specific environmental responses are included as u_{ei}** , which are normal random vari-
 126 ables with zero mean and unit variance that are independent through time but may be correlated
 127 between species. Demographic stochasticity arises from variations in births and deaths among
 128 individuals (e.g., same states, different fates), and is included in the model as a first-order, normal
 129 approximation (Lande et al. 2003, de Mazancourt et al. 2013). σ_{di}^2 is the demographic variance
 130 and $u_{di}(t)$ are independent normal variables with zero mean and unit variance. To derive analyt-
 131 ical predictions we solved a first-order approximation of Equation 2 (de Mazancourt et al. 2013
 132 and Appendix S1). Due to the linear approximation approach, our analytical predictions will
 133 likely fail in communities where species exhibit large fluctuations due to limit cycles and chaos
 134 (Loreau and de Mazancourt 2008). Indeed, one of the advantages of focusing on growth rates
 135 rather than abundances is that growth rates are more likely to be well-regulated around an equilib-
 136 rium value, if the long-term average of a species' growth rate is relatively small (e.g., $r < 2$).

137 Predictions

138 Our first prediction assumes no interspecific interactions, no environmental stochasticity, iden-
 139 tical intrinsic growth rates, and that demographic stochasticity is operating but all species have
 140 identical demographic variances. This limiting case, \mathcal{M}_D , represents a community where dynam-

ics are driven by demographic stochasticity alone. Our prediction for the synchrony of per capita growth rates for \mathcal{M}_D , ϕ_{R,\mathcal{M}_D} , is

$$\phi_{R,\mathcal{M}_D} = \frac{\sum_i p_i^{-1}}{\left(\sum_i p_i^{-1/2}\right)^2}, \quad (3)$$

where p_i is the average frequency of species i , $p_i = N_i/N_T$. When all species have identical abundances and $p_i = 1/S$, where S is species richness, synchrony equal $1/S$ (Loreau and de Mazancourt 2008).

Our second limiting case assumes only environmental stochasticity is operating (\mathcal{M}_E). Thus, we assume there are no interspecific interactions, demographic stochasticity is absent, intrinsic growth rates are identical, and environmental variance is identical for all species. Our prediction for the synchrony of per capita growth rates for \mathcal{M}_E , ϕ_{R,\mathcal{M}_E} , is

$$\phi_{R,\mathcal{M}_E} = \frac{\sum_{i,j} \text{cov}(u_{ei}, u_{ej})}{S^2}, \quad (4)$$

where $\text{cov}(u_{ei}, u_{ej})$ is the standardized covariance of environmental responses between species i and species j . Confronting our theoretical predictions with data requires estimates of species dynamics of large populations (no demographic stochasticity) growing in isolation (no interspecific interactions) to calculate the covariance of species' environmental responses. To estimate environmental responses in natural communities, we turn to our population models built using long-term demographic data.

EMPIRICAL ANALYSIS

Materials and methods

Data We use long-term demographic data from five semiarid grasslands in the western United States (described in detail by Chu and Adler 2015). Each site includes a set of 1-m² permanent

quadrats within which all individual plants were identified and mapped annually using a panto-graph (Hill 1920). The resulting mapped polygons represent basal cover for grasses and canopy cover for shrubs. Data come from the Sonoran desert in Arizona (Anderson et al. 2012), sagebrush steppe in Idaho (Zachmann et al. 2010), southern mixed prairie in Kansas (Adler et al. 2007), northern mixed prairie in Montana (Anderson et al. 2011), and Chihuahuan desert in New Mexico (Anderson et al. in preparation, Chu and Adler 2015) (Table 1).

