

1 **Competitive ecosystems are robustly stabilized by structured environments**

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5 **ABSTRACT**

6 Natural environments, like soils or the mammalian gut, frequently contain microbial consortia competing
7 within a niche, wherein many species contain genetic mechanisms of interspecies competition. Recent
8 computational work suggests that physical structures in the environment can stabilize competition
9 between species that would otherwise be subject to competitive exclusion under isotropic conditions.
10 Here we employ Lotka-Volterra models to show that physical structure stabilizes large competitive
11 ecological networks, even with significant differences in the strength of competitive interactions between
12 species. We show that for stable communities the length-scale of physical structure inversely correlates
13 with the width of the distribution of competitive fitness, such that physical environments with finer
14 structure can sustain a broader spectrum of interspecific competition. These results highlight the generic
15 stabilizing effects of physical structure on microbial communities and lay groundwork for engineering
16 structures that stabilize and/or select for diverse communities of ecological, medical, or industrial utility.

17

18 **AUTHOR SUMMARY**

19 Natural environments often have many species competing for the same resources and frequently one
20 species will out-compete others. This poses the fundamental question of how a diverse array of species
21 can coexist in a resource limited environment. Among other mechanisms, previous studies examined how
22 interactions between species – like cooperation or predation – could lead to stable biodiversity. In this
23 work we looked at this question from a different angle: we used computational models to examine the
24 role that the environment itself might play in stabilizing competing species. We modeled how species
25 arrange themselves in space when the environment contains objects that alter the interfaces along which
26 competing species meet. We found that these ‘structured’ environments stabilize species coexistence,
27 across a range of density of those objects and in a way that was robust to differing strengths of
28 interspecies competition. Thus, in addition to biological factors, our work presents a generic mechanism
29 by which the environment itself can influence ecological outcomes and biodiversity.

30 INTRODUCTION

31 Natural environments from scales of microbes¹⁻⁴ to large ecosystems⁵⁻⁸ are replete with communities
32 whose constituent species stably coexist at similar trophic levels, despite apparent competition for space
33 and resources. Generically, in spatially limited ecosystems species grow until resources and/or
34 interactions with other species (e.g. competition or predation) limit their populations, notably not
35 necessarily at a constant level through time⁹⁻¹¹. In some cases¹², the same set of species may exhibit
36 qualitatively distinct relationships in a way that depends on available resources, with corresponding
37 maintenance or loss of diversity. Species diversity and ecosystem stability have a complicated
38 relationship^{13,14}, and qualitatively different theories have been developed to explain variations in species
39 diversity and abundance in resource-limited natural environments^{15,16}. At one extreme, the principle of
40 competitive exclusion asserts that if more than one species is competing within a niche, variations in
41 species reproduction rates resulting from adaptation to the niche will necessarily lead one species to
42 dominate within that niche to the exclusion of all other species, potentially driving inferior competitors
43 into other niches¹⁷⁻²¹. Thus, competition for resources within a niche would push ecosystems toward
44 lower species diversity²². At the other extreme are so-called ‘neutral theories’ which offer the null-
45 hypothesis that organisms coexisting at similar trophic levels are – *per capita* – reproducing, consuming,
46 and migrating at similar rates, and hence maintenance of biodiversity is tantamount to a high-dimensional
47 random-walk through abundance space²³⁻²⁵. Such models often require connections to an external meta-
48 community to maintain long-term stability²⁶, lest random fluctuations will eventually drive finite systems
49 toward lower diversity^{27,28}. Many other mechanisms (which we cannot do justice to here) have also been
50 proposed for maintenance of diversity in competitive ecosystems, including by not limited to: stochasticity
51 and priority effects^{29,30}; environmental variability³¹; models that encode specific relationships between
52 species to maintain diversity³² (including the classic rock-paper-scissors spatial game¹¹, cross-feeding³³⁻³⁷,
53 metabolic trade-offs³⁸⁻⁴⁰, or cross-protection⁴¹); varied interaction models⁴²; higher-order interactions –
54 beyond pairwise – that stabilize diversity⁴³⁻⁴⁶; and systems where evolution and ecological competition
55 happen simultaneously^{47,48}. We do not take issue with any of these models / mechanisms, indeed, all of
56 them are likely relevant and useful within certain contexts. Rather, this work uses computational modeling
57 to argue that physical structure within an environment is a generic and robust mechanism for maintaining
58 biodiversity in competitive ecosystems, across differences in competitive parameters, length-scales of
59 physical structure, and for an arbitrary number of distinct species given lower-bound requirements on
60 available space.

61 Microbial ecosystems present a particularly attractive test-bed for these ecological ideas. From a practical
62 point of view, they are small and fast growing, relatively easy to genetically manipulate, and can be grown
63 in controlled and customizable synthetic environments^{35,49–52}, such as microfluidics^{53,54}. Conceptually,
64 characterizing the forces and principles that establish and maintain microbial biodiversity is of significant
65 interest in health-relevant settings like the human gut^{55–57} and in the myriad contexts where soil
66 microbiota impact natural or agricultural ecosystems^{1,58}. These contexts motivate the model herein
67 discussed, which can be conceptualized as a multi-species microbial ecosystem adherent to reasonable
68 simplifications that make computations tractable. We used a spatial Lotka-Volterra model and assumed
69 that all pairwise interspecies interactions were competitive. We focused on the role that physical
70 structure of the environment plays in long-term dynamics of such ecosystems. Within the context of this
71 model, our results were clear – steric structures distributed throughout the environment foster
72 biodiversity in a way that depends less on the specific arrangement of those structures and more on the
73 length scale of separation between the structures⁵⁹. This structural stabilization was robust even when
74 the ecosystem contained significant asymmetries in the competitive interactions between species, and
75 the degree of stabilization positively correlated with decreasing structural scale. Finally, we provide
76 evidence that the stabilizing effects of steric structure extend to an arbitrary number of species in
77 competition with each other, as long as there is enough space.

78

79 **Results**

80 **Competition and Structural Model**

81 We modeled interspecies interactions using the canonical spatial Lotka-Volterra (LV) framework, with
82 simplifying assumptions motivated by attributes of microbial ecosystems. For all species, we assumed that
83 the carrying capacity per unit area of the environment is the same, that the basal growth rate r is the
84 same, and that their migration can be described by random walks with the same diffusion coefficient D .
85 Using those assumptions, the system of partial differential equations (PDEs) that describe an N -species LV
86 model can be non-dimensionalized and, without loss of generality, written as

$$87 \quad \frac{\partial S_i}{\partial t} = \nabla^2 S_i + S_i \left(1 - \sum_{k=1}^N S_k (1 + (1 - \delta_{ik})/P_{ik}) \right).$$

88 Each focal species S_i has a local concentration from zero to one in units of the carrying capacity, time is
89 measured in units of inverse growth rate r^{-1} and the natural length scale $\lambda = \sqrt{D/r}$ is proportional to the

90 root mean squared distance an organism will move over a single doubling time. Self-interactions and
91 simple competition for space are accounted for by the constrained carrying capacity and the
92 corresponding sum over S_k , and thus the diagonal elements P_{ii} are removed by the Kronecker delta, δ_{ik} .
93 Pairwise interactions between species are described by the off-diagonal matrix elements P_{ik} which are
94 the concentrations of species S_k above which S_k actively reduces the concentration of S_i . Neglecting
95 intrinsic permutation symmetries, there are $N(N - 1)$ pairwise interaction parameters for each *in silico*
96 ecosystem, which can be thought of as a directed graph whose edges connect each pair of species. We
97 focused on the class of ecological graphs that correspond to all species in competition with all other
98 species, termed ‘all-to-all’ (ATA) competition, which corresponds to all off-diagonal elements $P_{ik} > 0$. This
99 work uses computationally tractable values of N to support general claims about the dynamics of ATA
100 ecosystems in structured environments, albeit such computations do not constitute a rigorous proof.

