

# Continuous assembly required: perpetual species turnover in two trophic level ecosystems

Jurg W. Spaak<sup>1,2,\*</sup>, Peter B. Adler<sup>3</sup>, Stephen P. Ellner<sup>1</sup>

1. Department of Ecology and Evolutionary Biology, Cornell University, Ithaca, NY, USA  
2. Institute for Environmental Sciences, University Koblenz-Landau, Fortstrasse 7, 76829 Landau in der Pfalz, Germany

3. Department of Wildland Resources and the Ecology Center, Utah State University, Logan, UT, USA

\* Corresponding author

*Email addresses:* j.w.spaak@gmail.com, peter.adler@usu.edu, spe2@cornell.edu

*Statement of authorship:* J.W.S. wrote the computer code. J.W.S. wrote the first draft, all authors discussed content and contributed to revisions.

*Open Research statement:* We created new computer code for the simulations of this manuscript. The computer code is publicly available at <https://zenodo.org/record/7544362#.Y8af2HaxND8> with DOI 10.5281/zenodo.7544362 Upon acceptance we will store the computer code on Zenodo. We did not use any new empirical data in this manuscript.

*Keywords:* Plankton | Species richness | Coexistence | Trait based approach | Ecological modeling

*Type of Article:* Article

*Words in abstract, Text and Boxes:* 156, 3528, -

## 22 Abstract

23 Community assembly is often treated as deterministic, converging on one or at most  
24 a few possible stable endpoints. However, in nature we typically observe continuous  
25 change in community composition, which is often ascribed to environmental change.  
26 But continuous changes in community composition can also arise in deterministic,  
27 time-invariant community models, especially food web models. Our goal was to  
28 determine why some models produce continuous assembly and others do not. We  
29 investigated a simple two trophic-level community model to show that continuous  
30 assembly is driven by the relative niche width of the trophic levels. If predators have  
31 a larger niche width than prey, community assembly converges to a stable equilib-  
32 rium. Conversely, if predators have a smaller niche width than prey, then community  
33 composition never stabilizes. Evidence that food webs need not reach a stable equilib-  
34 rium has important implications, as many ecological theories of community ecology  
35 based on equilibria may be difficult to apply to such food webs.

## 36 Introduction

37 Understanding how species assemble into communities is a central issue in commu-  
38 nity ecology (Fukami, 2015; Song *et al.*, 2021; Serván & Allesina, 2021). Community  
39 assembly is typically modeled as a sequence of invasions of species from a regional  
40 species pool into a local patch, where the success of each invasion may depend on  
41 both the environmental conditions as well as the local community itself (HilleRis-  
42 Lambers *et al.*, 2012; Barbier *et al.*, 2021).

43 How we view community structure affects how we interpret community assem-  
44 bly (Tilman, 2004). A view based on niche theory typically implies a deterministic  
45 community assembly process, where composition converges on the community best  
46 adapted to the environment (MacArthur, 1970; Tilman *et al.*, 1982; Cressman *et al.*,  
47 2017; Kremer & Klausmeier, 2017). For example, with competition for a single lim-  
48 iting resource, the species with the lowest resource requirement  $R^*$  replaces all its  
49 competitors with higher resource requirements (Tilman *et al.*, 1982; Tilman, 2004).  
50 Similar rules allow us to predict community assembly under competition for two re-  
51 sources (Tilman *et al.*, 1982), with predators (Holt & Lawton, 1994) or with mutualists  
52 (Johnson & Bronstein, 2019). In these models, resource competition leads determin-  
53 istically to a single community in which every available niche is occupied (Tilman,  
54 2004; Cressman *et al.*, 2017), independent of the assembly processes.

55 Communities with priority effects, or other historical contingencies, are no ex-  
56 ception: they also converge towards a predictable outcome of community assembly  
57 (Fukami, 2015; Serván & Allesina, 2021). However, in these cases the outcome can  
58 depend on the starting point and potentially on the community assembly process it-  
59 self. Understanding when and how the sequence of community assembly affects the  
60 final community may not be simple (Fukami *et al.*, 2016; Vannette & Fukami, 2014;  
61 Song *et al.*, 2021; Huisman & Weissing, 2001; Barbier *et al.*, 2021), but we still expect  
62 assembly to converge on one of several possible stable, uninvadable communities  
63 (Mordecai, 2011; Ke & Letten, 2018; Song *et al.*, 2021).

64 Conversely, we rarely observe stable community compositions in natural com-  
65 munities (Blowes *et al.*, 2019; Dornelas *et al.*, 2019; Hamm & Drossel, 2021). Rather  
66 natural communities appear to be in a continuous community assembly process. Of-  
67 ten, we observe a set of permanent species, typically called core species, and a set  
68 of transient species, typically called satellite species (Nee *et al.*, 1991). Typical ex-  
69 planations for these patterns include environmental change (Dornelas *et al.*, 2019) or  
70 neutral or stochastic processes (Hubbell, 2005). We accepted this view until recently  
71 when we investigated a two trophic-level plankton community model with mecha-  
72 nistic species interactions (Spaak *et al.*, 2022). In this model, community composition  
73 changed continuously over time, despite the lack of external environmental changes  
74 or any stochastic processes.

75 As demonstrated by our plankton community model, patterns of continuous com-  
76 munity assembly can also arise from internal species interactions in food web models  
77 that are purely deterministic and time-invariant (Hamm & Drossel, 2021; Morton  
78 & Law, 1997; Steiner & Leibold, 2004). Such models capture many of the patterns  
79 observed in nature such as food-chain length, number of average links per species,  
80 species-area relationships and average persistence time (Williams & Martinez, 2000;  
81 Loeuille & Loreau, 2005). However, not all food-web models lead to a continuous  
82 assembly pattern (Loeuille & Loreau, 2005) and some lead to a continuous assembly  
83 pattern only for higher trophic levels (Allhoff *et al.*, 2015). The drivers of continu-  
84 ous community assembly are understood in some simple phenomenological models  
85 (Bunin, 2017), but these models are based on randomly generated matrices of species  
86 interaction coefficients, which do not reflect natural communities (Eklöf *et al.*, 2013; Li  
87 *et al.*, 2022). Interaction strengths in food web models and real food webs are highly  
88 structured, so continuous assembly in food web models is a different phenomenon.  
89 For example, predation strength in many food web models is based on a Gaussian  
90 function of differences in body sizes, yet while some of these models lead to contin-

91 uous turnover others do not. Currently, we do not know which of the underlying  
92 assumptions of food web models are responsible for continuous community assem-  
93 bly.

94 Understanding the properties that lead to continuous community assembly is im-  
95 portant, as many of our ecological theories are based on assumptions of stable com-  
96 munity composition and equilibrium dynamics. For example, modern coexistence  
97 theory is based on invasions into stable communities at equilibrium (Ellner *et al.*, 2019;  
98 Spaak *et al.*, 2021; Barabás *et al.*, 2018), studies of biodiversity-ecosystem function typ-  
99 ically measure both biodiversity and ecosystem function at equilibrium (Loreau &  
100 Hector, 2001; Loreau, 2010; Bannar-Martin *et al.*, 2018), and ecosystem stability analy-  
101 sis is based on linear approximations around an equilibrium (May, 1972; Carpentier  
102 *et al.*, 2021; Allesina & Tang, 2012, 2015).

103 Here we analyze simple community models with one or two trophic levels  
104 (MacArthur & Levins, 1967; MacArthur, 1970) to answer two questions about con-  
105 tinuous invasion and extinction dynamics. 1. What are the necessary conditions for  
106 these dynamics to emerge? 2. Are there any constant properties within the disorder  
107 of continuous invasion and extinction?

## 108 **Methods**

### 109 **Community model and assembly**

110 We first observed continuous invasion and extinction in a mechanistic phytoplankton-  
111 zooplankton model (Spaak *et al.*, 2022). However, here we focus on a simpler two-  
112 trophic Lotka-Volterra community model because it offers greater generality and less  
113 complexity. The Lotka-Volterra community model is widely known and provides  
114 a phenomenological description of many different communities independent of the  
115 specific mechanisms underlying species interactions. Additionally, the Lotka-Volterra  
116 model is based on a few simple assumptions, which allows a more general under-  
117 standing of the phenomenon.

We assumed a two trophic level Lotka-Volterra community model

$$\frac{1}{B_i} \frac{dB_i}{dt} = \mu_i - \sum_j a_{ij} B_j - \sum_k b_{ik} P_k \quad (1)$$

$$\frac{1}{P_i} \frac{dP_i}{dt} = \mu_i^P + \epsilon \sum_j b_{ji} B_j \quad (2)$$

118 where  $B_i$  is the density of prey species  $i$  with intrinsic growth rate  $\mu_i$ ,  $a_{ij}$  is the species-  
 119 specific interaction between prey species  $i$  and  $j$ ,  $b_{ik}$  is the predation of predator  $k$   
 120 on prey species  $i$ ,  $P_k$  is the density of predator  $k$  and  $\mu_i^P$  is the mortality rate of the  
 121 predator. We assumed that there are no direct interactions between predators.  $\epsilon$  is the  
 122 trophic conversion efficiency between consumption of prey biomass and production  
 123 of predator biomass; we assumed a trophic efficiency of  $\epsilon = 0.1$ .

124 We defined the community parameters  $\mu_i$  and  $a_{ij}$  according to MacArthur & Levins  
 125 (1967) and Barabás & Mészéna (2009), which specifies a Lotka-Volterra model based  
 126 on underlying competition of prey species for a resource continuum. Each prey  
 127 species was identified by a single trait  $x_i$ , e.g. body mass, which defined its resource  
 128 consumption spectrum  $u_i$ , i.e.  $u_i(x) = u_B \exp\left(-\frac{(x-x_i)^2}{2(\sqrt{2}\sigma_B)^2}\right)$ , where  $x$  is the resource  
 129 identity, e.g. body mass of the resource,  $\sigma_B$  is the niche breadth and  $u_B$  is a normalizing  
 130 constant. The competitive interaction between two prey species  $i$  and  $j$  is given by  
 131  $a_{ij} = \int u_i(x)u_j(x)dx = \exp\left(-\frac{(x_i-x_j)^2}{2\sigma_B^2}\right)$ , and the scaling constant  $u_B$  was chosen such  
 132 that  $a_{ii} = 1$  (Barabás & Mészéna, 2009). The intrinsic growth rate  $\mu_i$  depended on  
 133 the carrying capacity of the resource  $R(x)$ , which we assumed to be a Gaussian, i.e.,  
 134  $R(x) = R_0 \exp\left(-\frac{x^2}{2(\omega^2-2\sigma_B^2)}\right)$ , where  $R_0$  is the maximum resource availability and  $\omega$  is  
 135 the breadth of the resource axis, such that  $\mu_i = \int u_i(x)R(x)dx - m_i = K \exp\left(-\frac{x_i^2}{2\omega^2}\right) -$   
 136  $m_i$ , where  $K$  denotes the maximum intrinsic growth rate,  $m_i = 0.1$  is the mortality  
 137 rate and  $\omega$  is the niche breadth.

138 We also assumed a Gaussian predation kernel for the predators. Each predator  
 139 species was defined by a single trait  $y_j$  for predator species  $j$  which defined its pre-  
 140 dation preferences. Predation coefficients were given by  $b_{ij} = \exp\left(-\frac{(x_i-y_j)^2}{2\sigma_P^2}\right)$ , where  
 141  $\sigma_P$  is the niche breadth of the predator. Finally, we assumed that all predators have the  
 142 same mortality rate  $\mu_i^P = -0.1$ .

143 Community assembly consisted of four steps:

- 144 1. Generate a random invader: This invader has a random trait location  $x_i \sim$   
 145  $\mathcal{N}(0, \sigma)$  and is either a prey or a predator species.  $\sigma = \omega \sqrt{\frac{2}{2.5} \log\left(\frac{K}{m_i}\right)}$  was  
 146 chosen such that about 98% of the invading prey species had a positive intrinsic  
 147 growth rate.
- 148 2. Compute the invasion growth rate of the invader: The invasion growth rate  
 149 is defined as  $r_i = \mu_i - \sum_j a_{ij}B_j^* - \sum_k b_{ik}P_k^*$  or  $\mu_i^P + \epsilon \sum_j b_{ji}B_j^*$ , depending on the  
 150 trophic level of the invader, where  $P_k^*$  and  $B_j^*$  are the equilibrium densities of

151 the current community. If  $r_i$  is negative the invasion fails and we move to the  
152 next time step.

153 3. Test feasibility: Compute the new equilibrium of the invader plus the resident  
154 species, and if all species have positive equilibrium densities the invader suc-  
155 cessfully invaded and we move to the next time step. If one species has negative  
156 equilibrium density move to step 4.

157 4. Find new resident community: If the invader replaced at least one species we  
158 need to find the new resident community. We computed the equilibrium of all  
159 possible sub-communities and removed all non-feasible sub-communities. For  
160 the feasible sub-communities we computed the invasion growth rates of the  
161 non-present species. If all non-present species have a negative invasion growth  
162 rate, the community is saturated. To determine the next resident community,  
163 we selected the most species-rich, feasible, saturated sub-community. If there  
164 were multiple communities of equivalent richness, we randomly selected one.  
165 This method of determining the new resident community led to the same qual-  
166 itative dynamics as introducing each invader at low densities in the model, and  
167 simulating the community dynamics until equilibrium was reached (Appendix  
168 S3, Figure S3)

169 In the main text we focus on a simplified version of community assembly which  
170 assumes that the time between invasions was sufficiently large that the community  
171 would reach an ecological equilibrium between invasions (Serván & Allesina, 2021).  
172 Additionally, we ignored transient dynamics as well as potential non-equilibrium  
173 behavior (Serván & Allesina, 2021; Law & Morton, 1996). In the Appendix we show  
174 that these simplifications do not affect our main conclusions (Appendix S3).