Calculating observed synchrony The data consist of records for individual plant size in quadrats for each year. To obtain estimates of percent cover for each focal species in each year, we summed the individual-level data within quadrats and then averaged percent cover, by species, over all quadrats. We calculated per capita growth rates as $\log(x_t) - \log(x_{t-1})$, where x is species' percent cover in year t . Using the community time series of per capita growth rates or percent cover, we calculated community synchrony using the metric of Loreau and de Mazancourt (2008) in the 'synchrony' package (Gouhier and Guichard 2014) in R (R Core Team 2013). Specifically, we calculated synchrony as

$$\phi_r = \frac{\sigma_T^2}{(\sum_i \sigma_{r_i})^2} \quad (5)$$

where σ_{r_i} is the temporal **standard deviation** of species i 's per capita population growth rate (r_i) and σ_T^2 is the temporal variance of the aggregate community-level growth rate. ϕ ranges from 0 at perfect asynchrony to 1 at perfect synchrony (Loreau and de Mazancourt 2008). We use the same equation to calculate observed synchrony of species' percent cover, which we present to relate our results to previous findings, even though we focus on synchrony of growth rates in our model simulations (see below).

Fitting statistical models Vital rate regressions are the building blocks of our dynamic models: an integral projection model (IPM) and an individual-based model (IBM). We followed the ap-

proach of Chu and Adler (2015) to fit statistical models for survival, growth, and recruitment (see Appendix S1 for full details). We modeled survival probability of each genet as function of genet size, temporal variation among years, permanent spatial variation among groups of quadrats, and local neighborhood crowding from conspecific and heterospecific genets. Regression coefficients for the effect of crowding by each species can be considered a matrix of interaction coefficients whose diagonals represent intraspecific interactions and whose off-diagonals represent interspecific interactions (Adler et al. 2010). These interaction coefficients can take positive (facilitative) or negative (competitive) values. We modeled growth as the change in size of a genet from one year to the next, which depends on the same factors as the survival model. We fit the survival and growth regressions using INLA (Rue et al. 2014), a statistical package for fitting generalized linear mixed effects models via approximate Bayesian inference (Rue et al. 2009), in R (R Core Team 2013). Crowding was treated as a fixed effect without a temporal component because most 95% credible intervals for random year effects on crowding broadly overlapped zero and, in a test case, including yearly crowding effects did not change our results. Spatial (quadrat groupings) variation was treated as a random effect on the intercept and temporal (interannual) variation was treated as random effects on the intercept and the effect of genet size in the previous year (Appendix S1).

We modeled recruitment at the quadrat scale, rather than the individual scale, because the original data do not attribute new genets to specific parents (Chu and Adler 2015). Our recruitment model assumes that the number of recruits produced in each year follows a negative binomial distribution with the mean dependent on the cover of the parent species, permanent spatial variation among groups, temporal variation among years, and inter- and intraspecific interactions as a function of total species' cover in the quadrat. We fit the recruitment model using a hierarchical Bayesian approach implemented in JAGS (Plummer 2003) using the 'rjags' package (Plummer 2014) in R (R Core Team 2013). Again, temporal and spatial variation were treated as random effects.

Building dynamic multi-species models Once we have fit the vital rate statistical models, building the population models is straightforward. For the IBM, we initialize the model by randomly assigning plants spatial coordinates, sizes, and species identities until each species achieves a density representative of that observed in the data. We then project the model forward by using the survival regression to determine whether a genet lives or dies, the growth regression to calculate changes in genet size, and the recruitment regression to add new individuals that are distributed randomly in space. Crowding is directly calculated at each time step since each genet is spatially referenced (as in the observed data). Environmental stochasticity is not an inherent feature of IBMs, but is easily included since we fit year-specific temporal random effects for each vital rate regression. To include temporal environmental variation, at each time step we randomly choose a set of estimated survival, growth, and recruitment parameters specific to one observation year. For all simulations, we ignore the spatial random effect associated with variation among quadrat groups, so our simulations represent an average quadrat for each site.

The IPM uses the same vital rate regressions as the IBM (Rees and Ellner 2009, Rees et al. 2014), but it is spatially implicit and does not include demographic stochasticity. Following Chu and Adler (2015), we use a mean field approximation that captures the essential features of spatial patterning to define the crowding index at each time step (Supporting Online Information). Temporal variation is included in exactly the same way as for the IBM. For full details on the IPMs we use, see Chu and Adler (2015).