101 This model is appropriate for describing diffusively-mediated locally competitive interactions; examples
102 of such ecosystems include situations where multiple species compete for the same pool of resources and
103 actively reduce competitor abundances through (e.g.) Type VI secretion system mediated killing^{60,61},
104 secretion of toxins^{62,63} or antibiotic antagonism^{64,65}. Analysis of bacterial genomes indicates that (at least)
105 a quarter of all sequenced species contain loci encoding for mechanisms of active competition toward
106 other species⁶⁶ (though not necessarily for the purposes of consuming them as prey). Additional PDEs
107 would be required to describe highly motile cells, chemotaxis in exogenous chemical gradients, or the
108 production, potency, transport and decay of rapidly diffusing secreted toxins. This system of PDEs (which
109 is not new^{67,68}) represents a baseline set of assumptions and corresponding phenomena from which to
110 build more complex models⁶⁹ of structured population dynamics.

111 The $O(N^2)$ dimensional parameter space is too large to exhaustively sample for large N , and thus we
112 employed statistical sampling techniques. We sampled a uniform random distribution of values for the
113 off-diagonal elements P_{ik} whose mean was $\langle P \rangle = 0.25$ and whose width was specified by the parameter
114 ΔP . The value $\langle P \rangle = 0.25$ indicates that on average when the local concentration of a given species
115 reaches one-quarter of the carrying capacity, active reduction of neighboring competitors will occur. For
116 each value of ΔP and structural parameters, we performed 30 to 50 simulations each with a unique
117 random sampling of the interaction parameters P_{ik} . All simulations had initial conditions in which every
118 grid position had a low (0.2%) probability of being populated by any one of the available species, such that
119 each species could grow and claim territory before competing. The data herein presented uses an 8-
120 species system (56 interaction parameters), though in the last section we examine larger values of N .

121 Our *in silico* environments were square 2D planes with steric pillars distributed in the simulation space.
122 Both the pillars and the bounding box were modeled with reflecting boundary conditions, thus, like a grain
123 in soil or tissue in a gut, these pillars do not allow free transport through them, nor microbes to occupy
124 them. Interspecies boundaries within the simulation area are primarily impacted by steric spacing⁷⁰, and
125 thus for simplicity the radii of the pillars were held fixed at $R = 3$ in dimensionless units for all simulations.
126 We varied the mean distance between steric objects relative to pillar radius ($\Delta x/R$), which we refer to as
127 the ‘structural scale’, and we varied the degree of disorder in the arrangement of those steric objects.
128 Disorder was introduced by translating each pillar in a random direction by an amount drawn from a
129 uniform random distribution whose width is reported relative to the structural scale. Thus, disorder is
130 characterized by a continuous dimensionless variable δ , which when equal to zero means the pillars are
131 arranged in an ordered triangular lattice, and as δ increases the pillars approach a random arrangement
132 in the simulation space (including the possibility of overlap) (see SI Fig. 1).

133 Finally, it is worth noting limitations and simplifications inherent in this modeling framework. These
134 systems of PDEs are deterministic, that is, with the same interaction parameters, simulation size and initial
135 conditions they produce the exact same dynamics. Stochasticity enters our simulation framework through
136 the random initial conditions, disorder, and random samplings of the interaction parameters. A number
137 of excellent studies have examined low- N systems using fully stochastic dynamics^{71–75}, revealing
138 quantitative differences between deterministic and stochastic models, as well as qualitative differences
139 over long time scales where stochastic fluctuations can drive a system into new parts of phase space, for
140 example, into extinction cascades^{76,77} or mobility-dependent biodiversity^{71,73,78}. Details of our
141 computational setup are discussed in the Methods section and all of our code is available upon request.

142

143 **Environmental structure stabilizes all-to-all competition**

144 We compared the spatial population dynamics of an 8-species system with and without the inclusion of
145 spatial structure. In both cases, each species engaged in active (population reducing) competition with
146 every other species, for a total of 56 pairwise interactions each characterized by the value of an off-
147 diagonal matrix element. In Fig. 1 we show the simplest version of this comparison, where the strength
148 of the competitive interaction is equal between all pairs of species (i.e. all off-diagonal elements have the
149 same value, $\Delta P = 0$). When a system lacks steric structure, and hence is spatially isotropic, a single
150 dominant competitor will emerge to the exclusion of all other species⁷⁹ (Fig. 1 A/B). Spatial population

151 dynamics are determined by an interplay between the curvature of the interface between any two species
152 and the relative values of the competition parameters for the species that meet at that interface⁷⁰. If
153 competition at a particular two-species interface is balanced (i.e. $P_{ik} = P_{ki}$) then interfacial curvature is the
154 only determinant of interface movement; straight interfaces do not translate and curved interfaces
155 translate in the direction that straightens them. However, if the interaction at a two-species interface is
156 unbalanced (i.e. $P_{ik} \neq P_{ki}$) then there is a critical interface curvature below which the stronger competitor
157 will invade the space of a weaker competitor, ultimately to the exclusion of the weaker competitor.
158 Excepting literal edge cases, wherein boundaries between species contact multiple parallel edges of the
159 simulation space, the dominance of a single competitor in isotropic space is robust to changes in the size
160 of the simulation space, the number of species and the values of interaction parameters, given enough
161 time.

162 In contrast, the inclusion of physical structure leads to long term, stable representation of multiple (and
163 often all) species across a range of structural scales and interaction parameters. In Fig. 1 C/D we show the
164 evolution of balanced competitive interactions between 8 species with the same initial conditions and
165 interaction parameters as Fig. 1 A/B, but in the presence of a triangular lattice of steric pillars. In this
166 system, the abundances of all 8 species rapidly equilibrated leading to stable coexistence. In this stable
167 state, each species established spatial domains whose boundaries were primarily composed of two-
168 species interfaces governed by the same rules of interfacial curvature and competitive parameters
169 discussed above (Fig. 1Di). The steric pillars also stabilized a number of distinct ‘junctions’ between
170 species, including free three-way junctions in open space (Fig. 1Dii), three-way junctions centered on a
171 pillar (Fig. 1Diii), and four-way junctions centered on a pillar (Fig. 1Div). Isotropic systems can transiently
172 support two-species interfaces and free three-way junctions (Fig. 1A), but the three- and four-way
173 junctions centered on a pillar can only exist in systems with steric objects. Junctions centered on pillars
174 can support more than four species if pillars are large in comparison to the length scale (thickness) of the
175 interface, though these did not occur in our simulations with random initial conditions – we only observed
176 these higher-species junctions under contrived conditions (see SI Fig.2).