## 175 Results

176 We simulated community assembly under two different conditions, with and without  
177 predators present (Fig. 1). Without predators, there was exactly one stable configu-  
178 ration of prey species, and the trait distance between prey species was roughly twice  
179 the niche breath of the prey species, i.e.  $2\sigma_B$  (MacArthur & Levins, 1967; Barabás *et al.*,  
180 2012). Community assembly always converged towards this single stable configu-  
181 ration, independent of the invasion history, which aligns with previous theoretical  
182 predictions (MacArthur, 1970). Over time, the probability of successful invasion by

183 a new arrival decreased towards zero (blue shaded area, Fig. 1 A). Overall, results  
184 for the one trophic level community model are consistent with the expectation of  
185 convergence towards a stable endpoint known from previous models.

186 The inclusion of a second trophic level qualitatively changed the dynamics. The  
187 two trophic level model did not lead to the typical trait distribution known from  
188 limiting similarity, with equally spaced species at a few unchanging trait values (fig.  
189 1A). Rather, the two trophic level community exhibited continuous invasion of new  
190 species and extinction of established species, although with no trend in species rich-  
191 ness. A late-arriving species did not have a lower probability of invasion success than  
192 an early-arriving one. Consequently, community assembly was not directed, and did  
193 not converge towards a stable end point.

194 Intuitively, we can understand this continuous invasion and extinction by consid-  
195 ering an example with just two prey species,  $B_1$  and  $B_2$ , and two predator species,  $P_1$   
196 and  $P_2$  (Schreiber & Rittenhouse, 2004). We assume that  $P_1$  is a better predator for  
197  $B_1$  and  $P_2$  a better predator for species  $B_2$ ; the predators are equivalent in all other  
198 aspects. Given the community composition  $(B_1, P_1)$ , the prey species  $B_1$  has low fit-  
199 ness because of strong predation pressure from  $P_1$ . Therefore, prey species  $B_2$  can  
200 invade and exclude  $B_1$ , leading to the community  $(B_2, P_1)$ . However,  $P_2$  is a better  
201 predator for  $B_2$  and will consequently displace  $P_1$ , leading to the community  $(B_2, P_2)$ .  
202 Under these conditions  $B_2$  will have low fitness because of strong predation pressure  
203 from  $P_2$ , therefore  $B_1$  will invade leading to  $(B_1, P_2)$ . Finally, to close the cycle,  $P_1$  will  
204 replace  $P_2$  as it is a superior predator for species  $B_1$ . Our model was driven by qual-  
205 itatively similar dynamics, though the randomness in the traits of potential invaders  
206 complicates the simple cycle.

207 This cycle depends on sufficiently specialized predators such that the commu-  
208 nity  $(B_1, B_2, P_1)$  is not stable (Schreiber & Rittenhouse, 2004). In our simulations,  
209 this meant that the niche width of the predator  $\sigma_P$  had to be smaller than the niche  
210 width of the prey species  $\sigma_B$  (Fig. 2). Results from limiting similarity theory give  
211 us an intuitive understanding of this condition. From limiting similarity we expect  
212 the coexisting species to be separated by roughly twice their niche breath, i.e.  $2\sigma$   
213 (MacArthur & Levins, 1967). This result is quite robust to changes in the fitness func-  
214 tion and the competition kernel (Barabás *et al.*, 2012). Let  $\Omega$  denote the length of the  
215 interval of feasible trait values for prey species, i.e.  $\Omega = \omega \sqrt{\frac{2}{2.5} \log\left(\frac{K}{m_i}\right)}$ , which is  
216 also roughly the interval of feasible trait values for predator species. Then we expect  
217  $\sim \Omega/2\sigma_B$  prey species and  $\sim \Omega/2\sigma_P$  predator species in a stable configuration. How-

218 ever, at stable equilibrium the number of predator species cannot exceed the number  
219 of prey species (Tilman *et al.*, 1982; Meszéna *et al.*, 2006). We therefore conclude that  
220 a stable configuration implies  $\sigma_P \geq \sigma_B$  (see Appendix S2 for a more precise proof).  
221 Note however, this argument only tells us that we should not expect a stable con-  
222 figuration for  $\sigma_P < \sigma_B$ , it does not necessarily imply that we should expect a stable  
223 configurations for  $\sigma_P > \sigma_B$ .

## 224 **Stability within the disorder**

225 The two trophic level community model led to unpredictable assembly, meaning that  
226 community composition cannot be predicted far into the future. In contrast, the  
227 trait distribution of the community (the number of species with traits in a particular  
228 interval of trait values) remained largely unchanged (Fig. 3). Typically, an invader re-  
229 placed a resident species with a similar trait, as the invader's presence has the largest  
230 effect on similar species (Vannette & Fukami (2014) and Fig. 3 A, D). Consequently,  
231 each individual invasion had no large effect on the trait distribution. On a longer  
232 time scale, the prey species used essentially all available resources: if a certain range  
233 of the resource spectrum remained unused, then an invader soon filled this gap. As  
234 a result, the trait distribution of the prey species mimicked the underlying resource  
235 distribution (MacArthur, 1970), which was constant over time.

236 Similarly, the trait distribution of the predator species was roughly constant, albeit  
237 more variable over time than the trait distributions of prey species. Intuitively, the  
238 predator trait distribution mimicked their underlying resource distribution, i.e. the  
239 abundance of prey species. However, this underlying resource distribution was not  
240 perfectly constant, but rather varied slightly over time. The trait distribution of the  
241 predator species is therefore a roughly constant approximation of the underlying  
242 roughly constant trait distribution of the prey species.

243 A consequence of this stable trait distribution was the over-dispersion of species  
244 traits compared to a randomly selected community without competitive interactions  
245 (Fig. 4, C and D). Although we did not observe any strict lower limit to the trait  
246 difference between two coexisting competing species, we rarely observed coexisting  
247 species with very similar traits.



## 248 Discussion

249 Our paper highlights the idea that community assembly does not always move to-  
250 wards a stable endpoint, but rather that communities can remain indefinitely in  
251 transient-like behavior with high species turnover. For such communities, the term  
252 community assembly is somewhat inappropriate, as there is no final community to  
253 be assembled. Our modeling results make it clear that this "continuous assembly"  
254 dynamic depends only on the presence of sufficiently specialized predators (Fig. 1,  
255 Appendix S2). The open question then is how widespread we should expect such  
256 dynamics to be in nature.

257 Whether this mechanism is actually present in natural communities is currently  
258 difficult to answer, as three conceptually different mechanisms can lead to the con-  
259 tinuous assembly observed in nature (Dornelas *et al.*, 2019). Specifically, continuous  
260 assembly can be driven by external environmental changes (Dornelas *et al.*, 2019),  
261 stochastic fluctuations based on neutral dynamics (Hubbell, 2001) or internal dynam-  
262 ics as described here. Yet, these different underlying mechanisms lead to different  
263 links between invasion and extinction events. In the neutral model invasion and ex-  
264 tinctions are independent of each other. In the case of external environmental change,  
265 the invasion and extinction are not causally linked but are both driven by the same  
266 external factor. We would therefore expect a correlation, but no causal link. Finally,  
267 in the case of internal dynamics, invasions cause extinctions and vice-versa, and we  
268 would therefore expect a causal link as well as a positive correlation.

269 The BioTIME data set offers a possibility to assess whether invasions and extinc-  
270 tions are correlated and potentially linked. As a cursory analysis, we investigated  
271 the correlations between invasions and extinctions in the BioTIME data (Appendix  
272 S1). We found that in 24 of the 44 datasets ( $\sim 55\%$ ), the observed correlation was  
273 significantly higher than expected by chance, i.e.,  $p < 0.05$  (Fig 5). For 17 of the 44  
274 datasets ( $\sim 40\%$ ), the observed correlation was stronger than any correlations found  
275 in 1000 randomizations. Aquatic ecosystems in particular showed a stronger correla-  
276 tion than expected by chance. Interestingly, Li *et al.* (2022) found that predation kernel  
277 width scales differently with body size in aquatic ecosystems compared to terrestrial  
278 ecosystems, which potentially explains why continuous assembly is more frequent  
279 in aquatic communities. The strong correlation between invasion and extinctions is  
280 consistent with either internal or externally driven invasion and extinction, however  
281 we were not able to test whether there is indeed a causal link between invasions  
282 and extinctions. Additionally, one might test whether invasion and extinction events

283 correlate with strong changes in environmental factors to understand whether and  
284 which external factors drive this continuous community assembly.

## 285 **Why do we see continuous assembly?**

286 Our first research question focused on the conditions necessary for continuous assem-  
287 bly to emerge in our model. We found that sufficient specialization of the predators  
288 was the key condition (Schreiber & Rittenhouse, 2004, Appendix S2), because it allows  
289 prey species to competitively exclude other prey while not sharing their predators. To  
290 understand this dynamic intuitively, we observe that a prey species with no special-  
291 ist predator will have high fitness, allowing it to reach high abundance and displace  
292 competitors with similar traits. However, as the prey species reaches high abundance,  
293 a niche is created for a predator with the corresponding trait to invade. The preda-  
294 tor then reduces the prey species' fitness and abundance, opening the possibility for  
295 other prey species with similar traits to invade. If predators are sufficiently special-  
296 ized, some of these new invading prey species will not experience high predation  
297 pressure and will have high fitness. Predators do not drive the prey species to extinc-  
298 tion directly, rather they reduce the fitness of their prey to the point where they can  
299 no longer compete with neighboring prey species that experience far less predation  
300 pressure.

301 Abrams & Matsuda (1997) described a similar pattern of continuous assembly in  
302 evolutionary dynamics. They investigated a community with two prey species  $B_1$  and  
303  $B_2$  and one predator which alters its predation preference either through evolution  
304 or behavioral changes. Whenever a prey species becomes abundant the predator  
305 shifts its preference towards this prey species, reducing its abundance. The other  
306 prey species, without any predation pressure, becomes abundant until the predator  
307 switches its preference again. Essentially, the predator is chasing the food in the  
308 trait-space. In our model, the same dynamics drive continuous assembly, though  
309 individual predators do not change their predation preferences, but rather a new  
310 predator invades the community.

311 We emphasize that building a model capable of producing continuous assem-  
312 bly is relatively easy. Continuous assembly has emerged independently in several  
313 different community models of various complexity, including our two-trophic Lotka-  
314 Volterra model, a size based predation model (Law & Morton, 1993; Morton & Law,  
315 1997), a two-trophic level mechanistic resource competition model based on empirical  
316 plankton traits (Spaak *et al.*, 2022), various food-web models (Hamm & Drossel, 2021;

317 Allhoff *et al.*, 2015; Loeuille & Loreau, 2005) and Lotka-Volterra community models  
318 with random species interactions (Bunin, 2017; Barbier *et al.*, 2018). In addition, the  
319 evolutionary dynamics of Abrams & Matsuda (1997) have been confirmed in other  
320 theoretical models (Cortez & Ellner, 2010; Cortez, 2016) and empirical observations  
321 (Becks *et al.*, 2010). To our knowledge, none of these investigators designed their  
322 model to produce continuous assembly – it emerged on its own, indicating that the  
323 phenomenon is robust to different model assumptions.

324 Continuous assembly has also been described in Lotka-Volterra community mod-  
325 els with random species interaction matrices (Bunin, 2017), but the underlying mech-  
326 anism appears to be different. The random interaction models show continuous com-  
327 munity assembly if the circle containing the eigenvalues of the interaction coefficients  
328 matrix approaches 0, which is related to the variance of inter-specific interaction  
329 strengths (Bunin, 2017) and conceptually similar to the classical diversity-stability  
330 debate (May, 1972; Allesina & Tang, 2012). However, the eigenvalue distributions  
331 for the two trophic level community model investigated here are not similar to the  
332 eigenvalue distributions of random interaction coefficient matrices.

### 333 **What remains stable in this disorder?**

334 While the continuous assembly process leads to unpredictability in community com-  
335 position in our model, we found that species richness and the trait distribution re-  
336 maind largely constant over time (Fig. 3, Appendix S4, Figure S5). The stable trait  
337 distribution matches experimental findings from Goldford *et al.* (2018), who assem-  
338 bled multiple microbial communities and found large differences in species com-  
339 position among replicates. However, the relative abundance of taxonomic families  
340 remained largely constant across different replicates, similar to how the trait distri-  
341 bution remained constant in our model. Similarly, the fraction of predator species  
342 remained relatively stable, despite the continuous turnover of species. This matches  
343 findings from food-web models which found a continuous community assembly, but  
344 relatively stable trophic level distributions (Hamm & Drossel, 2021; Allhoff *et al.*,  
345 2015).

### 346 **Limitations and future work**

347 Our theoretical model predicts that the relative niche breadth of the trophic levels  
348 have strong implications for the stability of the emerging community. But what  
349 does this mean in a natural community? In building our model we imagined a

350 trophic food-web where predation is driven by body-size, e.g. zooplankton as the  
351 prey species and small fish as the predator species (Hamm & Drossel, 2021; Allhoff  
352 *et al.*, 2015; Williams & Martinez, 2000). In this context, different niche breadth im-  
353 plies that the fish consume a smaller range of different zooplankton body-sizes than  
354 the range of different phytoplankton body-sizes the zooplankton consume. Unfortu-  
355 nately, we do not know whether higher trophic levels actually are more specialized  
356 than lower trophic levels. Li *et al.* (2022) analyzed the ratio of predator to prey body  
357 masses and found that larger species tend to have slightly wider niches than smaller  
358 species. However, Li *et al.* (2022) analyzed link probability and did not include any  
359 information about link strength. Additionally, they focused on the effect of predator  
360 body size on niche width, and not how trophic status itself affects niche width, al-  
361 though trophic status and body size are generally well correlated (Riede *et al.*, 2011).  
362 What niche breadth implies in a context of plants and herbivores is less clear. Per-  
363 haps it means that herbivore diets have tighter stoichiometric constraints than plant  
364 resource requirements. On the other hand, we know of many specialist predators and  
365 pathogens (Bever *et al.*, 2012) which might promote a continuous assembly pattern  
366 (Schreiber & Rittenhouse, 2004).