Simulation experiments We performed simulation experiments where drivers (environmental stochasticity, demographic stochasticity, or interspecific interactions) were removed one-by-one and in combination. To remove interspecific interactions, we set the off-diagonals of the interaction matrix for each vital rate regression to zero. This retains intraspecific interactions, and thus density-dependence, and results in simulations where species are growing in isolation. We cannot definitively rule out the effects of species interactions on all parameters, meaning that a true monoculture could behave differently than our simulations of a population growing with-

out interspecific competitors. To remove the effect of a fluctuating environment, we removed the temporal (interannual) random effects from the regression equations. To remove the effect of demographic stochasticity, we use the IPM rather than the IBM because the IPM does not include demographic stochasticity (demographic stochasticity cannot be removed from the IBM). Since the effect of demographic stochasticity on population dynamics depends on population size (Lande et al. 2003), we can control the strength of demographic stochasticity by simulating the IBM on areas (e.g. plots) of different size. Indeed, results from an IBM with infinite population size would converge on results from the IPM. Given computational constraints, the largest landscape we simulate is a 25 m² plot.

We conducted the following six simulation experiments: (1) IBM: All drivers (environmental stochasticity, demographic stochasticity, or interspecific interactions) present; (2) IPM: Demographic stochasticity removed; (3) IBM: Environmental stochasticity removed; (4) IBM: Interspecific interactions removed; (5) IPM: Interspecific interactions and demographic stochasticity removed; (6) IBM: Interspecific interactions and environmental stochasticity removed. We do not include a simulation with only interspecific interactions because our population models run to deterministic equilibriums in the absence of environmental or demographic perturbations. We ran IPM simulations for 2,000 time steps, after an initial 500 iteration burn-in period. This allowed species ~~time~~ to reach their stable size distribution. We then calculated the synchrony of species' per capita growth rates over 100 randomly selected contiguous 50 time-step sections. We ran IBM simulations for 100 time steps, and repeated the simulations 100 times for each simulation experiment. From those, we retained only the simulations in which no species went extinct due to demographic stochasticity. Synchrony was calculated over the 100 time steps for each no extinction run within a model experiment. To explore the effect of demographic stochasticity in different sized populations, we ran simulations (1) and (6) on plot sizes of 1, 4, 9, 16, and 25 m². All other IBM simulations were run on a 25 m² landscape.

Results from our simulation experiments also allow us to test our theoretical predictions. First, in the absence of interspecific interactions and demographic stochasticity, populations can

only fluctuate in response to the environment. Therefore, we can use results from simulation (5) to estimate the covariance of species' responses to the environment ($\text{cov}(u_{ie}, u_{je})$) and parameterize Equation 4. Parameterizing Equation 3 does not require simulation output because the only parameters are the species' relative abundances. Second, simulations (5) and (6) represent the simulated version of our limiting case theoretical predictions. Thus, we directly test the theoretical predictions by comparing them to observed synchrony and simulated synchrony.

Results

Synchrony of species' per capita growth rates at our study sites range from 0.36 to 0.89 and synchrony of percent cover ranged from 0.15 to 0.92 (Table 2). Synchrony tends to be higher in communities with few species (Arizona and New Mexico) and/or with relatively high temporal variability in percent cover (e.g., Montana). Synchrony is lowest in Idaho, the only data set that includes two life forms: a shrub and three perennial grasses (Table 1). Synchrony of per capita growth rates and CV of percent cover are positively correlated (Pearson's $\rho = 0.72$). For all five communities, species synchrony from IPM and IBM simulations closely approximated observed synchrony (Fig. S1). IBM-simulated synchrony is consistently, but only slightly, lower than IPM-simulated synchrony (Fig. S1), likely due to the desynchronizing effect of demographic stochasticity.

Across the five communities, our limiting case predictions closely matched synchrony from the corresponding simulation experiment (Fig. 1 and Table S1). The correlation between our analytical predictions and simulated synchrony was 0.97 for ϕ_{R, \mathcal{M}_D} and 0.997 for ϕ_{R, \mathcal{M}_E} . The largest difference between predicted and simulated synchrony was 0.05 in New Mexico for ϕ_{R, \mathcal{M}_D} (Table S1).