177

178 **Stabilization is robust to fluctuations in structure and competition asymmetries**

179 Next we held the degree of structural disorder fixed at zero ($\delta = 0$) and explored how changes in the
180 structural scale affected the number of stably coexisting species. Along one dimension, we held $\langle P \rangle =$

181 0.25 and varied the interaction parameter ΔP subject to the constraint that $\Delta P/2 < \langle P \rangle$, which ensured
182 that all *in silico* ecosystems remained in the ATA graph class. Along a second parametric dimension, we
183 varied the structural scale while holding pillar radii fixed. In Fig. 2 we measured the mean number of
184 species at equilibrium as a function of both the width of the interaction-parameter distribution and the
185 structural scale, with 30 replicates per parameter set for a total $\sim 11,000$ simulations. Consistent with
186 previous work on two-species systems⁷⁰, the average number of surviving species declined sharply both
187 as competition asymmetry increased (i.e. as $\Delta P/\langle P \rangle$ increased) and as the structural scale increased.
188 Conversely, systems with smaller structural scales and/or smaller competitive asymmetries robustly
189 retained all eight species in the long-time limit. The structural scale sets the maximum interface curvature
190 that can exist in an ordered environment, and hence limits the values of $\Delta P/\langle P \rangle$ for which all species can
191 survive, that relationship is given by

$$192 \left(\frac{\Delta x}{R}\right)_{\text{crit}} = 2 \frac{\lambda}{R} \sqrt{1 + \left(\frac{\langle P \rangle}{\Delta P}\right)^2}$$

193 derived by setting the maximum geometric curvature equal to the curvature due to competitive
194 asymmetry (see SI of ⁷⁰). This relationship approximates the boundary between the regime of stable
195 coexistence of all species and reduced species coexistence, as shown overlaid on Fig. 2.

196 While these results are supportive of the stabilizing effect of steric structure on long-term species
197 coexistence, rarely do natural environments contain highly ordered ($\delta = 0$) steric structures, thus we
198 explored how disorder affects species abundance at a fixed structural scale. First, we simulated the
199 simpler case where all eight species had balanced competitive interactions (like Fig. 1) and examined the
200 population dynamics in the presence of disordered steric structures ($\delta = 1$). Like the ordered case,
201 disordered systems with balanced competitive interactions displayed stable representation of all eight
202 species (Fig. 3A). We then compared the probability distribution for the number of coexisting species at
203 equilibrium across four conditions (1,000 simulations for each): with and without competitive asymmetry,
204 and with and without structural disorder, as shown in Fig. 3B. When $\Delta P/\langle P \rangle = 0$ the number of species
205 remained at the maximum value across all 1,000 simulations whether or not the steric structures were
206 disordered. When competitive asymmetry was introduced the probability distribution for the number of
207 stably coexisting species expanded across all possible values (1 to 8) and peaked between 6 and 7 species,
208 regardless of whether the system was ordered or disordered. Those distributions were quantitatively
209 similar, indicating that disorder was not a strong determinant of stable species coexistence.

210 We examined the survival probability distributions and applied the simplest possible rule that emerges
211 from the statistical ensemble of initial conditions, competitive asymmetries, and disorder. For a given set
212 of conditions we assumed that there is some probability α that a species randomly selected from the full
213 ensemble will survive in the long-term. This corresponds to a binomial distribution whose normalization
214 is modified to account for the fact that there is no chance that all N species will die

$$215 \quad p_n(N, \alpha) = \frac{N! \alpha^n (1 - \alpha)^{N-n}}{n! (N - n)! (1 - (1 - \alpha)^N)}$$

216 where N is the maximum (initial) number of species and p_n is the probability of $1 \leq n \leq N$ species
217 coexisting at equilibrium. We used maximum-likelihood estimation to fit this model to the survival
218 distributions and thus determined the value $0 < \alpha < 1$ that corresponds to the ensemble average
219 probability that any single species survives in equilibrium given the number of species N , simulation size
220 L , structural parameters Δx and R , the disorder δ , and sampling parameters $\langle P \rangle$ and ΔP ; the exact
221 functional dependence between those parameters and α is not yet clear. This model captures the bulk of
222 the survival distributions and mis-estimates the occurrence of rare events compared to the raw data. The
223 fit values demonstrate that smaller systems and systems with higher competitive asymmetries both have
224 lower per-capita survival probabilities (α). For instance, examining systems with higher competitive
225 asymmetry, we found that larger systems ($L = 150$) with or without disorder had quantitatively similar
226 survival probabilities – $\alpha = 0.746_{-0.010}^{+0.009}$ and $\alpha = 0.767_{-0.009}^{+0.009}$ respectively – whereas under the same
227 conditions a smaller system ($L = 75$) had survival probabilities of $\alpha = 0.600_{-0.011}^{+0.011}$ and $\alpha = 0.626_{-0.011}^{+0.011}$,
228 respectively (See SI Fig. 3).

229 We used those same 4,000 simulations to assess the variability in the amount of area that each species
230 occupied at equilibrium divided by the total simulation area, giving a dimensionless quantity bounded
231 between 0 and 1 that characterizes variability in species abundance. For each set of parameters, we
232 measured the standard deviation in abundance across all species and all replicates to generate a
233 probability distribution for the degree of variation – values closer to zero indicate that all species have
234 roughly the same abundance. In the case of balanced competitive interactions, the probability
235 distributions for abundance variations were nearly identical for the ordered and disordered systems, and
236 the mean value of the variation was low (~ 0.05), meaning that if competitive interactions are balanced all
237 species are have roughly the same abundance. However, introducing moderate competitive asymmetry
238 meant that some species intrude into the territory of other species, leading both to lower species diversity
239 and to larger variations in species abundance. As such, we report the distribution of abundance variations

240 for all simulations that had equilibrium species numbers of $S = 6, 7$ and 8 (Fig. 3 C). Again, disorder had
241 little effect on those probability distributions. Systems that experienced extinctions of zero ($S = 8$), one (S
242 $= 7$) or two ($S = 6$) species had a higher mean variation (by a factor of 3 to 5) and wider distribution of
243 variations as compared to balanced competition. Additionally, we performed a wider sampling of the
244 degree of disorder and the competitive asymmetry, and found that the average number of stably surviving
245 species showed little dependence on the degree of structural disorder (Fig. 3D). When we correlated the
246 mean number of surviving species as a function of the competitive asymmetry across all values of δ , the
247 average correlation coefficient was 0.97 (see SI Fig. 4), meaning that the relationship between average
248 number of surviving species and competitive asymmetry showed little dependence on disorder in the
249 range $0 \leq \delta \leq 1$.

250 As a final characterization of spatial structure, we examined the density with which interspecies
251 boundaries connect steric objects. Ignoring edge cases, every steric object has a set of Voronoi nearest
252 neighbors, typically 5 to 7 in disordered systems and exactly 6 in a triangular lattice (see SI Fig. 5). Across
253 our simulations, the vast majority ($\sim 98\%$) of all interspecies boundaries connected pillars that were
254 Voronoi nearest neighbors, which is expected given geometric constraints. The number of those
255 connections per unit area relative to the total number of possible Voronoi connections per unit area is a
256 dimensionless measure of the amount of competition in a physically structured system – below we refer
257 to this as the ‘connection density’, whose values lie between 0 and 1. When examined through that lens,
258 disorder, at least for balanced interactions, had a significant effect on the distribution of connection
259 densities across the ensemble of simulations, with ordered systems exhibiting higher connection densities
260 (see SI Fig. 5). However, when examined under moderate levels of competitive asymmetry connection
261 density significantly decreased (consistent with abundance variation increasing) and the difference
262 between ordered and disordered systems again became small. These data suggest that structured systems
263 with higher levels of competitive asymmetry, somewhat counterintuitively, have lower levels of
264 competition as measured by the density of competitive interfaces in the system, because boundaries
265 between mismatched competitors are less stable.