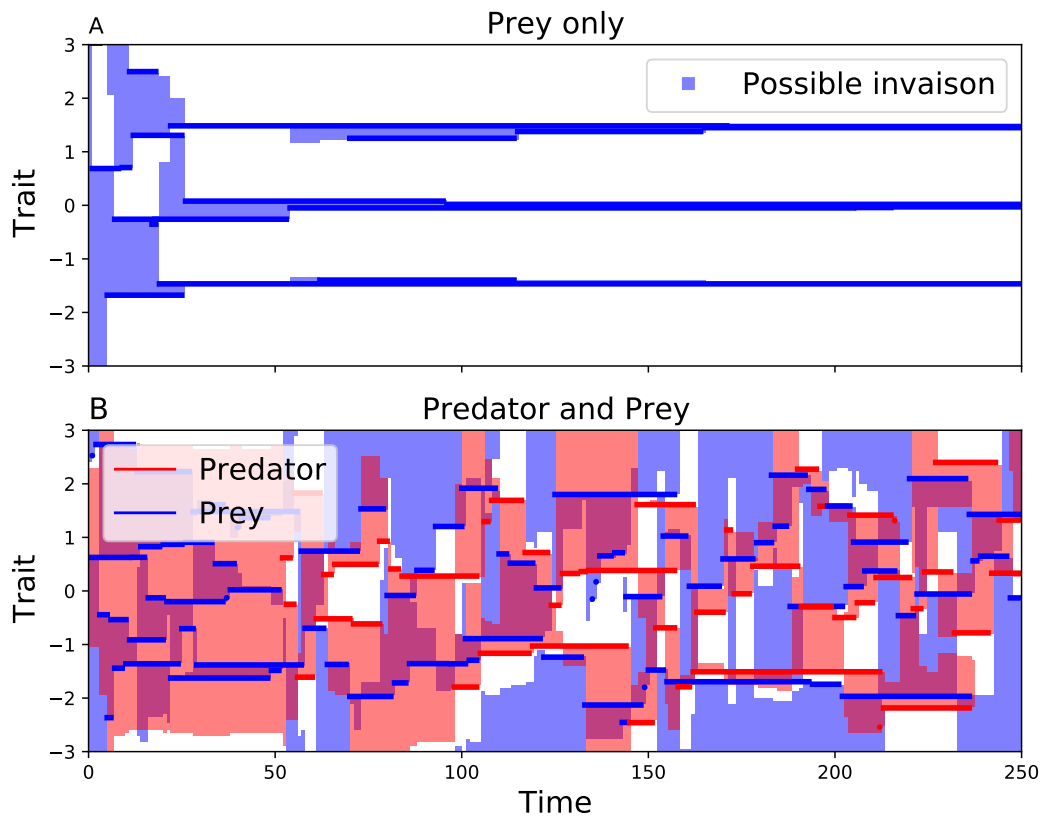
367 Our model was relatively simple, allowing only for two-trophic levels and no  
368 omnivory or cannibalism, which is widespread in natural communities (Williams  
369 & Martinez, 2000; Allhoff *et al.*, 2015). It would be interesting to see whether our  
370 findings apply to more complex niche-based food-webs. Currently food-web models  
371 typically assume that predation kernels are independent of trophic status or body  
372 size (Loeuille & Loreau, 2005; Emmerson & Raffaelli, 2004; Allhoff *et al.*, 2015; Hamm  
373 & Drossel, 2021; Williams & Martinez, 2000; Brose, 2010). That is, these models as-  
374 sume  $\sigma_B = \sigma_P$ , which is exactly what we have identified as the boundary between  
375 continuous assembly and stable equilibria. This potentially explains why some of  
376 these show a pattern of continuous assembly (Hamm & Drossel, 2021; Allhoff *et al.*,  
377 2015), while others show stable community compositions (Loeuille & Loreau, 2005).  
378 However, the models also differ in other aspects, such as the response function to  
379 predation or the number of traits per species. It is currently unclear which of these  
380 model differences affect the community assembly process.

381 If the changes in community composition observed in natural communities are in-  
382 deed driven by internal mechanisms as described here, then we would have to recon-  
383 sider core concepts of community ecology which are based on equilibrium dynam-  
384 ics. Specifically, modern coexistence theory and its dependence on invasion growth  
385 rates into stable equilibrium dynamics (Ellner *et al.*, 2019; Spaak & De Laender, 2020;

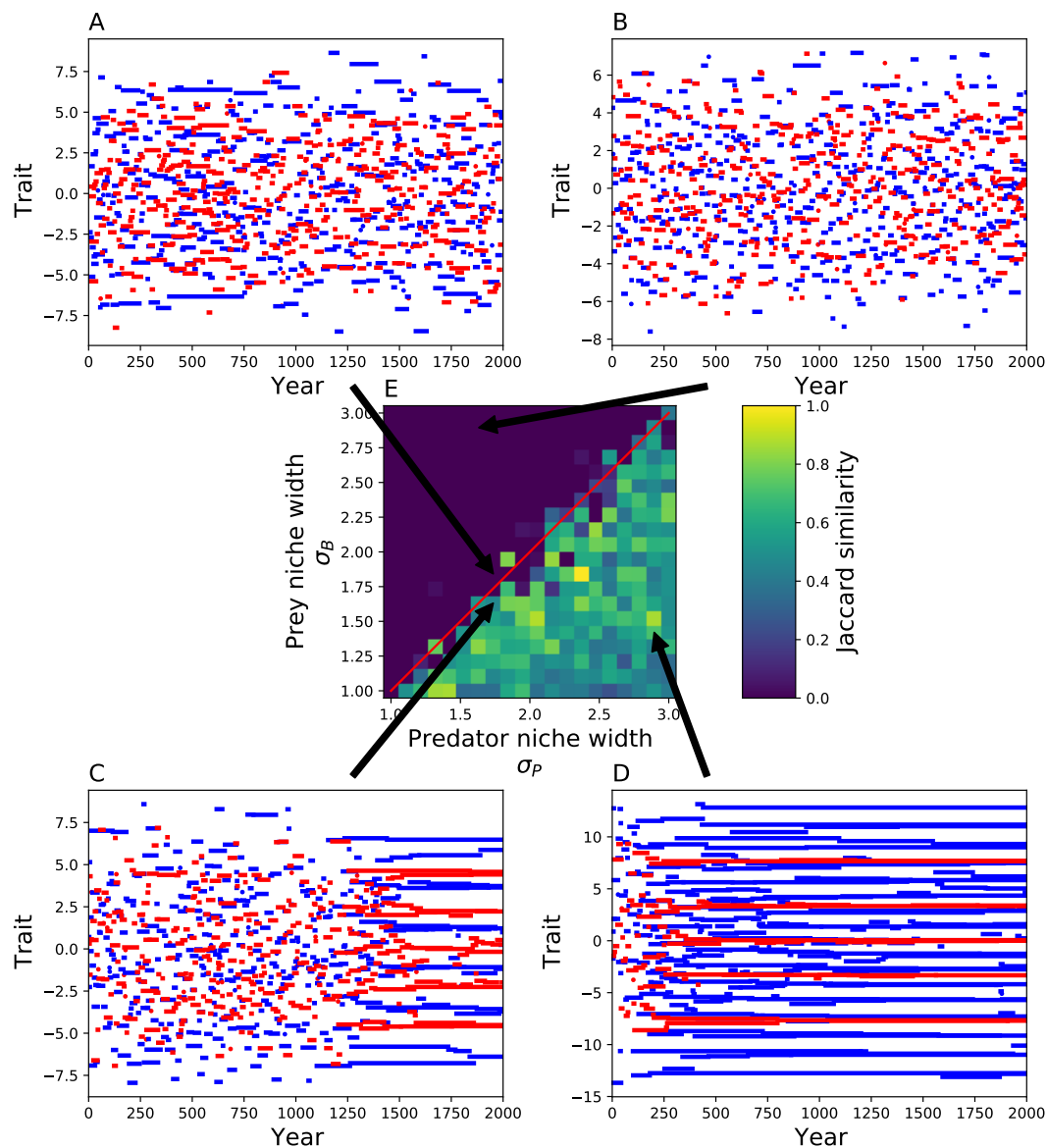
386 Barabás *et al.*, 2018), ecosystem stability based on linearization of the community dy-  
387 namics near the equilibrium (May, 1972; Allesina & Tang, 2012, 2015) and potentially  
388 biodiversity ecosystem-function relationships, which are typically evaluated after the  
389 community has fully assembled (Bannar-Martin *et al.*, 2018; De Laender *et al.*, 2016).

## 390 **Acknowledgments**

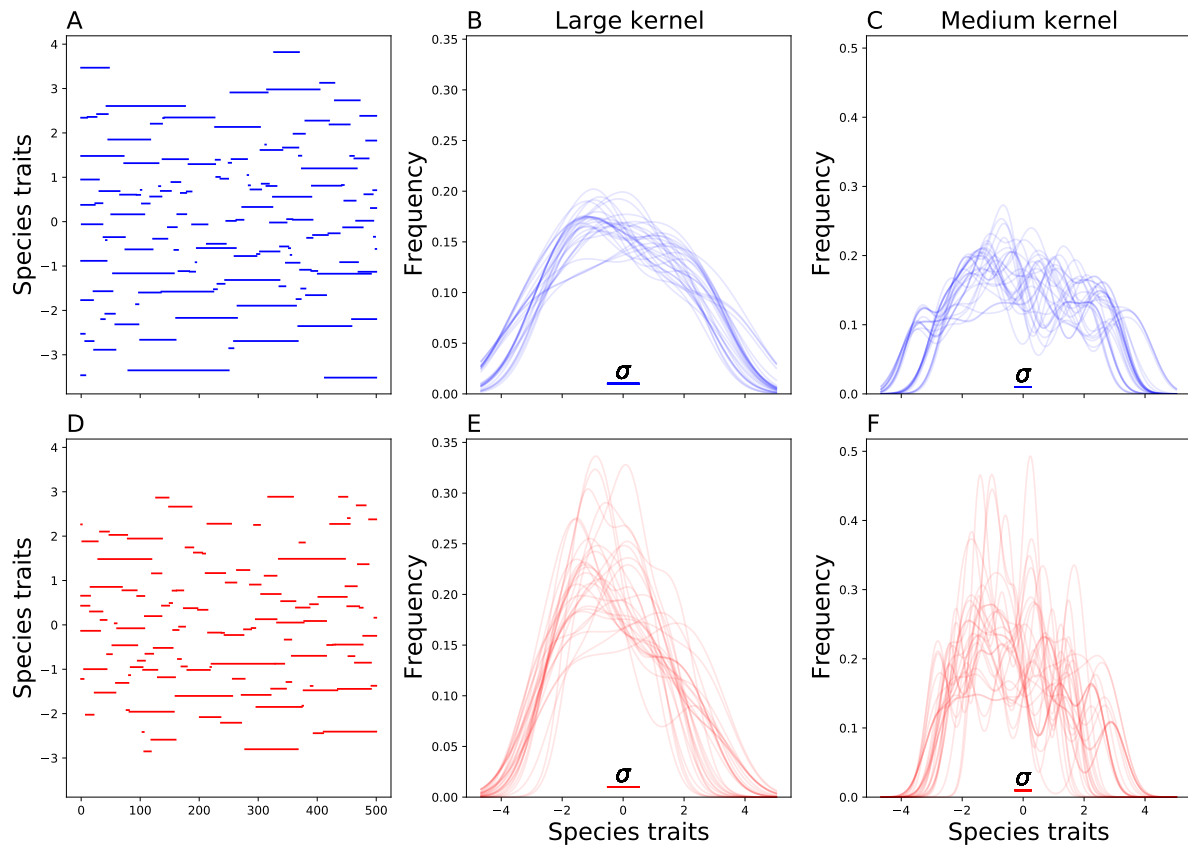
391 We thank Matthieu Barbier for his insightful comments and our understanding of  
392 continuous invasion in random matrices. J.W.S was supported by the Swiss national  
393 science foundation SNSF under the project P2SKP3\_194960. S.P.E. was supported by  
394 US NSF grant DEB-1933497. P.B.A. was supported by US NSF grant DEB-1933561.



**Figure 1:** We simulated community assembly in one- (A) and two-trophic-level (B) communities. Each year (x-axis) a new species with a random trait (y-axis) is introduced to the community and potentially replaces residents. A: In the absence of predators, the prey species self-organize into a regular pattern known as limiting similarity. This final composition is stable and does not depend on the community assembly process. B: The inclusion of predators changes the community assembly from being deterministic and stable to unpredictable, characterized by continuous invasions and extinctions. There is no stable, uninvadable configuration. Shaded regions indicate trait values for which a potential invader would be successful. Without predators, these regions disappear over time. Conversely, in the presence of predators, invasion by a prey species tends to increase the potential for invasion by predator species, and vice versa.