Simulation experiments revealed that removing environmental fluctuations has the largest impact on synchrony, leading to a reduction in synchrony of species growth rates in four out of five communities (Fig. 1). Removing environmental fluctuations ("No E.S" simulations) de-

creased synchrony by 33% in Arizona, 48% in Kansas, 39% in Montana, and 40% in New Mexico. Only in Idaho did removing environmental fluctuations cause an increase in synchrony (Fig. 1), but the effect was small (9% increase; Table S2). Overall, species' temporal random effects in the statistical vital rate models are positively correlated (Table S3). Species interactions are weak in these communities (Table S4 and Chu and Adler 2015), and removing interspecific interactions had little effect on synchrony (Fig. 1; "No Comp." simulations). Removing interspecific interactions caused, at most, a 5% change in synchrony (Fig. 1). Removing demographic stochasticity ("No D.S." simulations) caused synchrony to increase slightly in all communities (Fig. 1), with an average 6% increase over synchrony from IBM simulations on a 25m² area.

The desynchronizing effect of demographic stochasticity, which increases as population size decreases, modestly counteracted the synchronizing force of the environment, but not enough to lower synchrony to the level observed when only demographic stochasticity is operating (Fig. 2). In the largest, 25 m² plots, synchrony was driven by environmental stochasticity (e.g., \mathcal{M}_E). At 1 m², synchrony reflected demographic stochasticity and environmental stochasticity (e.g., between \mathcal{M}_E and \mathcal{M}_D). For context, population sizes increased from an average of 17 individuals per community in 1 m² IBM simulations to an average of 357 individuals per community in 25 m² IBM simulations.

For all five communities, the synchrony of species' growth rates when growing in isolation almost perfectly matched species synchrony in polyculture (Fig. 3). Results for synchrony of percent cover are qualitatively similar, but simulation results were more variable and less consistent with analytical predictions and observed synchrony (Appendix S1, Figs. S2-S3).

DISCUSSION

Our study produced four main findings that were generally consistent across five natural plant communities: (1) limiting-case predictions from the theoretical model were well-supported by simulations from the empirical models; (2) demographic stochasticity decreased community syn-

chrony, as expected by theory, and its effect was largest in small populations; (3) environmental fluctuations increased community synchrony relative to simulations in constant environments because species-specific responses to the environment were positively, though not perfectly, correlated; and (4) interspecific interactions were weak and therefore had little impact on community synchrony. We also found that analyses based on synchrony of species' percent cover, rather than growth rates, were uninformative (Figs. S2-S3) since the linear approximation required for analytical predictions is a stronger assumption for abundance than growth rates, especially given relatively short time-series (Appendix S1). Thus, our results provide further evidence that it is difficult to decipher mechanisms of species synchrony from abundance time series, as expected by theory (Loreau and de Mazancourt 2008). Observed synchrony of per capita growth rates was positively correlated with the variability of percent cover across our focal communities, which confirms that we are investigating an important process underlying ecosystem stability.

Simulations support theoretical predictions

Our theoretical predictions were derived from a simple model of population dynamics and required several simplifying assumptions, raising questions about their relevance to natural communities. For example, the species in our communities do not have equivalent environmental and demographic variances (Figs. S4-S7), as required by our predictions. However, the theoretical predictions closely matched results from simulations of population models fit to long-term data from natural plant communities (Table 3). Such strong agreement between our analytical predictions and the simulation results should inspire confidence in the ability of simple models to inform our understanding of species synchrony even in complex natural communities, and allows us to place our simulation results within the context of contemporary theory.