266

267 **Structure stabilizes larger numbers of species with system-size dependence**

268 All of the simulations discussed up to this point were performed within the same size grid $L = 150$ (with
269 the exception of SI Fig. 3, $L = 75$). Under any set of parametric conditions, the absolute minimum domain

270 size for a given species is set by the area of a triangle formed by three pillars that are all mutual Voronoi
271 neighbors (so-called ‘Delaunay triangles’⁸⁰), thus *any* system that is not large enough to contain domains
272 of at least that size for each of N unique species cannot support all N species – this establishes a minimum
273 system size for a particular number of species that scales as $N(\Delta x)^2$. However, disordered systems have
274 an additional system-size dependence – all else being equal, as the system size grows the probability
275 distribution for the equilibrium number of species (e.g. Fig. 3B) shifts toward the maximum number of
276 species (i.e. $\alpha \rightarrow 1$). The mechanism behind this shift is that as the system increases in size, there are more
277 opportunities for disordered steric objects to create a zone in which a weaker competitor is enclosed by
278 an effectively smaller structural scale. We confirmed this by measuring the system size-independent
279 distribution of local structural scale (SI Fig. 6). In an ordered system, the distribution of local structural
280 scale is a delta-function centered on the lattice constant. As disorder increased we found that Voronoi
281 zones emerged whose maximum convex edge-length was smaller than the lattice constant, meaning these
282 were zones in which a species that would be too weak to compete in an ordered system, could potentially
283 survive. The average number of these zones per unit area is scale-independent, thus increasing system
284 size linearly increases the average number of those zones, and thus the per-capita survival probability α
285 increases (e.g. compare Figs. 3B and SI Fig. 3), as does the survival probability of weaker competitors.

286 Finally, in an ordered system we explored the effects of system size and competitive asymmetry as a
287 function of the initial number of species, across the range $2 \leq N \leq 12$. First, we measured the ensemble
288 survival probability (α) as a function of both competitive asymmetry and the initial number of species,
289 with 50 replicates for each parameter set (Fig. 4A). For low competitive asymmetry across all values of N ,
290 the ensemble survival probability was approximately 1, meaning all species survived, and hence the initial
291 and final species numbers were equal. However, similar to Fig. 2, as competitive asymmetry increased
292 species loss increased (α decreased), and the decrease in α was more dramatic the larger the initial
293 number of species. One potential mechanism behind this species-number dependent change in α is that
294 larger values of N offer a wider sampling of the matrix elements P_{ik} , and thus increase the likelihood that
295 a single competitor dominates over many other weaker species and/or that ‘ultra weak’ competitors
296 emerge.

297 Another potential link between species-number and decreasing α was system-size. To test this, we ran
298 simulations across the same range of species number at the highest value of competitive asymmetry for
299 two different system sizes ($L = 100$ and $L = 200$). For both system sizes, survival probability dropped as
300 species number increased (Fig. 4B), but the smaller system experienced a significantly faster drop in

301 survival probability with species number. This indicates that decreasing system size accounts for part, but
302 not all, of the decrease in survival probability. We also examined the role of disorder in this context;
303 consistent with our previous results disorder had a relatively minor effect as determined by 95%
304 confidence intervals of MLE for the values of α (see SI Fig. 7 for confidence intervals). Together, these
305 results add support to the finding that disorder at a fixed structural scale is not a strong determinant of
306 stable biodiversity, but that system size and the number of initially competing species each modulate
307 survival probability and hence equilibrium biodiversity.

308

309 **DISCUSSION**

310 In this work we used simulations to provide evidence that – within a range of structural scales and
311 competitive parameters – the class of ecological graphs encompassed by all-to-all (ATA) competition is
312 stable in structured environments. Other well-known ecological ‘games’, such as rock-paper-scissors (RPS)
313 and its higher species-number analogs^{73,81}, also reside within the ATA graph class. That is, values in the
314 matrix P that produce stable intransitive (e.g. RPS) oscillations adhere to the same conditions as the ATA
315 class, but are subject to additional constraints on their relative values. The RPS sub-class distinguishes
316 itself by exhibiting two important features. First, unlike non-oscillatory systems that lie within ATA,
317 oscillatory systems with spatial isotropy can exhibit stable representation of all species^{43,71,82}, albeit with
318 each species in constant spatial flux. Second, our previous work showed that in a symmetric game of RPS⁷⁰,
319 structure could have a destabilizing effect that ultimately led to extinction cascades ending with a single
320 dominant species. Thus, while the vast majority of parameter combinations for P_{ik} likely yield systems that
321 are stabilized by structure, RPS graphs present the possibility of being destabilized by structure. Given
322 that virtually all natural environments present structural anisotropy, destabilization of RPS networks due
323 to structure may contribute to answering why RPS networks are only rarely observed outside of the
324 lab^{21,83–85}.

325 Similarly, systems in which species cooperate or have competitive alliances – neither of which lie within
326 the ATA graph class – can, by virtue of the specific localization of each species, be stabilized by structure.
327 For instance, consider the simplest, non-ATA graph for which this can be true: A and B compete, B and C
328 compete, and A predaes C (see SI Fig. 8A). If in a structured environment species C is stably and spatially
329 isolated from A by the arrangement of B , then all three species will stably coexist due to the effects of
330 physical structure, even though an interspecies boundary between A and C is unstable regardless of

331 structural parameters. The idea that specific spatial arrangements of species can be stable in a structured
332 environment extends to other non-ATA graphs (e.g. SI Fig. 8B), and is consistent with established findings
333 that spatially structured communities maintain biodiversity by localizing interactions among community
334 members^{86–88}. This also suggests the possibility that physical structure and positioning of species play a
335 role in shaping their ecological and evolutionary relationships. Thus assessing the interplay between
336 physical structure, graph structure, and ecological dynamics is a rich area of inquiry, one in which structure
337 may play a qualitatively important role.

338 For simplicity and ease-of-display we explored 2D systems in this work, however many natural systems
339 are three dimensional. This work does not allow us to directly comment on what will happen in 3D
340 systems, however: (i) graph structure and its attendant parameters as encoded by the interaction matrix
341 are independent of dimensionality, (ii) the relationship between interface curvature and competitive
342 asymmetry that underlies many of the results herein described have a natural extension into three
343 dimensions, where the mean curvature of the 2D interspecies boundary in 3D space plays the analogous
344 role as 1D curvature of a line interface in 2D space, and (iii) the measures herein described (e.g.
345 dimensionless disorder, structural scale, connection density, survival probabilities, etc.) have natural
346 extensions into 3D, meaning that direct comparisons can be made between 2D and 3D systems. Similarly,
347 there are illuminating comparisons to be made with other physical and biological systems, in particular
348 the pinning phenomena that here slow or halt genetic coarsening play important roles in domain-wall
349 stabilization in Ising-like systems due to pinning at random spatial impurities⁸⁹, pinning-induced
350 transitions of super-cooled liquids into glassy states⁹⁰, arrest of lipid-bilayer domain coarsening in the
351 presence of biopolymers that impose structure on the bilayer⁹¹, and have been shown to impact
352 genotype-specific range expansion⁹². Likewise, other physical mechanisms, such as flow⁹³, have been
353 found to slow or halt coarsening in phase-separating systems, and still other work focuses on flow^{94,95} or
354 chemical gradients⁹⁶ in structuring communities. Thus structure is one of multitude physical mechanisms
355 shaping communities in complex environments.