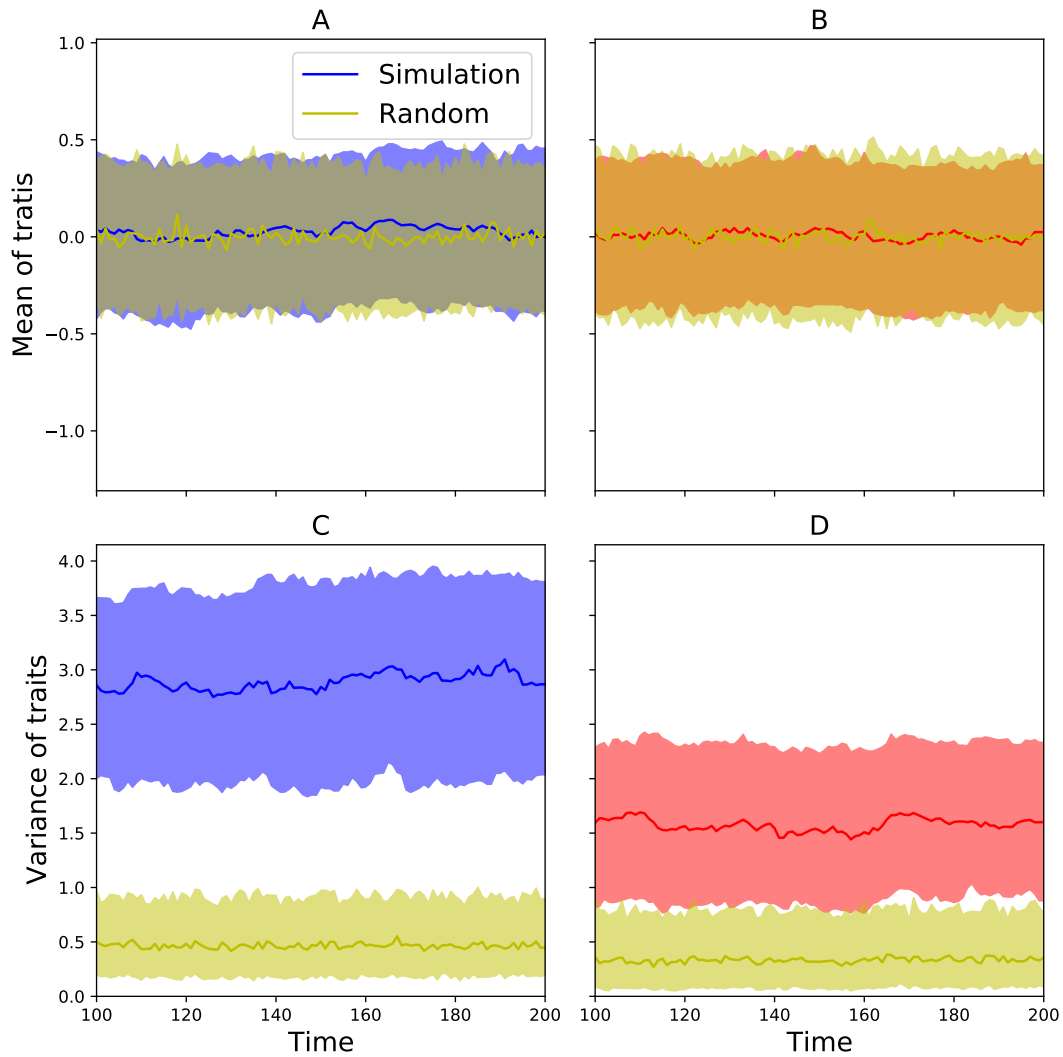


**Figure 2:** We simulated the two-trophic community with different values of niche width for predator and prey communities for 2000 invasion cycles. A-D show examples of community dynamics, the arrows show to the corresponding niche width values. E: We report the Jaccard similarity of the community at the end and the community 200 steps before the end point. Communities with higher prey niche width (y-axis) than predator niche width (x-axis) show continuous assembly patterns (e.g. Panel A and B). Conversely, communities with higher predator niche width converge towards a stable community (Panel C and D). The environmental niche breath was chosen as  $\omega = 3\sigma_p$  to avoid boundary issues (Appendix S2).

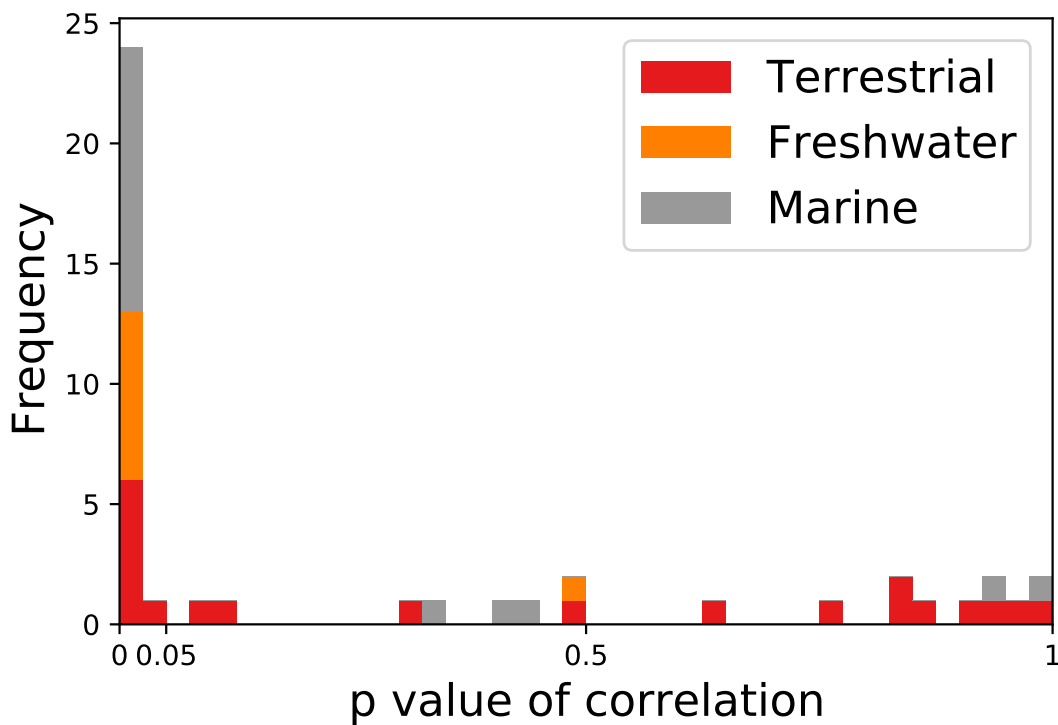


**Figure 3:** A,D: The specific species composition at each time-point is stochastic and changes very fast. B,E: We computed the trait distribution with a Gaussian kernel density estimate, the kernel size is shown with the inlet. Each line corresponds to a given time point. The resulting trait distribution is largely stable for both predator and prey species. D,F: The resulting trait distribution is less stable at a smaller kernel size. Generally, we expect the trait distribution to be roughly stable if the kernel size corresponds to the competition kernel of the species.





**Figure 4:** We compared the trait distribution resulting from the community assembly (blue for prey species [left column] and red for predator species [right column]) to distributions from random species selection (yellow). A,B: The trait mean from the community assembly did not differ from a randomly selected sample of species. C,D: However, the species traits were overdispersed over the available trait space, compared to randomly selected species. A-D: Lines show median across replicate simulations, shaded areas show 25-75% percentile lines.



**Figure 5:** We report the p-value of the correlation between invasions and extinctions observed in the BioTIME datasets compared to correlations based on random rearrangements of the years in each dataset. For around 50% of the data sets the correlation was significantly higher than expected by chance, as expected from theory. This pattern appears to be driven by freshwater and marine communities.

## References

- 395  
396 Abrams, P.A. & Matsuda, H. (1997). Prey Adaptation as a Cause of Predator-Prey  
397 Cycles. *Evolution*, 51, 1742–1750.
- 398 Allesina, S. & Tang, S. (2012). Stability criteria for complex ecosystems. *Nature*, 483,  
399 205–208.
- 400 Allesina, S. & Tang, S. (2015). The stability–complexity relationship at age 40: a  
401 random matrix perspective. *Population Ecology*, 57, 63–75.
- 402 Allhoff, K.T., Ritterskamp, D., Rall, B.C., Drossel, B. & Guill, C. (2015). Evolutionary  
403 food web model based on body masses gives realistic networks with permanent  
404 species turnover. *Scientific Reports*, 5, 1–12.
- 405 Bannar-Martin, K.H., Kremer, C.T., Ernest, S.M., Leibold, M.A., Auge, H., Chase, J.,  
406 Declerck, S.A., Eisenhauer, N., Harpole, S., Hillebrand, H., Isbell, F., Koffel, T.,  
407 Larsen, S., Narwani, A., Petermann, J.S., Roscher, C., Cabral, J.S. & Supp, S.R.  
408 (2018). Integrating community assembly and biodiversity to better understand  
409 ecosystem function: the Community Assembly and the Functioning of Ecosystems  
410 (CAFE) approach. *Ecology Letters*, 21, 167–180.
- 411 Barabás, G., D’Andrea, R. & Stump, S.M. (2018). Chesson’s coexistence theory. *Eco-*  
412 *logical Monographs*, 88, 277–303.
- 413 Barabás, G. & Meszéna, G. (2009). When the exception becomes the rule: The dis-  
414 appearance of limiting similarity in the Lotka–Volterra model. *Journal of Theoretical*  
415 *Biology*, 258, 89–94.
- 416 Barabás, G., Pigolotti, S., Gyllenberg, M., Dieckmann, U. & Meszéna, G. (2012). Con-  
417 tinuous coexistence or discrete species? A new review of an old question. *Evolu-*  
418 *tionary Ecology Research*, 14, 523–554.
- 419 Barbier, M., Arnoldi, J.F., Bunin, G. & Loreau, M. (2018). Generic assembly patterns  
420 in complex ecological communities. *Proceedings of the National Academy of Sciences*,  
421 115, 2156–2161.
- 422 Barbier, M., de Mazancourt, C., Loreau, M. & Bunin, G. (2021). Fingerprints of High-  
423 Dimensional Coexistence in Complex Ecosystems. *Physical Review X*, 11, 011009.

- 424 Becks, L., Ellner, S.P., Jones, L.E. & Hairston Jr, N.G. (2010). Reduction of adaptive  
425 genetic diversity radically alters eco-evolutionary community dynamics: Genetic  
426 variance alters eco-evo dynamics. *Ecology Letters*, 13, 989–997.
- 427 Bever, J.D., Platt, T.G. & Morton, E.R. (2012). Microbial Population and Community  
428 Dynamics on Plant Roots and Their Feedbacks on Plant Communities. *Annual*  
429 *Review of Microbiology*, 66, 265–283.
- 430 Blowes, S.A., Supp, S.R., Antão, L.H., Bates, A., Bruelheide, H., Chase, J.M., Moyes, F.,  
431 Magurran, A., McGill, B., Myers-Smith, I.H., Winter, M., Bjorkman, A.D., Bowler,  
432 D.E., Byrnes, J.E.K., Gonzalez, A., Hines, J., Isbell, F., Jones, H.P., Navarro, L.M.,  
433 Thompson, P.L., Vellend, M., Waldock, C. & Dornelas, M. (2019). The geography of  
434 biodiversity change in marine and terrestrial assemblages. *Science*, 366, 339–345.
- 435 Brose, U. (2010). Body-mass constraints on foraging behaviour determine population  
436 and food-web dynamics. *Functional Ecology*, 24, 28–34.
- 437 Bunin, G. (2017). Ecological communities with Lotka-Volterra dynamics. *Physical*  
438 *Review E*, 95, 042414.
- 439 Carpentier, C., Barabás, G., Spaak, J.W. & De Laender, F. (2021). Reinterpreting the  
440 relationship between number of species and number of links connects community  
441 structure and stability. *Nature Ecology & Evolution*.
- 442 Cortez, M.H. (2016). How the Magnitude of Prey Genetic Variation Alters Predator-  
443 Prey Eco-Evolutionary Dynamics. *The American Naturalist*, 188, 329–341.
- 444 Cortez, M.H. & Ellner, S.P. (2010). Understanding Rapid Evolution in Predator-Prey  
445 Interactions Using the Theory of Fast-Slow Dynamical Systems. *The American Nat-*  
446 *uralist*, 176, E109–E127.
- 447 Cressman, R., Halloway, A., McNickle, G.G., Apaloo, J., Brown, J.S. & Vincent, T.L.  
448 (2017). Unlimited niche packing in a Lotka–Volterra competition game. *Theoretical*  
449 *Population Biology*, 116, 1–17.
- 450 De Laender, F., Rohr, J.R., Ashauer, R., Baird, D.J., Berger, U., Eisenhauer, N., Grimm,  
451 V., Hommen, U., Maltby, L., Meliàn, C.J., Pomati, F., Roessink, I., Radchuk, V.  
452 & Van den Brink, P.J. (2016). Reintroducing Environmental Change Drivers in  
453 Biodiversity–Ecosystem Functioning Research. *Trends in Ecology & Evolution*, 31,  
454 905–915.