Demographic stochasticity decreases synchrony

Demographic stochasticity partially counteracted the synchronizing effects of environmental fluctuations and interspecific interactions on per capita growth rates, but only when populations were small (Fig. 2), in agreement with theory (Loreau and de Mazancourt 2008). Even in small populations, however, demographic stochasticity was not strong enough to compensate the synchronizing effects of environmental fluctuations and match the analytical prediction where only demographic stochasticity is operating (\mathcal{M}_D in Fig. 2). These results confirm the theoretical argument by Loreau and de Mazancourt (2008) that independent fluctuations among interacting species in a non-constant environment should be rare. Only in the Idaho community does synchrony of per capita growth rates approach \mathcal{M}_D in a non-constant environment (Fig. 2). This is most likely due to the strong effect of demographic stochasticity on the shrub *Artemisia tripartita* since even a 25 m² quadrat would only contain a few individuals of that species.

Our analysis of how demographic stochasticity affects synchrony demonstrates that synchrony depends on the observation area. As the observation area increases, population size increases and the desynchronizing effect of demographic stochasticity lessens (Fig. 2). Thus, our results suggest that community-wide species synchrony will increase as the observation area increases, rising from \mathcal{M}_D to \mathcal{M}_E . Such a conclusion assumes, however, that species richness remains constant as observation area increases, which is unlikely (Taylor 1961). Recent theoretical work has begun to explore the linkage between ecosystem stability and spatial scale (Wang and Loreau 2014, 2016), and our results suggest that including demographic stochasticity in theoretical models of metacommunity dynamics may be important for understanding the role of species synchrony in determining ecosystem stability across spatial scales.

Environmental fluctuations drive community synchrony

In large populations where interspecific interactions are weak, synchrony is expected to be driven exclusively by environmental fluctuations (Equation 4). Under such conditions community syn-

chrony should approximately equal the synchrony of species' responses to the environment (Loreau and de Mazancourt 2008). Two lines of evidence lead us to conclude that environmental fluctuations drive species synchrony in our focal plant communities. First, in our simulation experiments, removing interspecific interactions resulted in no discernible change in community-wide species synchrony of per capita growth rates (Fig. 1). Second, removing environmental fluctuations from simulations consistently reduced synchrony (Fig. 1), and the synchrony of species in isolation was a very strong predictor of synchrony of species in polyculture (Fig. 3). Our results lead us to conclude that environmental fluctuations, not species interactions, are the primary driver of community-wide species synchrony in the communities we studied. Given accumulating evidence that niche differences in natural communities are large (reviewed in Chu and Adler 2015), and thus species interactions are likely to be weak, our results may be general in natural plant communities.

In the Idaho community, removing environmental fluctuations did not cause a large decrease in synchrony. However, that result appears to be an artifact. Removing environmental variation results in a negative invasion growth rate for *A. tripartita*. Although we only analyzed IBM runs in which *A. tripartita* had not yet gone extinct, it was at much lower abundance than in the other simulation runs. When we removed *A. tripartita* from all simulations, the Idaho results conformed with results from all other sites: removing environmental stochasticity caused a significant reduction in species synchrony (Fig. S8). Our main results for Idaho (Fig. 2), with *A. tripartita* included, demonstrate how the processes that determine species synchrony interact in complex ways. *A. tripartita* has a facilitative effect on each grass species across all vital rates, except for a small competitive effect on *H. comata*'s survival probability (Tables S8-S10). At the same time, all the perennial grasses have negative effects on each other for each vital rate (Tables S8-S10). We know synchrony is affected by interspecific competition (Loreau and de Mazancourt 2008), but how facilitative effects manifest themselves is unknown. The interaction of facilitation and competition is clearly capable of having a large effect on species synchrony, and future theoretical efforts should aim to include a wider range of species interactions.

~~A challenge to the generality of our results is that we were only able to model common, co-occurring species [see @Chu2015]. Most communities are dominated by few common species and many rare species [McGill2007], meaning that the low number of common species in our focal communities is not unusual. Rather, the generality of our results hinges upon the influence of rare species. Rare species could be kept at low densities by competitive suppression due to strong interspecific interactions. If we had been able to model rare species, we might have found a larger effect of competition on community synchrony. However, recent theory predicts that persistent rare species may actually experience even weaker interspecific competition, and thus stronger niche differences, than common species [Yenni2012], in which case synchrony would remain predominantly driven by environmental responses. Rare species could also be limited by generalist natural enemies whose effects are density-independent but alter competitive hierarchies [Mordecai2011]. Under such conditions, synchrony will depend on the degree of pathogen-induced fitness differences and the pathogen's response to environmental conditions. Neither our model nor current theory explicitly considers the effects of pathogens on species synchrony, and this highlights the need for theoretical work on the interaction between mechanisms of species coexistence and mechanisms of species synchrony [Loreau2010].~~