356 Finally, even within this 2D reductionist framework we wonder how robust are pinned competition
357 interfaces to: (i) stochastic spatial fluctuations caused either by finite organism size or other forms of
358 motility (besides diffusion), (ii) tunable interaction strengths, such as with competition sensing^{97,98}, or (iii)
359 phenotypic differentiation⁹⁹? Whether the details of interactions matter⁶⁹ or not¹⁰⁰, the stabilizing effect
360 of structure is fundamentally related to how interspecies boundaries – which appear in many extensions
361 of the LV model – interact with the boundary conditions imposed by structure, and hence we anticipate

362 that qualitatively, these results extend to a wider class of boundary-forming models (e.g. incorporating
363 Allee effects⁷⁰). Ultimately, an understanding of the interplay between ecological relationships,
364 environmental structure, and other physical factors (like flow or chemical gradients) paves the way toward
365 rational design of structured environments that tune the range of competitive asymmetries and/or
366 stochastic fluctuations that an environment can stably support, and shift system dynamics and stability to
367 favor particular species or interaction topologies.

368

369 **METHODS**

370 In the 2D simulation space, each species was seeded by randomly choosing 0.2% of all valid pixels in the
371 simulation box and setting the concentration of that species to $1/N$ of the carrying capacity, where N is
372 the number of species being simulated; each species was represented by its own field matrix. Steric pillars
373 were placed with the specified radius R , spacing Δx , and degree of disorder δ within a simulation box
374 whose side lengths were L . All reported length measures (R , L , Δx) are in units of 1.29λ , with the
375 computational pixel scale set so that $1.29\sqrt{D} = 1.29\lambda = 5$. Microbial density that coincided with pillar
376 locations was removed from the simulation. The bounding box and pillar edges were modeled as reflecting
377 boundary conditions. At each simulated time step ($\Delta t = 0.01t$, with t in inverse growth rate), populations
378 diffused via a symmetric and conservative Gaussian convolution filter with standard deviation set by the
379 diffusion coefficient, $\sigma = \sqrt{4D\Delta t}$. After the diffusion step, changes in population density (growth and
380 death) were calculated using the equations given in the main text, and used to update the density of each
381 species matrix according to a forward Euler scheme. In combination with the small dimensionless time-
382 step and concentration-conserving convolution filter, hard upper and lower bounds (1 and 0 in units of
383 carrying capacity, respectively) were enforced on each species field to ensure numerical stability of
384 simulations; populations densities outside this range were set to 1 and 0, respectively. We monitored a
385 subset of the simulations and found that simulations were sufficiently stable that those hard limits were
386 never encountered. For each set of structural scale ($\Delta x/R$) and competitive asymmetry (P_{ik}) values, 30 to
387 50 independently initialized replicates were simulated for 5000 doubling times or until equilibrium was
388 reached, as defined by spatially averaged change in all species matrices falling below 0.001 between time
389 steps. Mean population abundances of the simulation were recorded at an interval of $100 \Delta t$ for the
390 duration of the simulation. Extinction was defined as the mean population density of any species dropping
391 below a threshold value of $((2R)^2 - \pi R^2)/4A$, where R is the pillar radius and A the area of lattice points
392 not obstructed by pillars. This non-zero threshold accounts for surviving populations ‘trapped’ between a

393 pillar and the corner of the simulation box and therefore not in contact with the rest of the simulation;
394 this threshold value lies well below the minimum set by the local Delaunay triangulation.

395 To create a controlled level of pillar-position disorder, each pillar center was displaced from a triangular
396 lattice in a random direction by an amount drawn from a uniform random distribution whose width is
397 characterized by the dimensionless parameter defined as $\delta = 2w/(\Delta x - R)$, where w is the width of the
398 uniform distribution. The competition parameters between all species were generated by choosing the
399 mean strength of competition $\langle P \rangle$ and then sampling a uniform random distribution of width ΔP about
400 that mean for each directed interaction (i.e. the interaction matrix is not symmetric), subject to the
401 constraint that $\Delta P/2 < \langle P \rangle$, which ensures that all random samplings remain in the ATA graph class.

402 *Model Fitting*

403 Fitting to the modified binomial distribution was performed using maximum-likelihood estimation with
404 all 1,000 simulations for each set of conditions; reported uncertainties for α are 95% confidence intervals.

405 *Data availability*

406 Code files to run simulations and analyses are available as supplemental files that can be downloaded on
407 the publisher website. Raw simulation output is available upon request.

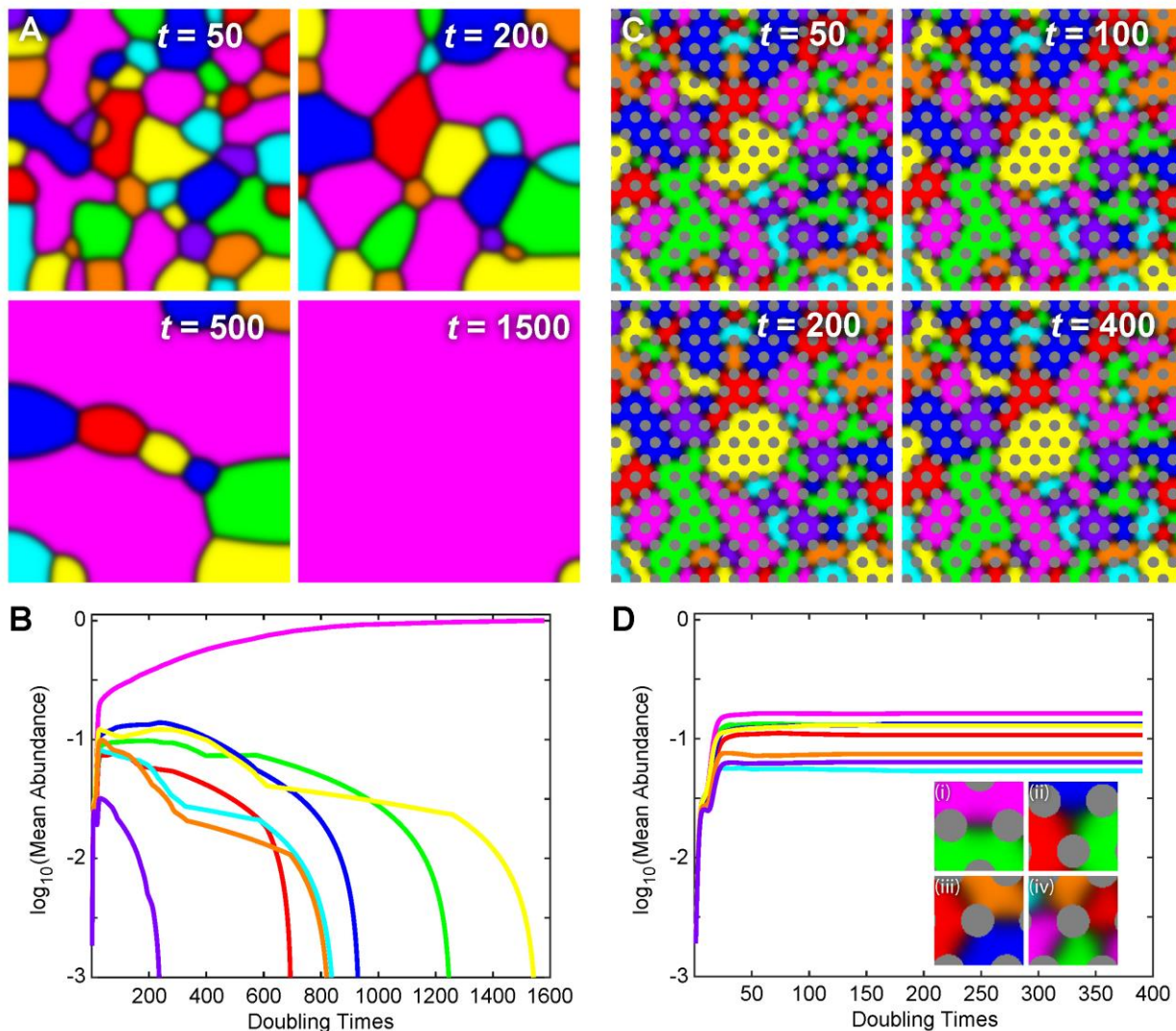
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409 **ACKNOWLEDGEMENTS**