455 Dornelas, M., Antão, L.H., Moyes, F., Bates, A.E., Magurran, A.E., Adam, D., Akhmet-  
456 zhanova, A.A., Appeltans, W., Arcos, J.M., Arnold, H., Ayyappan, N., Badihi,  
457 G., Baird, A.H., Barbosa, M., Barreto, T.E., Bässler, C., Bellgrove, A., Belmaker,  
458 J., Benedetti-Cecchi, L., Bett, B.J., Bjorkman, A.D., Błażewicz, M., Blowes, S.A.,  
459 Bloch, C.P., Bonebrake, T.C., Boyd, S., Bradford, M., Brooks, A.J., Brown, J.H., Bru-  
460 elheide, H., Budy, P., Carvalho, F., Castañeda-Moya, E., Chen, C.A., Chamblee, J.F.,  
461 Chase, T.J., Siegwart Collier, L., Collinge, S.K., Condit, R., Cooper, E.J., Cornelis-  
462 sen, J.H.C., Cotano, U., Kyle Crow, S., Damasceno, G., Davies, C.H., Davis, R.A.,  
463 Day, F.P., Degraer, S., Doherty, T.S., Dunn, T.E., Durigan, G., Duffy, J.E., Edelist,  
464 D., Edgar, G.J., Elahi, R., Elmendorf, S.C., Enemar, A., Ernest, S.K.M., Escribano,  
465 R., Estiarte, M., Evans, B.S., Fan, T.Y., Turini Farah, F., Loureiro Fernandes, L.,  
466 Farneda, F.Z., Fidelis, A., Fitt, R., Fosaa, A.M., Daher Correa Franco, G.A., Frank,  
467 G.E., Fraser, W.R., García, H., Cazzolla Gatti, R., Givan, O., Gorgone-Barbosa, E.,  
468 Gould, W.A., Gries, C., Grossman, G.D., Gutierrez, J.R., Hale, S., Harmon, M.E.,  
469 Harte, J., Haskins, G., Henshaw, D.L., Hermanutz, L., Hidalgo, P., Higuchi, P.,  
470 Hoey, A., Van Hoey, G., Hofgaard, A., Holeck, K., Hollister, R.D., Holmes, R.,  
471 Hoogenboom, M., Hsieh, C.h., Hubbell, S.P., Huettmann, F., Huffard, C.L., Hurl-  
472 bert, A.H., Macedo Ivanauskas, N., Janík, D., Jandt, U., Jażdżewska, A., Johan-  
473 nessen, T., Johnstone, J., Jones, J., Jones, F.A.M., Kang, J., Kartawijaya, T., Kee-  
474 ley, E.C., Kelt, D.A., Kinnear, R., Klanderud, K., Knutsen, H., Koenig, C.C., Ko-  
475 rtz, A.R., Král, K., Kuhnz, L.A., Kuo, C.Y., Kushner, D.J., Laguionie-Marchais, C.,  
476 Lancaster, L.T., Min Lee, C., Lefcheck, J.S., Lévesque, E., Lightfoot, D., Lloret, F.,  
477 Lloyd, J.D., López-Baucells, A., Louzao, M., Madin, J.S., Magnússon, B., Mala-  
478 mud, S., Matthews, I., McFarland, K.P., McGill, B., McKnight, D., McLarney, W.O.,  
479 Meador, J., Meserve, P.L., Metcalfe, D.J., Meyer, C.F.J., Michelsen, A., Milchakova,  
480 N., Moens, T., Moland, E., Moore, J., Mathias Moreira, C., Müller, J., Murphy, G.,  
481 Myers-Smith, I.H., Myster, R.W., Naumov, A., Neat, F., Nelson, J.A., Paul Nelson,  
482 M., Newton, S.F., Norden, N., Oliver, J.C., Olsen, E.M., Onipchenko, V.G., Pabis,  
483 K., Pabst, R.J., Paquette, A., Pardede, S., Paterson, D.M., Pélissier, R., Peñuelas,  
484 J., Pérez-Matus, A., Pizarro, O., Pomati, F., Post, E., Prins, H.H.T., Priscu, J.C.,  
485 Provoost, P., Prudic, K.L., Pulliainen, E., Ramesh, B.R., Mendivil Ramos, O., Rass-  
486 weiler, A., Rebelo, J.E., Reed, D.C., Reich, P.B., Remillard, S.M., Richardson, A.J.,  
487 Richardson, J.P., van Rijn, I., Rocha, R., Rivera-Monroy, V.H., Rixen, C., Robinson,  
488 K.P., Ribeiro Rodrigues, R., de Cerqueira Rossa-Feres, D., Rudstam, L., Ruhl, H.,  
489 Ruz, C.S., Sampaio, E.M., Rybicki, N., Rypel, A., Sal, S., Salgado, B., Santos, F.A.M.,  
490 Savassi-Coutinho, A.P., Scanga, S., Schmidt, J., Schooley, R., Setiawan, F., Shao, K.T.,

- 491 Shaver, G.R., Sherman, S., Sherry, T.W., Siciński, J., Sievers, C., da Silva, A.C., Ro-  
492 drrigues da Silva, F., Silveira, F.L., Slingsby, J., Smart, T., Snell, S.J., Soudzilovskaia,  
493 N.A., Souza, G.B.G., Maluf Souza, F., Castro Souza, V., Stallings, C.D., Stanforth,  
494 R., Stanley, E.H., Mauro Sterza, J., Stevens, M., Stuart-Smith, R., Rondon Suarez,  
495 Y., Supp, S., Yoshio Tamashiro, J., Tarigan, S., Thiede, G.P., Thorn, S., Tolvanen,  
496 A., Teresa Zugliani Toniato, M., Totland, O., Twilley, R.R., Vaitkus, G., Valdivia,  
497 N., Vallejo, M.I., Valone, T.J., Van Colen, C., Vanaverbeke, J., Venturoli, F., Verheye,  
498 H.M., Vianna, M., Vieira, R.P., Vrška, T., Quang Vu, C., Van Vu, L., Waide, R.B.,  
499 Waldock, C., Watts, D., Webb, S., Wesolowski, T., White, E.P., Widdicombe, C.E.,  
500 Wilgers, D., Williams, R., Williams, S.B., Williamson, M., Willig, M.R., Willis, T.J.,  
501 Wipf, S., Woods, K.D., Woehler, E.J., Zawada, K. & Zettler, M.L. (2018). BioTIME:  
502 A database of biodiversity time series for the Anthropocene. *Global Ecology and*  
503 *Biogeography*, 27, 760–786.
- 504 Dornelas, M., Gotelli, N.J., Shimadzu, H., Moyes, F., Magurran, A.E. & McGill, B.J.  
505 (2019). A balance of winners and losers in the Anthropocene. *Ecology Letters*, 22,  
506 847–854.
- 507 Eklöf, A., Jacob, U., Kopp, J., Bosch, J., Castro-Urgal, R., Chacoff, N.P., Dalsgaard, B.,  
508 de Sassi, C., Galetti, M., Guimarães, P.R., Lomáscolo, S.B., Martín González, A.M.,  
509 Pizo, M.A., Rader, R., Rodrigo, A., Tylianakis, J.M., Vázquez, D.P. & Allesina, S.  
510 (2013). The dimensionality of ecological networks. *Ecology Letters*, 16, 577–583.
- 511 Ellner, S.P., Snyder, R.E., Adler, P.B. & Hooker, G. (2019). An expanded modern  
512 coexistence theory for empirical applications. *Ecology Letters*, 22, 3–18.
- 513 Emmerson, M.C. & Raffaelli, D. (2004). Predator-prey body size, interaction strength  
514 and the stability of a real food web. *Journal of Animal Ecology*, 73, 399–409.
- 515 Fukami, T. (2015). Historical Contingency in Community Assembly: Integrating  
516 Niches, Species Pools, and Priority Effects. *Annual Review of Ecology, Evolution,*  
517 *and Systematics*, 46, 1–23.
- 518 Fukami, T., Mordecai, E.A. & Ostling, A. (2016). A framework for priority effects.  
519 *Journal of Vegetation Science*, 27, 655–657.
- 520 Goldford, J.E., Lu, N., Baji, D., Sanchez-Gorostiaga, A., Segrè, D., Mehta, P. &  
521 Sanchez, A. (2018). Emergent simplicity in microbial community assembly. *Sci-*  
522 *ence*, 361, 469–474.

- 523 Hamm, M. & Drossel, B. (2021). The concerted emergence of well-known spatial and  
524 temporal ecological patterns in an evolutionary food web model in space. *Scientific*  
525 *Reports*, 11, 1–12.
- 526 HilleRisLambers, J., Adler, P., Harpole, W., Levine, J. & Mayfield, M. (2012). Rethink-  
527 ing Community Assembly through the Lens of Coexistence Theory. *Annual Review*  
528 *of Ecology, Evolution, and Systematics*, 43, 227–248.
- 529 Holt, R.D. & Lawton, J.H. (1994). The ecological consequences of shared natural  
530 enemies. *Annual Review of Ecology, Evolution, and Systematics*, pp. 495–520.
- 531 Hubbell, S.P. (2001). *The unified neutral theory of biodiversity and biogeography*. Princet.
- 532 Hubbell, S.P. (2005). Neutral theory in community ecology and the hypothesis of  
533 functional equivalence. *Functional Ecology*, 19, 166–172.
- 534 Huisman, J. & Weissing, F.J. (2001). Fundamental Unpredictability in Multispecies  
535 Competition. *The American Naturalist*, 157, 488–494.
- 536 Johnson, C.A. & Bronstein, J.L. (2019). Coexistence and competitive exclusion in  
537 mutualism. *Ecology*, p. e02708.
- 538 Ke, P.J. & Letten, A.D. (2018). Coexistence theory and the frequency-dependence of  
539 priority effects. *Nature Ecology & Evolution*, 2, 1691–1695.
- 540 Kremer, C.T. & Klausmeier, C.A. (2017). Species packing in eco-evolutionary models  
541 of seasonally fluctuating environments. *Ecology Letters*, 20, 1158–1168.
- 542 Law, R. & Morton, R.D. (1993). Alternative Permanent States of Ecological Commu-  
543 nities. *Ecology*, 74, 1347–1361.
- 544 Law, R. & Morton, R.D. (1996). Permanence and the Assembly of Ecological Commu-  
545 nities. *Ecology*, 77, 762–775.
- 546 Li, J., Luo, M., Wang, S., Gauzens, B., Hirt, M.R., Rosenbaum, B. & Brose, U. (2022).  
547 A size-constrained feeding-niche model distinguishes predation patterns between  
548 aquatic and terrestrial food webs. *Ecology Letters*, p. ele.14134.
- 549 Loeuille, N. & Loreau, M. (2005). Evolutionary emergence of size-structured food  
550 webs. *Proceedings of the National Academy of Sciences*, 102, 5761–5766.

- 551 Loreau, M. (2010). Linking biodiversity and ecosystems: towards a unifying ecological theory. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365,  
552 49–60.
- 554 Loreau, M. & Hector, A. (2001). Partitioning selection and complementarity in biodiversity experiments. *Nature*, 412, 72–76.
- 556 MacArthur, R. (1970). Species packing and competitive equilibrium for many species. *Theoretical Population Biology*, 1, 1–11.
- 558 MacArthur, R. & Levins, R. (1967). The Limiting Similarity, Convergence, and Divergence of Coexisting Species. *The American Naturalist*, 101, 377–385.
- 560 May, R.M. (1972). Will a large complex system be stable? *Nature*, 238, 413–414.
- 561 Meszéna, G., Gyllenberg, M., Pásztor, L. & Metz, J.A. (2006). Competitive exclusion and limiting similarity: A unified theory. *Theoretical Population Biology*, 69, 68–87.
- 563 Mordecai, E.A. (2011). Pathogen impacts on plant communities: unifying theory, concepts, and empirical work. *Ecological Monographs*, 81, 429–441.
- 565 Morton, R. & Law, R. (1997). Regional Species Pools and the Assembly of Local Ecological Communities. *Journal of Theoretical Biology*, 187, 321–331.
- 567 Nee, S., Gregory, R.D. & May, R.M. (1991). Core and Satellite Species: Theory and Artefacts. *Oikos*, 62, 83.
- 569 Riede, J.O., Brose, U., Ebenman, B., Jacob, U., Thompson, R., Townsend, C.R. & Jonsson, T. (2011). Stepping in Elton’s footprints: a general scaling model for body masses and trophic levels across ecosystems: Stepping in Elton’s footprints. *Ecology Letters*, 14, 169–178.
- 573 Schreiber, S.J. & Rittenhouse, S. (2004). From simple rules to cycling in community assembly. *Oikos*, 105, 349–358.
- 575 Serván, C.A. & Allesina, S. (2021). Tractable models of ecological assembly. *Ecology Letters*, 24, 1029–1037.
- 577 Song, C., Fukami, T. & Saavedra, S. (2021). Untangling the complexity of priority effects in multispecies communities. *Ecology Letters*, 24, 2301–2313.



- 579 Spaak, J.W., Adler, P.B. & Ellner, S.P. (2022). Modeling phytoplankton-zooplankton  
580 interactions: opportunities for species richness and challenges for modern coexis-  
581 tence theory. preprint, *Ecology*.
- 582 Spaak, J.W. & De Laender, F. (2020). Intuitive and broadly applicable definitions of  
583 niche and fitness differences. *Ecology Letters*, 23, 1117–1128.
- 584 Spaak, J.W., Godoy, O. & De Laender, F. (2021). Mapping species niche and fitness  
585 differences for communities with multiple interaction types. *Oikos*, 130, 2065–2077.
- 586 Steiner, C. & Leibold, M.A. (2004). Cyclic assembly trajectories and scale-dependent  
587 productivity-diversity relationships. *Ecology*, 85, 107–113.
- 588 Szabó, P. & Meszéna, G. (2006). Limiting similarity revisited. *Oikos*, 112, 612–619.
- 589 Tilman, D. (2004). Niche tradeoffs, neutrality, and community structure: A stochastic  
590 theory of resource competition, invasion, and community assembly. *Proceedings of*  
591 *the National Academy of Sciences*, 101, 10854–10861.
- 592 Tilman, D., Kilham, S.S. & Kilham, P. (1982). Phytoplankton Community Ecology:  
593 The Role of Limiting Nutrients. *Annual Review of Ecology and Systematics*, 13, 349–  
594 372.
- 595 Vannette, R.L. & Fukami, T. (2014). Historical contingency in species interactions:  
596 towards niche-based predictions. *Ecology Letters*, 17, 115–124.
- 597 Williams, R.J. & Martinez, N.D. (2000). Simple rules yield complex food webs. *Nature*,  
598 404, 180–183.