Interspecific interactions had little impact on community synchrony

We expected community synchrony of per capita growth rates to decrease when we removed interspecific interactions (Loreau and de Mazancourt 2008). We found that community synchrony was virtually indistinguishable between simulations with and without interspecific interactions (Fig. 1). The lack of an effect of interspecific interactions on synchrony is in contrast to a large body of theoretical work that predicts a strong role for competition in creating compensatory dynamics (Tilman 1988) and a recent empirical analysis (Gross et al. 2014).

Our results do not contradict the idea that competition can lead to compensatory dynamics, but they do highlight the fact that interspecific competition must be relatively strong to influence

species synchrony. The communities we analyzed are composed of species with very little niche overlap (Chu and Adler 2015) and weak interspecific interactions (Tables S1, S3-S17). Mechanistic consumer-resource models (Lehman and Tilman 2000) and phenomenological Lotka-Volterra models (Lehman and Tilman 2000, Loreau and de Mazancourt 2013) both confirm that the effect of competition on species synchrony diminishes as niche overlap decreases. In that sense, our results are not surprising: interspecific interactions are weak, so of course removing them does not affect synchrony.

However, our results do contrast with a recent analysis of several biodiversity-ecosystem functioning experiments showing that competition drives the degree of species synchrony in grasslands (Gross et al. 2014). The apparent inconsistency between our results and those of Gross et al. (2014) may be explained by the differences between our studies. Gross et al.'s results are based on rapidly assembling experimental communities that are, at most, 11 years old. The natural, relatively undisturbed communities we studied consist of species that have co-occurred for decades (Chu and Adler 2015) and represent a much later stage of community assembly. In theory, species interactions should weaken through time as community assembly proceeds (Kokkoris et al. 1999), meaning that in biodiversity-ecosystem functioning experiments the processes driving competitive exclusion are still operating. Such communities may be highly influenced by transient, but strong, interspecific competition that can mask the synchronizing effects of the environment.

In contrast, the degree of synchrony may be driven by environmental fluctuations in older communities. In other words, the dominant driver of community synchrony should shift from competition to environmental fluctuations through time. One way to test this prediction is to continue collecting data from biodiversity-ecosystem functioning experiments and conduct the analysis of Gross et al. (2014) every few years.

Our conclusion that species interactions have little impact on synchrony only applies to single trophic level communities. Species interactions almost certainly play a strong role in multi-

436 trophic communities where factors such as resource overlap (Vasseur and Fox 2007), dispersal
437 (Gouhier et al. 2010), and the strength of top-down control (Bauer et al. 2014) are all likely to
438 affect community synchrony.

439 CONCLUSIONS

440 Species-specific responses to temporally fluctuating environmental conditions is an important
441 mechanism underlying asynchronous population dynamics and, in turn, ecosystem stability
442 (Loreau and de Mazancourt 2013). When we removed environmental variation, we found that
443 synchrony decreased in four out of the five grassland communities we studied (Fig. 1). A tempt-
444 ing conclusion is that our study confirms that compensatory dynamics are rare in natural commu-
445 nities, and that ecologically-similar species will exhibit synchronous dynamics (e.g., Houlihan et
446 al. 2007). Such a conclusion misses an important subtlety. The perennial grasses we studied do
447 have similar responses to the environment (Table S2), which will tend to synchronize dynamics.
448 However, if community-wide species synchrony is less than 1, as it is in all our focal communi-
449 ties, some degree of compensatory dynamics must be present (Loreau and de Mazancourt 2008).
450 In agreement with other studies (Rocha et al. 2011, Vasseur et al. 2014), we find that environmen-
451 tal responses are primarily responsible for the degree of synchrony among ecologically-similar
452 species. This result contrasts with a recent analysis of several biodiversity-ecosystem functioning
453 experiments showing that competition drives community synchrony (Gross et al. 2014). Recently
454 assembled communities, such as experimental plots, may exhibit strong species interactions that
455 will weaken over time (Kokkoris et al. 1999). Future research on the influence of community
456 assembly on synchrony could reconcile inconsistent observations on the biotic and abiotic forces
457 that jointly drive community dynamics.