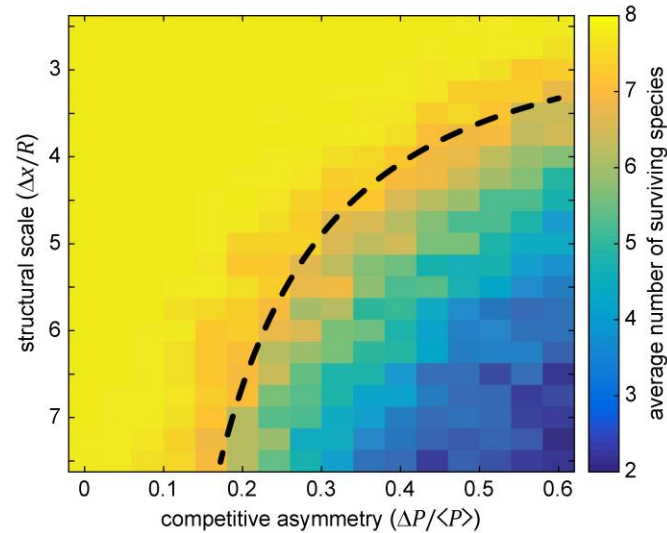
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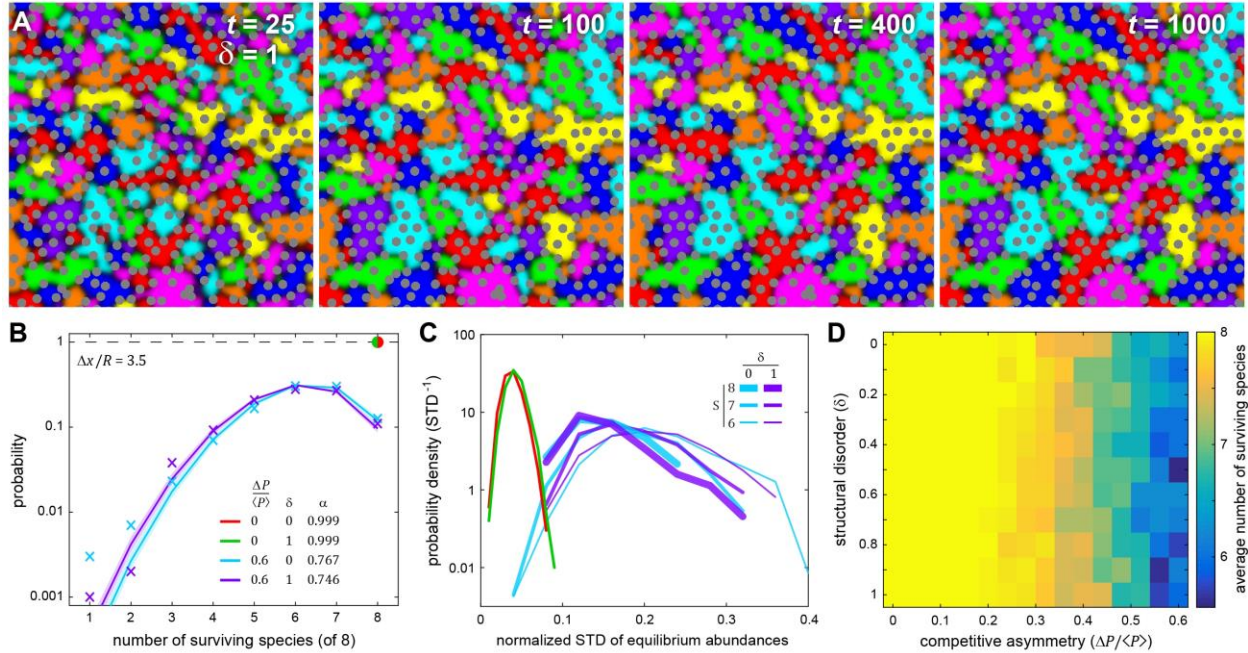


415
 416 **Figure 1: Steric structures stabilize an *in silico* multi-species ecosystem.** Shown here are two 8-species
 417 *in silico* ecosystems in which all species are actively competing with all other species and the competition
 418 parameters are equal for all pairwise interactions. **(A & B)** Simulation of competition in an isotropic
 419 environment. If initial species representation is statistically equal, each species has equal probability of
 420 dominating the environment in the long-time limit. However, in any single simulation the dynamics of
 421 interspecies boundaries lead to a single dominant competitor in the long-time limit. **(C & D)** When species
 422 compete in an environment with ordered steric structures ($R = 3$, $\Delta x/R = 3.5$, and $\delta = 0$), interspecies
 423 boundaries that are mobile under isotropic conditions quickly ‘pin’ between steric objects and arrest the
 424 genetic-phase coarsening that leads to a single dominant competitor, thereby robustly producing stable
 425 representation of all species. Steric structures also permit situations where 3 or more species form a
 426 ‘junction’ around a steric object (Diii and Div). In both simulations $L = 150$, $\langle P \rangle = 0.25$, and $\Delta P = 0$.