## 599 Appendix

### 600 S1 BioTIME data

601 We compared the patterns from the simulations to patterns in empirical data from Bi-  
602 oTIME, a database of community assemblage time-series across the world (Dornelas  
603 *et al.*, 2018). We focused on presence-absence patterns and therefore aggregated each  
604 time-series to annual scale, i.e. a species was assumed to be present if it was observed  
605 at least once in a given year, otherwise it was assumed to be absent. To observe pat-  
606 terns over time, we focused on datasets with at least 30 years of sampling. We found  
607 a total of 44 suitable datasets representing different taxonomic groups (birds, fish, in-  
608 vertebrates, terrestrial plants, benthos, mammals and amphibians), different biomes  
609 (lakes, rivers, different marine waters, different types of forests and prairies) with  
610 latitude ranging from 62.1° south to 67.1° north. The species richness ranged from 1  
611 to 2000 per year and from 6 to 4120 over the respective observation periods.

612 We computed species richness, the proportion of invasions, and the proportion of  
613 extinctions per year for each dataset. The proportion of invaders in year  $t$  was defined  
614 as the number of species present in year  $t$  which were not present in year  $t - 1$  divided  
615 by the species richness in year  $t$ . Similarly, the proportion of extinctions in year  $t$  was  
616 the number of species present in year  $t$  but not in year  $t + 1$  divided by the species  
617 richness in year  $t$ . We then computed the correlation between the proportion of  
618 invaders in year  $t$  and the proportion of species going extinct between year  $t$  and  $t - 1$ .  
619 We compared the observed correlation of each dataset to the correlation of invasions  
620 and extinctions in the same dataset if the years were randomly reshuffled. We report  
621 the p-value of observing a correlation as high or higher than 1000 randomizations.

### 622 S2 Stable communities

623 In the main text we have focused on the cases where the two trophic levels lead to  
624 continuous changes in community composition. Generally, this is observed to be the  
625 case if the niche width of the predator is smaller than the niche width of the prey.  
626 If the niche width of the predator is sufficiently large then a stable community is  
627 possible (Fig. 2). Note that “stable community” here means both internal and external  
628 stability: the species that are present are coexisting at a locally stable equilibrium, and  
629 no potential invader has a positive invasion growth rate.

630 In this section we prove that a stable community cannot occur if  $\sigma_P$  is sufficiently  
631 small compared to  $\sigma_B$ , under two additional assumptions.

- 632 1. The prey species are evenly spaced at some distance  $D_B$ .
- 633 2. The niche space is very large, i.e.  $\omega \gg \sigma_B$ , and effectively infinite (the precise  
634 meaning of “effectively infinite” will be clarified below).
- 635 3. The consumption kernels of the predators are sufficiently narrow that each  
636 predator effectively consumes only one prey species, i.e.  $\sigma_P$  is small relative  
637 to  $D_B$ .

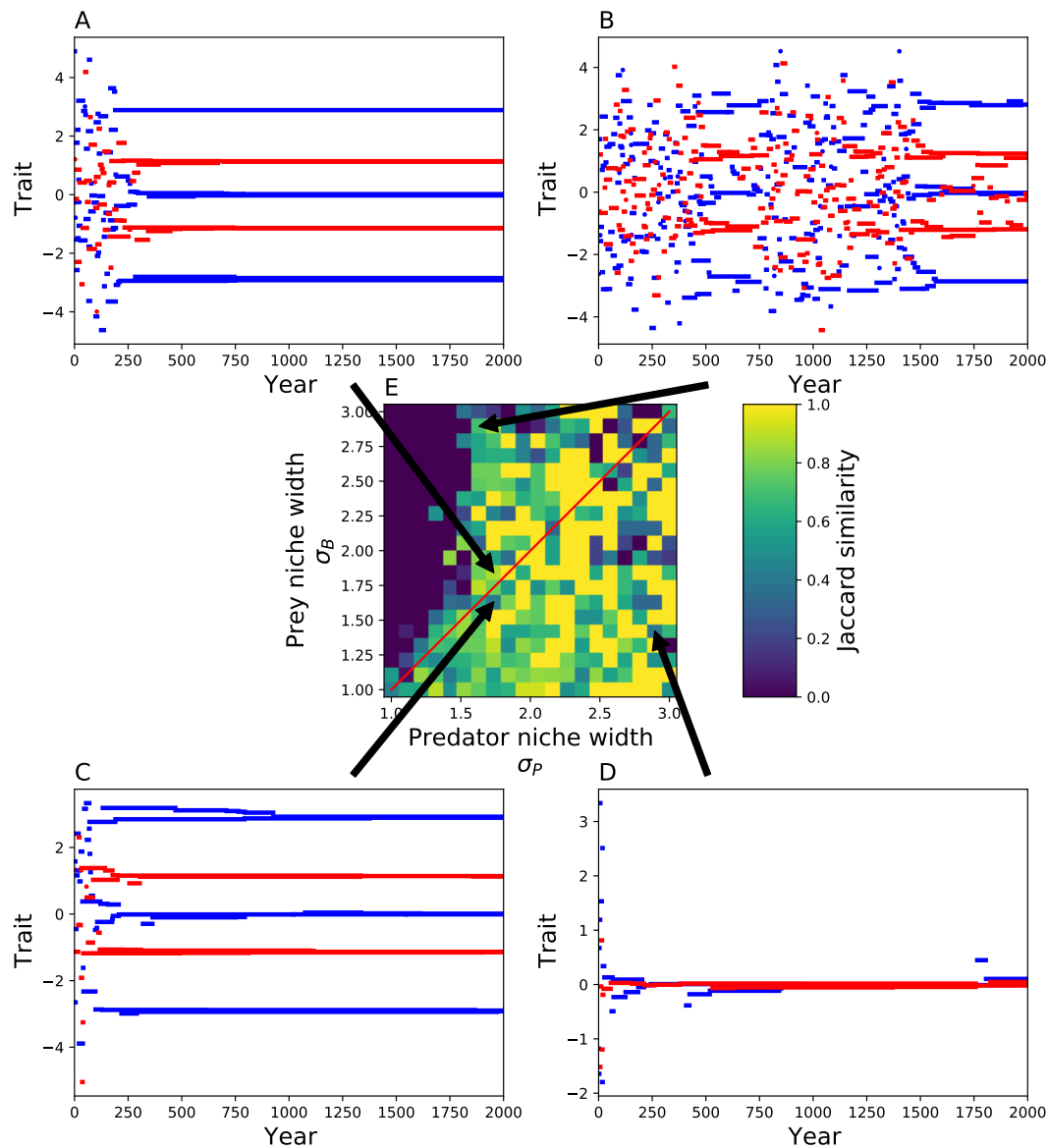
638 In our simulations, stable communities (when they occur) always have prey species  
639 evenly spaced, except near the boundary of the niche space. Other theoretical studies  
640 (Szabó & Mészéna, 2006; MacArthur & Levins, 1967; Barabás *et al.*, 2012) have also  
641 generally found that species are evenly spaced, for a wide range of intrinsic growth  
642 rates and competition kernels. When the trait space is unbounded, rescaling the niche  
643 axis relative to  $\sigma_B$  implies that the equilibrium prey spacing  $D_B$  is proportional to  $\sigma_B$ .  
644 Assuming that  $\sigma_P$  is small relative to  $D_B$  is thus equivalent to assuming that  $\sigma_P$  is  
645 small compared to  $\sigma_B$ . In our simulations, stability ceases to occur when  $\sigma_P$  is only  
646 slightly smaller than  $\sigma_B$ , but our arguments here only show that stability is impossible  
647 when  $\sigma_P$  is considerably smaller than  $\sigma_B$ .

648 Assumption 2 implies that all prey species have identical intrinsic growth rates.  
649 Mathematically, we will use assumption 3 to show that each predator species must be  
650 located “on top of” a prey species (i.e., it must have the same trait value as one of the  
651 prey species). Assumption 1 will be used to show that a prey with a predator directly  
652 on top of it can be invaded by a prey species with a slightly similar trait value, hence  
653 a community with that feature cannot be stable. These two properties together imply  
654 that a stable community cannot occur.

655 Importantly, without assumption 2, stable communities are possible even when  
656  $\sigma_P$  is small. Specifically, if we assume  $\omega < \sigma_P < \sigma_B$ , then one example of a stable  
657 consists of exactly one predator and one prey species, both having trait value 0 (Fig.  
658 S1).

## 659 **S2.1 Predators cannot be located between prey species in a stable** 660 **community**

We show that each predator in a stable configuration must have a prey with identical  
trait. We prove this by assuming that a predator  $j$  exists with trait  $x_j$ , and the closest



**Figure S1:** Similar to figure 2 we simulated the two trophic level community with different values of niche width for predator and prey communities for 2000 invasion cycles. However, we here chose a fixed environmental niche width of  $\omega = 2.5$ . Because the predator niche width  $\sigma_P$  is comparable to the environmental niche width  $\omega$  communities can be stable despite  $\sigma_P < \sigma_B$ , e.g. panel B. A-D show examples of community dynamics, the arrows show to the corresponding niche width values. E: We report the Jaccard similarity of the community at the end and the community 200 steps before the end point.

prey species has trait  $x_0 \neq x_j$ . Then the growth rate of the predator, which must by assumption be 0, is

$$0 = \frac{1}{P_j} \frac{dP_j}{dt} = \mu_j^P + \epsilon \sum_i b_{ji} B_i \quad (\text{S3})$$

$$\approx \mu_j^P + B_0 \epsilon \exp\left(-\frac{(x_j - x_0)^2}{2\sigma_p^2}\right) \quad (\text{S4})$$

$$< \mu_j^P + B_0 \epsilon \quad (\text{S5})$$

661 From S3 to S4 we used the fact that prey species are equally spaced at distance  $D_B$ ,  
 662 and the consumption rates of the predator  $j$  on all other prey species are therefore  
 663 0. Equation S5 then shows that a invading predator with trait  $x = x_0$  would have a  
 664 positive growth rate, so the the system is therefore not stable. Consequentially, each  
 665 predator in a stable community is located exactly on top of a prey species.

666 From the same calculation it follows that if a predator has the identical trait as a  
 667 prey species, there can be no other predator  $j'$  with trait value consuming the same  
 668 prey species, for any such predator would have a negative population growth rate.

669 This leads to two additional insights for situations where  $\omega$  is large compared to  
 670  $\sigma_B$  but finite, and  $\sigma_P$  is small compared to  $\sigma_B$ :

671 1. Each prey close to the center of the niche space has a predator with identical  
 672 trait and all prey species close to the center of the niche have identical equilibrium  
 673 abundance.

674 2. All predators at the center of the niche have identical equilibrium abundance and  
 675 are also equally spaced with distance  $D_B$ .

676 Note, this does not correspond to the stable systems observed in figure 2 because in  
 677 those communities we do not have a small  $\sigma_P$ . For large  $\sigma_P$  a predator can (and will)  
 678 have a trait value between prey species.

## 679 **S2.2 Predators cannot be located on prey species in a stable com-** 680 **munity**

681 As shown above, in any stable community with sufficiently small  $\sigma_P$  we must have  
 682 equidistantly spaced prey and predator species, separated by distance  $D_B$ . Without  
 683 loss of generality we can assume that one of the prey species has trait value  $x = 0$  (i.e.,  
 684 we pick one prey species, and measure traits relative to that of the chosen species).  
 685 We will show that a species with some trait  $x = \epsilon$  with  $|\epsilon| \ll 1$  has a positive invasion

686 growth rate, therefore the community is actually not stable. This shows that a stable  
687 community cannot actually exist.

688 Let  $r(\varepsilon)$  denote the invasion growth rate of a species with trait  $\varepsilon$  very close to 0.  
689 We must have  $r(0) = 0$ , as the species with trait value 0 is at equilibrium. Further,  
690 if  $r'(0) \neq 0$  at  $x = 0$ , then  $r(x)$  is positive for some  $x \approx 0$ , implying a nonstable  
691 community. So it suffices to show that the second derivative  $r''(0)$  is positive, because  
692 when  $r'(0) = 0$  the second-order Taylor series  $r(\varepsilon) \approx r(0) + \frac{1}{2}\varepsilon^2 r''(0)$  implies that  
693  $r(\varepsilon) > 0$  for sufficiently small  $\varepsilon$  when  $r''(0) > 0$ .

Prey invasion growth rate in general is  $K - \sum_j a_{ij} B_j - \sum_k b_{ik} P_k$ , so the second derivative is

$$r''(0) = K''(0) - \sum_j a''_{ij}(0) B_j - \sum_k b''_{ik}(0) P_k$$

694 where  $\bullet''$  indicates the second derivative of the interaction coefficients with respect to  
695 trait  $x$ , evaluated at  $x = 0$ . Note that  $K'' \rightarrow 0$  as  $\omega \rightarrow \infty$  because  $K$  becomes constant;  
696 here we specify that  $\omega$  is “effectively infinite” in the sense that  $K''(0)$  is small relative  
697 to the other terms and can be neglected in calculating  $r''(0)$ .