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468 Table 1: Site descriptions and focal species.

Site Name	Biome	Location (Lat, Lon)	Obs. Years	Species
New Mexico	Chihuahuan Desert	32.62° N, 106.67° W	1915-1950	<i>Bouteloua eriopoda</i> <i>Sporobolus flexuosus</i>
Arizona	Sonoran Desert	31°50' N, 110°53' W	1915-1933	<i>Bouteloua eriopoda</i> <i>Bouteloua rothrockii</i>
Kansas	Southern mixed prairie	38.8° N, 99.3° W	1932-1972	<i>Bouteloua curtipendula</i> <i>Bouteloua hirsuta</i> <i>Schizachyrium scoparium</i>
Montana	Northern mixed prairie	46°19' N, 105°48' W	1926-1957	<i>Bouteloua gracilis</i> <i>Hesperostipa comata</i> <i>Pascopyrum smithii</i> <i>Poa secunda</i>
Idaho	Sagebrush steppe	44.2° N, 112.1° W	1926-1957	<i>Artemisia tripartita</i> <i>Pseudoroegneria spicata</i> <i>Hesperostipa comata</i> <i>Poa secunda</i>

Table 2: Observed synchrony among species' per capita growth rates (ϕ_R), observed synchrony among species' percent cover (ϕ_C), the coefficient of variation of total community cover, and species richness for each community. Species richness values reflect the number of species analyzed from the community, not the actual richness.

Site	ϕ_R	ϕ_C	CV of Total Cover	Species richness
New Mexico	0.86	0.92	0.51	2
Arizona	0.89	0.80	0.47	2
Kansas	0.54	0.15	0.30	3
Montana	0.53	0.54	0.52	4
Idaho	0.36	0.18	0.19	4