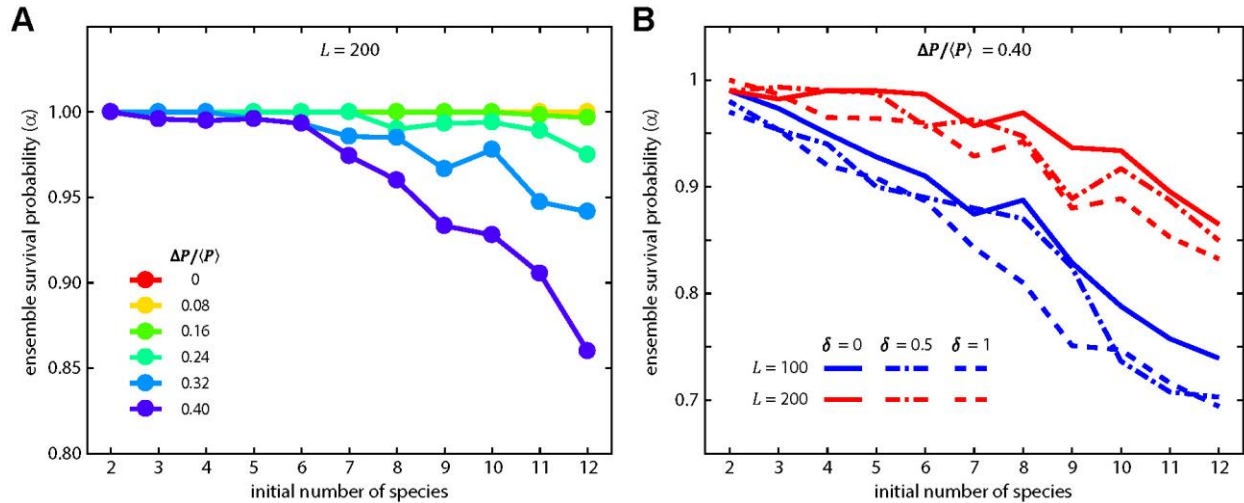
427

428 **Figure 2: The number of species an environment can stably support depends on the degree of**
429 **competition asymmetry and the structural scale.** Simulations were performed across a range of
430 competitive asymmetries characterized by the dimensionless parameter $\Delta P/\langle P \rangle$ and across a range of
431 structural scales characterized by the dimensionless parameter $\Delta x/R$. Each pixel corresponds to the mean
432 of 30 simulations each with a unique random sampling of initial conditions (as described in Methods), a
433 unique random sampling of the interaction matrix elements using ΔP and $\langle P \rangle$, and a fixed structural scale.
434 Structural scale and competitive asymmetry were both potent modulators of species coexistence, with
435 smaller structural scale and lower competitive asymmetries leading to stable representation of all species
436 (yellow region). The black dashed line is a zero-fit parameter model relating the competitive asymmetry
437 to the maximum curvature possible for a given structural scale, showing that relatively simple geometric
438 considerations capture the onset of species loss. In all simulations $L = 150$, $\langle P \rangle = 0.25$, $R = 3$, and $\delta =$
439 0.



440

441 **Figure 3: Species coexistence is robust in the presence of structural disorder.** (A) Similar to Fig. 1C, these
 442 panes show the time evolution of an 8-species system where steric pillars were randomly perturbed from
 443 a perfect triangular lattice ($\delta = 1$). From random initial conditions the system rapidly equilibrated to a
 444 stable configuration that supported all 8 species. (B) Simulations were performed to measure the
 445 probability distribution for the number of surviving species under four conditions (1,000 each): high and
 446 low competitive asymmetry and high and low structural disorder. The structural scale was held fixed.
 447 Without competitive asymmetry all species survived in all simulations, with or without disorder
 448 (red/green dot). With high competitive asymmetry, the probability distributions spread across all possible
 449 numbers of species with relatively little distinction between ordered and disordered systems (colored X's).
 450 Those distributions were well-described by a modified binomial distribution (solid lines) with an ensemble
 451 average single-species survival probability of $\alpha \sim 0.75$. The distributions exhibit larger variation where
 452 there are less data (i.e. lower probabilities, from one to three surviving species). (C) For each simulation,
 453 the normalized standard deviation (NSD) in equilibrium abundances was measured, and those values are
 454 shown here as a histogram for each of the four conditions. In the absence of competitive asymmetry
 455 (green, red), the mean NSD was low (~ 0.05 on maximum scale of 1). When competitive asymmetry was
 456 high, we examined the NSD for all simulations that had 6, 7, or 8 surviving species (cyan, purple). All of
 457 those distributions were significantly wider and had significantly higher mean NSD's, meaning that
 458 competitive asymmetry increases the variation in species abundance at equilibrium, regardless of how
 459 many species stably coexist. (D) We compared the average number of surviving species across a range of
 460 competitive asymmetry and disorder ($0 \leq \delta \leq 1$). Those distributions showed little variation with
 461 disorder and, as a function of competitive asymmetry, had a mean pairwise correlation of 0.97 (see SI Fig.
 462 4). Thus our data suggest that structural scale has a stronger effect than disorder (at least over this range).
 463 In all simulations $L = 150$, $\langle P \rangle = 0.25$, and $R = 3$.

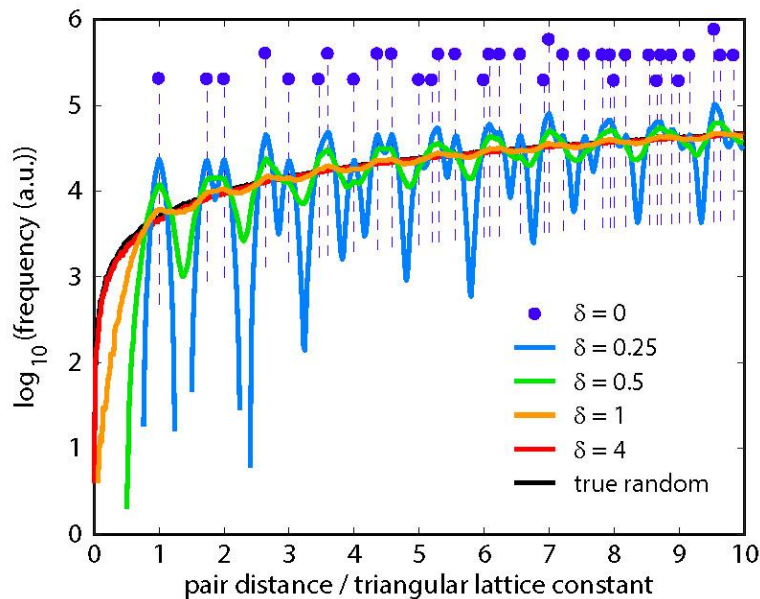


464

465 **Figure 4: Structure stabilizes larger numbers of species, but increasing competitive asymmetry**
 466 **increases species loss. (A)** Holding the structural scale fixed with no disorder, we measured the survival
 467 probability as a function of the initial number of species, between 2 and 12, across multiple values of
 468 competitive asymmetry. For lower values of competitive asymmetries, the final and initial numbers of
 469 species were essentially equal ($\alpha \sim 1$). Higher levels of competitive asymmetry resulted in increasing
 470 degrees of species loss as the number of species increased. This amplification of species loss is related, at
 471 least in part, to the same interplay between structural scale and maximum interface curvature that caused
 472 species loss in Fig. 2. **(B)** Comparing identical conditions between two different system sizes ($L = 100$
 473 and $L = 200$), the effects of disorder are relatively small in comparison to the effects system size, with
 474 smaller system sizes (blue lines) showing a significant amplification of reduction in survival probability as
 475 compared to the larger system. In all simulations $\langle P \rangle = 0.25$ and $R = 3$.