To evaluate the second derivatives we differentiate the Gaussian kernel twice,

$$\frac{d^2}{dx^2} \left( \exp \left( -\frac{(x - x_0)^2}{2\sigma^2} \right) \right) = -\sigma^{-2} \left( 1 - \frac{(x - x_0)^2}{\sigma^2} \right) \left( \exp \left( -\frac{(x - x_0)^2}{2\sigma^2} \right) \right).$$

698 We therefore have (with all sums running over all species in the community)

$$r''(0) = \frac{1}{2} \left[ B\sigma_B^{-2} \sum_j \left( 1 - \frac{x_j^2}{\sigma_B^2} \right) \exp \left( -\frac{(x_j)^2}{2\sigma_B^2} \right) + P\sigma_P^{-2} \sum_k \left( 1 - \frac{y_k^2}{\sigma_P^2} \right) \exp \left( -\frac{(y_k)^2}{2\sigma_P^2} \right) \right] \quad (\text{S6})$$

699 The right-hand side in (S6) is positive when the sums run over the set  $\mathbb{Z}$  of all integers;  
700 this follows the fact that

$$\sum_{j \in \mathbb{Z}} \left( 1 - \frac{j^2}{\sigma^2} \right) \exp \left( -\frac{j^2}{2\sigma^2} \right) > 0 \quad (\text{S7})$$

701 which we will prove below, and the fact that prey and predators occur at trait values  
702  $\pm jD_B, j = 0, 1, 2, \dots$ . We now specify that  $\omega$  is “effectively infinite” in the sense that  
703 the set of species in the community (equally-spaced prey and predators, across some

704 symmetric neighborhood around 0) is broad enough that the sign of (S6) is already  
 705 positive when the sums run over all species in the community, as it is when the sums  
 706 run of  $\mathbb{Z}$ . This implies  $r''(0) > 0$ , so the only possible stable community is in fact not  
 707 stable.

To finish, we now prove (S7), using the Poisson summation formula

$$\sum_{j \in \mathbb{Z}} f(j) = \sum_{k \in \mathbb{Z}} \hat{f}(k),$$

708 where  $\hat{f}$  is the Fourier transform of  $f$ , i.e.  $\hat{f}(k) = \int_{-\infty}^{\infty} f(x) \exp(-2i\pi kx) dx$ , where  
 709  $i$  is not an index but rather  $\sqrt{-1}$ . We now compute the Fourier transform of  $(1 -$   
 710  $\frac{j^2}{\sigma^2}) \exp(-\frac{j^2}{2\sigma^2})$  as follows:

$$\begin{aligned} \hat{f}(k) &= \int_{-\infty}^{\infty} \left(1 - \frac{x^2}{\sigma^2}\right) \exp\left(-\frac{x^2}{2\sigma^2}\right) \exp(-2i\pi kx) dx \\ &= \int_{-\infty}^{\infty} \left(1 - \frac{x^2}{\sigma^2}\right) \exp\left(-\frac{(x + 2i\pi k\sigma^2)^2}{2\sigma^2}\right) \exp(-2\pi^2 k^2 \sigma^2) dx \\ &= \exp(-2\pi^2 k^2 \sigma^2) \int_{-\infty}^{\infty} \left(1 - \frac{x^2}{\sigma^2}\right) \exp\left(-\frac{(x + 2i\pi k\sigma^2)^2}{2\sigma^2}\right) dx \quad (\text{S8}) \\ &= \exp(-2\pi^2 k^2 \sigma^2) \sqrt{2\pi\sigma^2} \left(1 - \frac{\sigma^2 - (2i\pi k\sigma^2)^2}{\sigma^2}\right) \\ &= \exp(-2\pi^2 k^2 \sigma^2) (2\pi)^{5/2} \sigma^3 k^2 \end{aligned}$$

711 This last expression is positive for all  $k$ , therefore the sum  $\sum_{k \in \mathbb{Z}} \hat{f}(k)$  is also positive.  
 712 The integral was evaluated using the fact that  $\frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$  describes a  
 713 normal distribution with mean  $\mu$  and variance  $\sigma^2$ .

Name	Resource consumption $u_{x_i}(x)$
Gaussian	$\frac{a}{\sqrt{\sigma}} \exp\left(-\frac{1}{2} \left(\frac{x_i-x}{b\sigma}\right)^2\right)$
Flattened Gaussian	$\frac{a}{\sqrt{\sigma}} \exp\left(-\frac{1}{2} \left(\frac{x_i-x}{b\sigma}\right)^4\right)$
Flat kernel	$\frac{a}{\sqrt{\sigma}} u_{[-1,1]}\left(\frac{x_i-x}{b\sigma}\right)$
Triangular kernel	$\frac{a}{\sqrt{\sigma}} u_{[-1,1]}\left(\frac{x_i-x}{b\sigma}\right) \cdot \left(1 - \left \frac{x_i-x}{b\sigma}\right \right)$
Quadratic kernel	$\frac{a}{\sqrt{\sigma}} u_{[-1,1]}\left(\frac{x_i-x}{b\sigma}\right) \cdot \left(1 - \left(\frac{x_i-x}{b\sigma}\right)^2\right)$
Asymmetric kernel	$\frac{a}{\sqrt{\sigma}} u_{[-1,0]}\left(1 - \left \frac{x_i-x}{b\sigma}\right \right) + \frac{a}{\sqrt{\sigma}} u_{[0,1]}\left(1 - \frac{x_i-x}{3b\sigma}\right)$

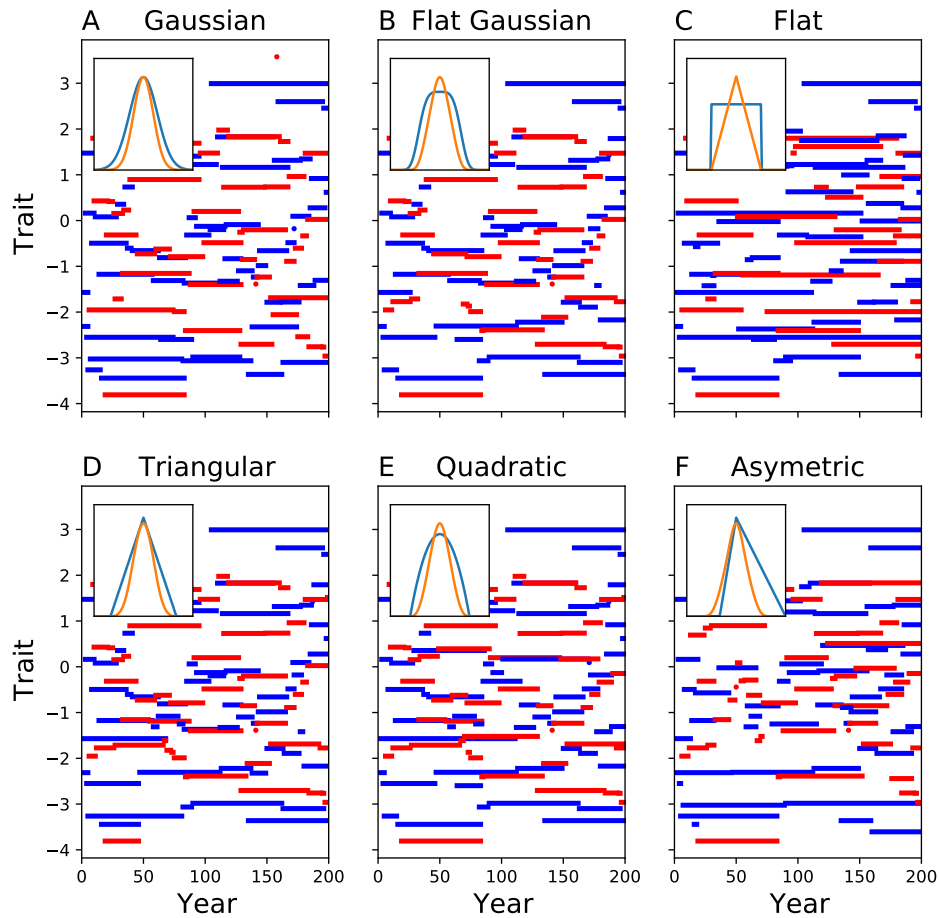
**Table S1:** The different competition kernels we have investigated.  $u_{[x_1, y_2]}$  is the indicator function of the interval  $[x_1, x_2]$ , i.e.  $u_{[x_1, y_2]}(x) = 1$  if  $x_1 < x < x_2$ , otherwise it is zero. Fig. S2 shows a visual representation of these kernels. The scaling parameters  $a$  and  $b$  are chosen such that  $\int_{-\infty}^{\infty} u_{x_i}(x) dx = \int_{-\infty}^{\infty} (u_{x_i}(x))^2 dx = 1$ .

### 714 S3 More general cases

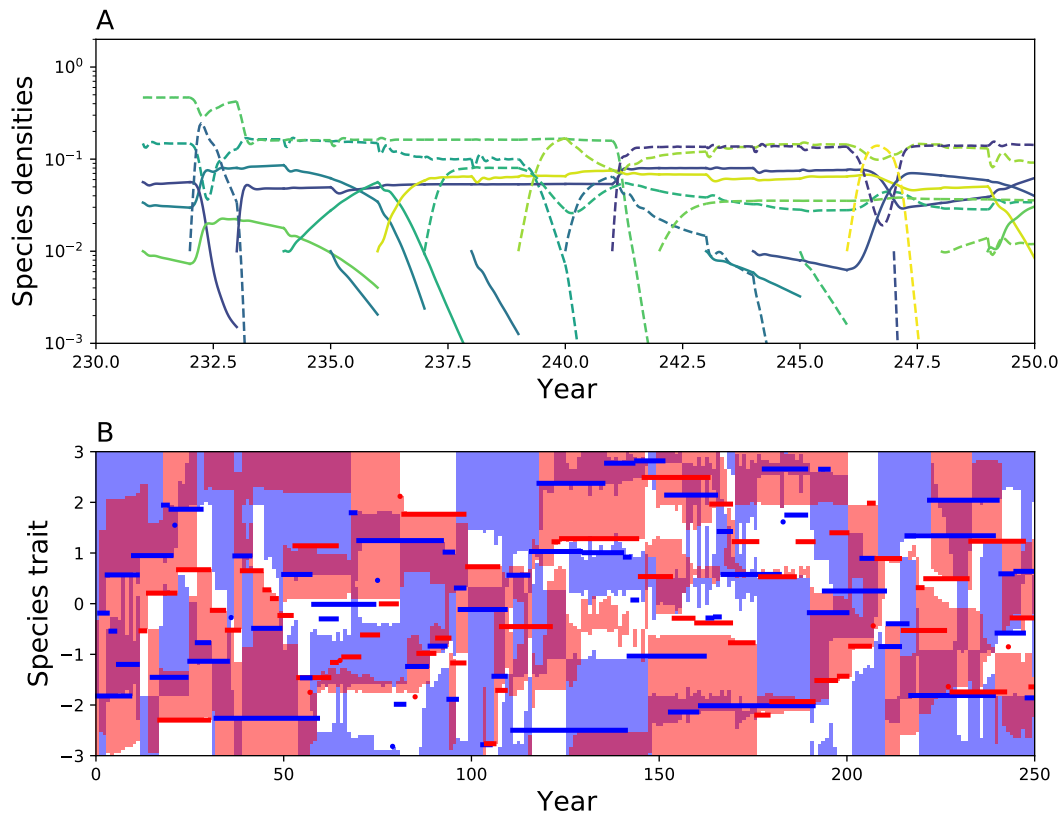
715 In the main text we have, for simplicity, focused on specific model. We show here that  
 716 our main finding, i.e. continuous community assembly, is robust to many different  
 717 scenarios, including different resource consumption and competition kernels (Fig.  
 718 S2), simulating population densities over time over time instead of computing the  
 719 equilibrium dynamics directly (Fig. S3) and a finite regional species pool (Fig. S4).

720 We investigate a total of six different competition kernels: Gaussian kernel, flat-  
 721 tened Gaussian, flat kernel, triangular, quadratic and asymmetric (Table S1). Each  
 722 resource consumption kernel  $u_{x_i}(x)$  is described by the location of maximal resource  
 723 consumption  $x_i$ , the width of the kernel  $\sigma$  and two scaling factors  $a$  and  $b$ . The co-  
 724 efficient of competition between two prey species with traits  $x_i$  and  $x_j$  is given by  
 725  $a(x_i, x_j) = \int_{-\infty}^{\infty} u_{x_i}(x) u_{x_j}(x) dx$ . The scaling factors are chosen such that  $a(x_i, x_i) = 1$   
 726 and  $\int_{-\infty}^{\infty} u_{x_i}(x) dx = 1$ , i.e. the kernel only affects the shape of the competition, not  
 727 however how strong intraspecific competition is, nor how much a predator consumes  
 728 in total.