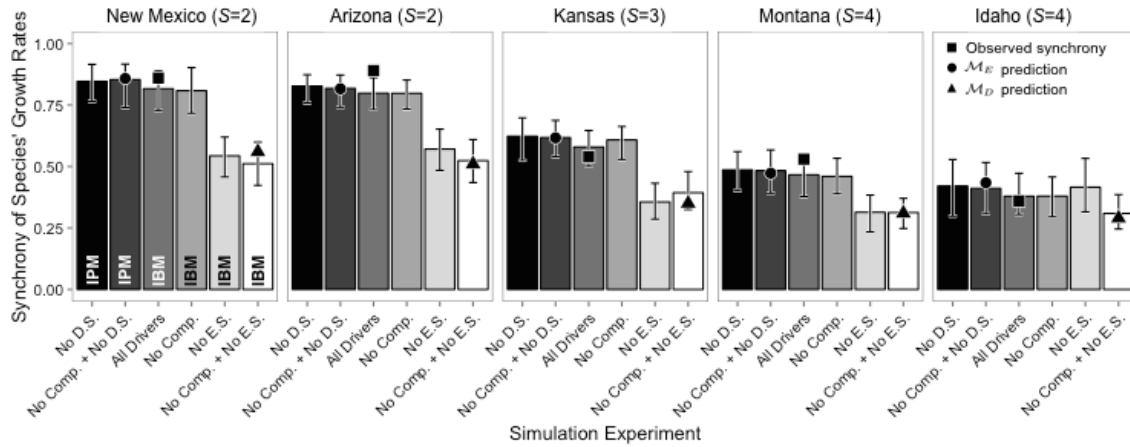


Figure 1: Community-wide species synchrony of per capita growth rates from model simulation experiments. Synchrony of species' growth rates for each study area are from simulation experiments with demographic stochasticity, environmental stochasticity, and interspecific interactions present ("All Drivers"), demographic stochasticity removed ("No D.S."), environmental stochasticity removed ("No E.S."), interspecific interactions removed ("No Comp."), interspecific interactions and demographic stochasticity removed ("No Comp. + No D.S."), and interspecific interactions and environmental stochasticity removed ("No Comp. + No E.S."). Abbreviations within the bars for the New Mexico site indicate whether the IBM or IPM was used for a particular simulation. Error bars represent the 2.5% and 97.5% quantiles from model simulations. All IBM simulations shown in this figure were run on a 25 m² virtual landscape. Points show observed and predicted synchrony aligned with the model simulation that corresponds with each observation or analytical prediction.

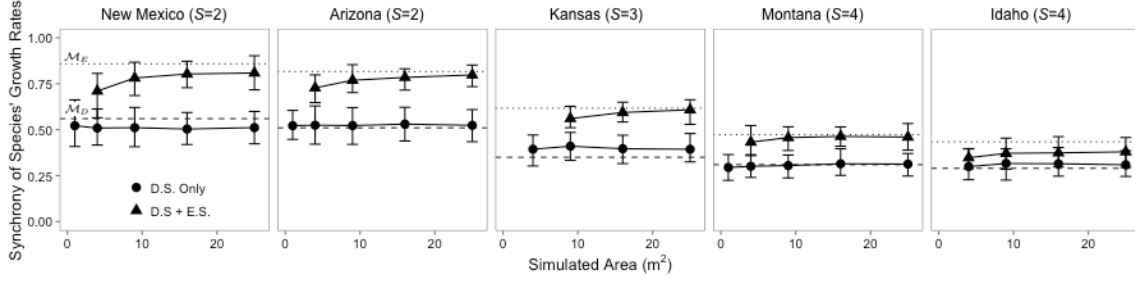


Figure 2: Synchrony of species' growth rates for each study area from IBM simulations across different landscape sizes when only demographic stochasticity is present ("D.S. Only") and when environmental stochasticity is also present ~~removed~~ ("D.S. + E.S."). The horizontal lines show the analytical predictions \mathcal{M}_D (dashed line) and \mathcal{M}_E (dotted line). The strength of demographic stochasticity decreases as landscape size increases because population sizes also increase. Theoretically, "D.S. Only" simulations should remain constant across landscape size, whereas "D.S. + E.S." simulations should shift from the \mathcal{M}_D prediction to the \mathcal{M}_E prediction as landscape size, and thus population size, increases, but only if demographic stochasticity is strong enough to counteract environmental forcing. Error bars represent the 2.5% and 97.5% quantiles from model simulations.

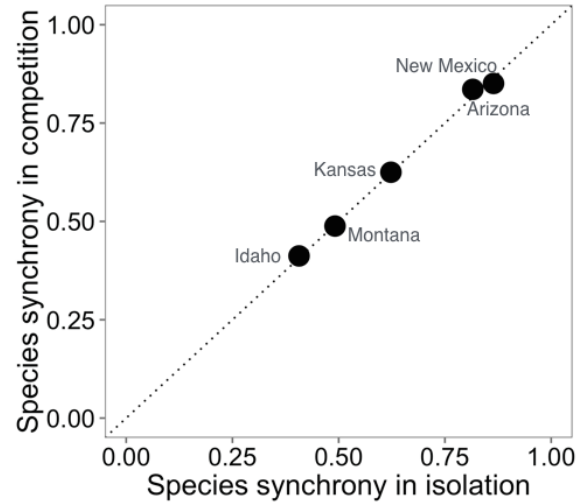


Figure 3: Synchrony of species per capita growth rates when species are growing in isolation (IPM without species interactions) versus synchrony in polycultures (IPM with species interactions). ~~We used the same sequence of random year effects for both simulations (with and without species interactions) to mimic biodiversity ecosystem functioning experiments.~~ The dashed line is the line of equality. Simulation results in this figure are analagous to “No Comp. + No D.S.” (species in isolation) and “No D.S.” (species in competition) in Fig. 1, but here we control the time series of random year effects.

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