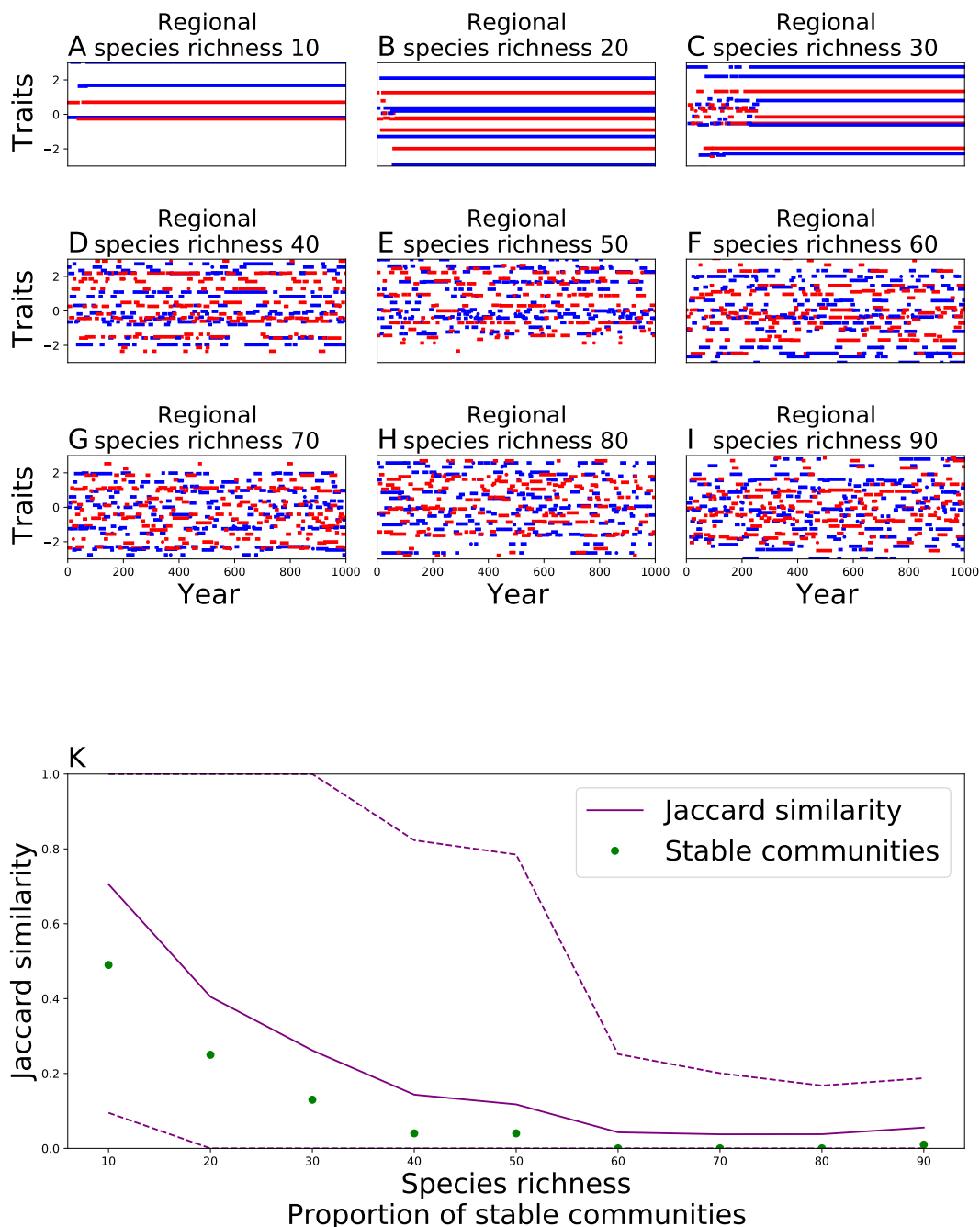




**Figure S2:** Community dynamics for different resource consumption kernels. For all the different kernels we still observe the continuous community assembly. The inset in each panel shows the resource consumption vector (blue) and the resulting competition kernel for two competing prey species (orange).

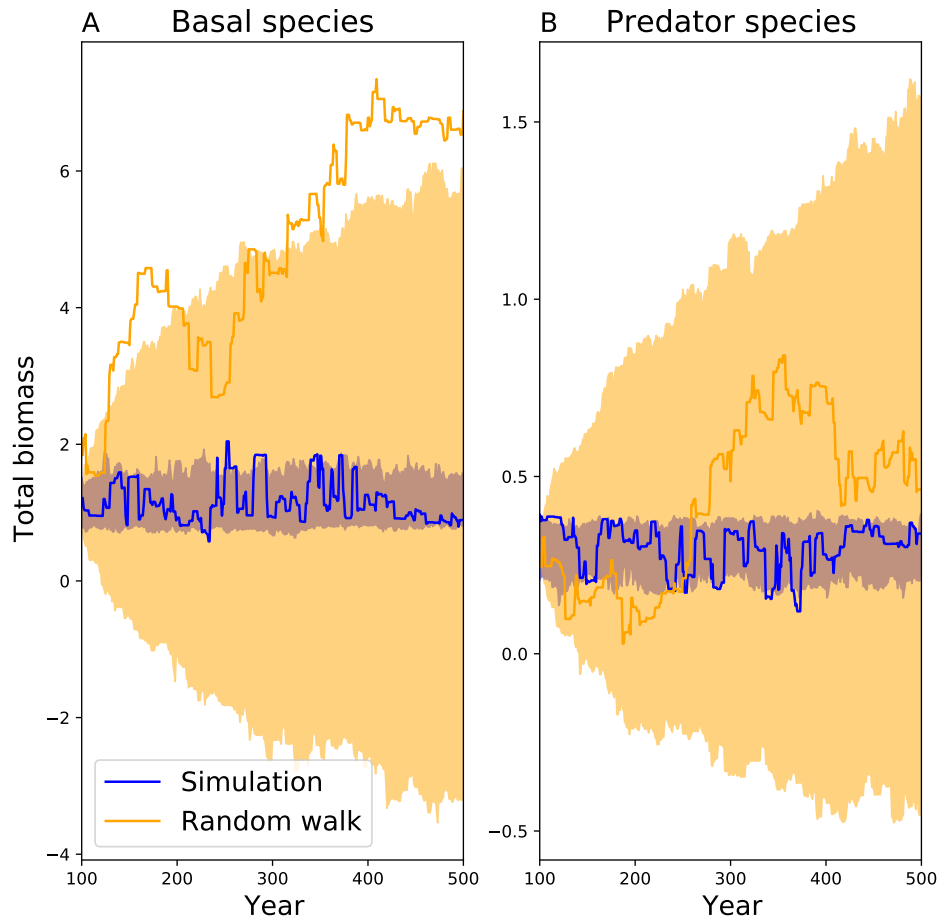


**Figure S3:** In the main text we did not simulate the community dynamics between invasions, rather we assumed that invasions happen infrequently such that the local community is always at equilibrium when a new species invades. Even if we relax this assumption we still obtain the same the continuous assembly dynamics. A: Densities over time for the last 20 years of the community assembly. Invaders are introduced at density  $10^{-2}$  and go extinct if they fall below  $10^{-3}$  of the total density. B: Species traits of the present species. The shaded areas show where traits of potentially successful invaders.

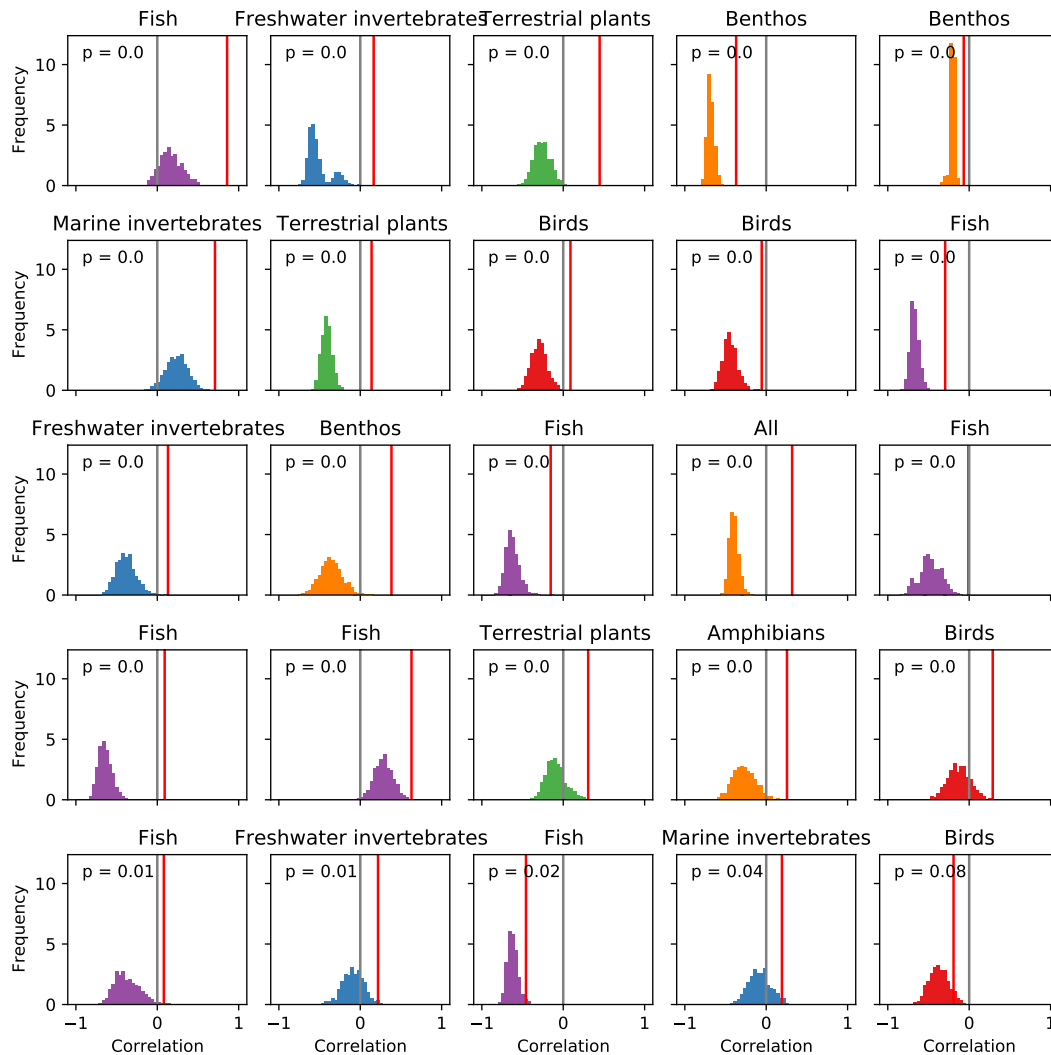


**Figure S4:** In the main text we assumed an infinite regional species pool. Here we investigate the effects of finite species pools. A-I show sample runs with species richness ranging from 10 to 90 species. Some of these converge towards eventual stability with respect to the regional species pool (A, B and C). The others are also driven by continuous species turnover, although there might be a community composition which is stable in each of these regional species pools, there are  $2^n$  possible communities which prohibits a complete search of all possibilities. K: We ran 100 simulations for each species richness. Green dots show the proportion of stable communities, increasing species richness implied lower probability of a stable community. Purple lines show the Jaccard similarity of the end-point with the year 800.

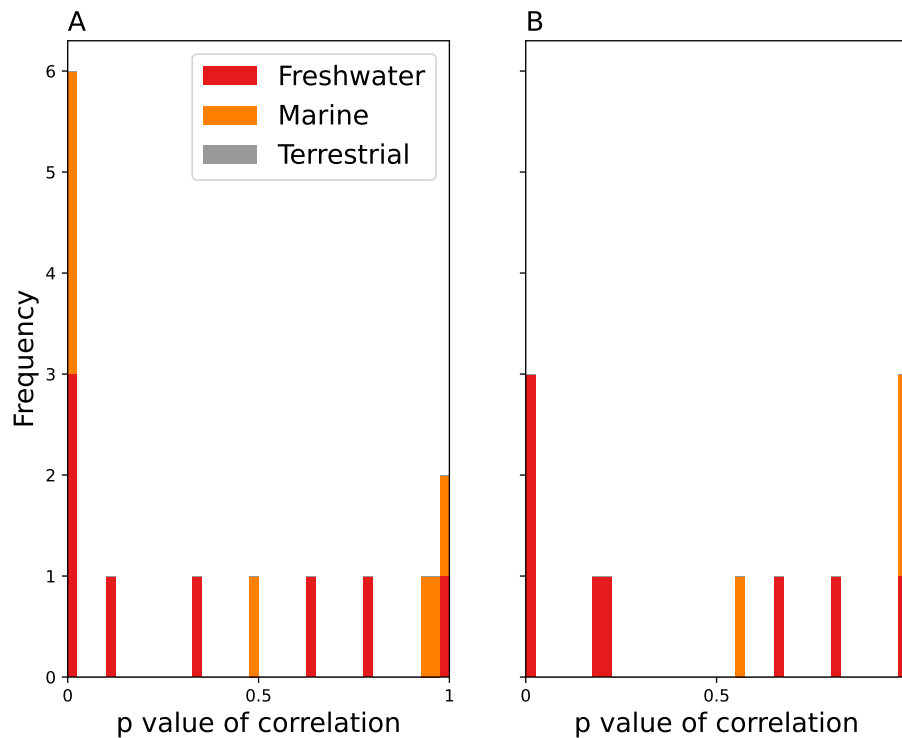
## 729 S4 Additional figures



**Figure S5:** Despite the changes in community composition the total biomass is relatively stable. The blue line shows biomass over time in one specific run, the blue shaded area indicates the 5 and 95% percentile curves of total biomass over multiple runs. We compared this fluctuation in total biomass to a fluctuations in total biomass stemming from a random walk (orange line and shaded area). At each year biomass changes randomly, the changes in biomass are drawn from the actually observed changes in biomass from the community model. As expected, the drift in total biomass in the actual community model is much smaller than the drift in total biomass stemming from the random walk.



**Figure S6:** We compare the actual correlation of invasion and extinction in the Bio-TIME datasets (red vertical line) to the correlation obtained by reshuffling the years 1000 times (histograms). We report the results for the 25 datasets with the lowest p-values (shown in top left corner of each panel).



**Figure S7:** The empirical data from BioTIME contained datasets with very strong fluctuations of species richness (e.g. from over 100 species present to 1 species present within one year). To ensure that our results are not driven by these questionable underlying data we performed two additional tests. Panel A: We have excluded all years in which species richness was below 5 (this threshold was chosen arbitrarily). The total number of datasets remained unchanged by this. Panel B: We have completely excluded all datasets where the maximum species richness is at least four times higher than the minimal species richness, which excluded 18 of the 44 total communities. In both methods we retain the strong correlation of invasions and extinctions.