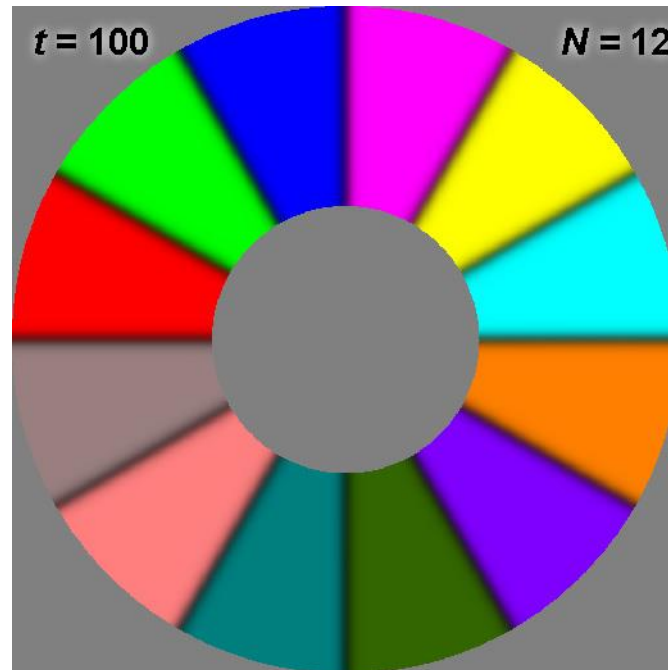
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Supplementary Information:
Competitive ecosystems are robustly stabilized by structured environments
Tristan Ursell, Department of Physics, University of Oregon



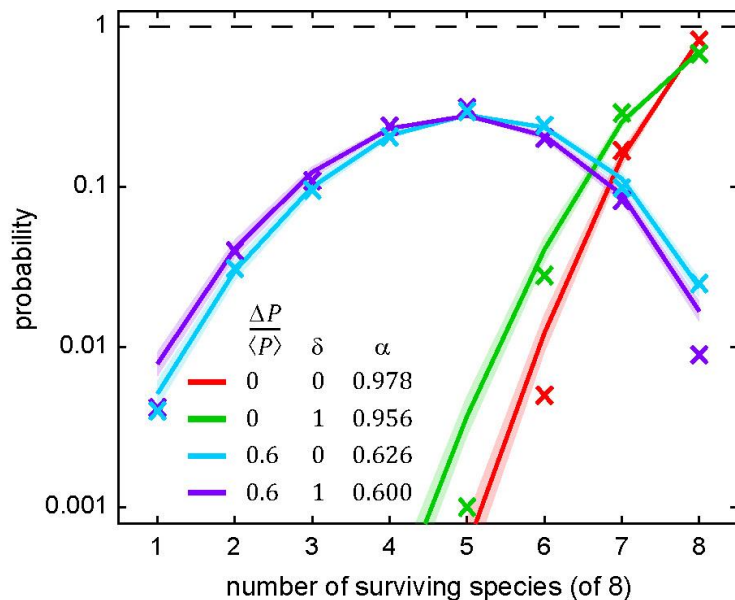
480

481 **SI Figure 1.** The pairwise distance distribution as a function of the disorder parameter δ . The distribution
482 of separations between any two steric pillars does not depend on the size of the space in which those
483 objects exist, assuming that the density of those objects is held fixed. For a perfect triangular lattice ($\delta =$
484 0), that distribution is a series of delta-functions (purple dots). Adding structural disorder ($\delta > 0$) makes
485 the distributions continuous, with increasing degrees of disorder ultimately approaching the distribution
486 expected for randomly placed objects at a fixed density (black line). As δ increases, the arrangement of
487 steric pillars transitions smoothly from a triangular lattice to a random arrangement – in this work, we
488 explored $0 \leq \delta \leq 1$.



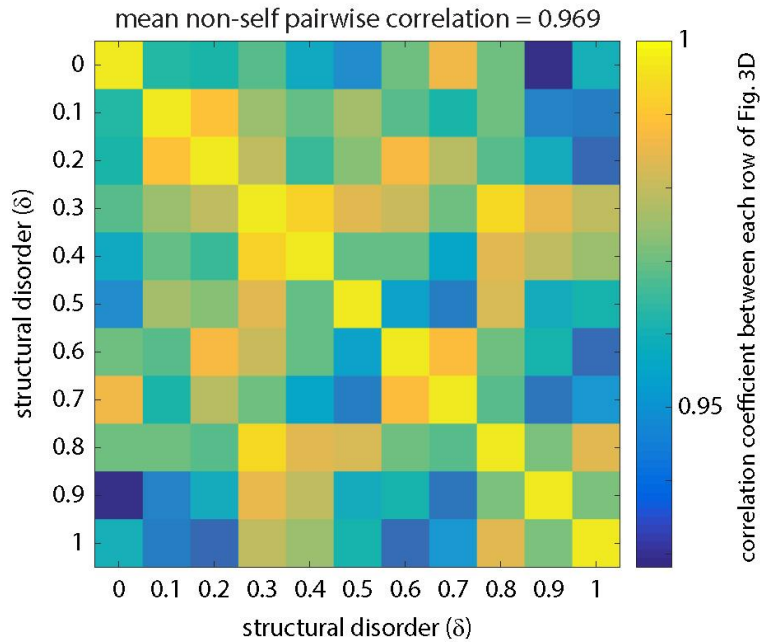
489

490 **SI Figure 2.** Here a simulation is contrived via initial conditions to have 12 species stably coexist, each
491 making contact with the same steric object (gray circle in the center). The outer edge is also circular which
492 permits stable coexistence of multiple species in a single open space. This figure demonstrates that, for a
493 sufficiently large steric object as compared to the width of the interspecies transition zone, any number
494 of species can 'share' a boundary with an object. However, in an environment with many steric objects
495 in proximity, the local Voronoi neighborhood limits the maximum number of species that can exist around
496 an object, usually to 3 or 4.



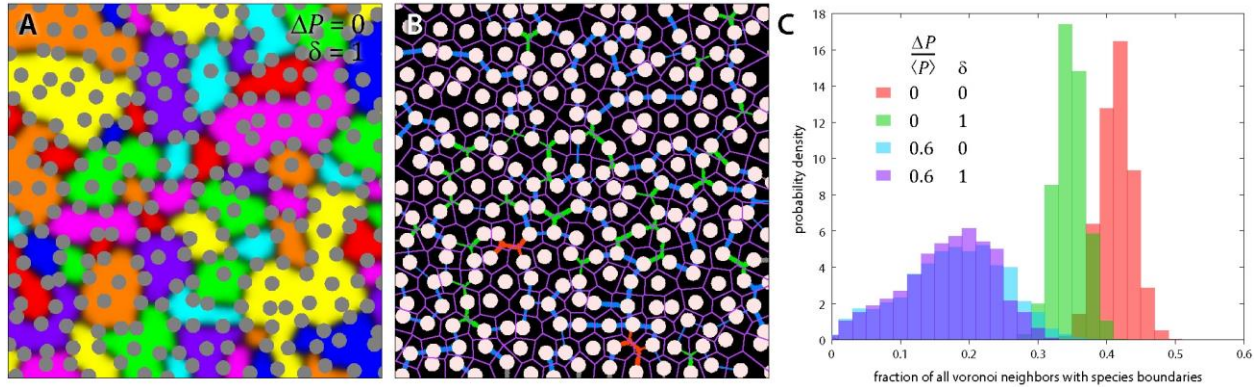
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498 **SI Figure 3.** The type and format of data herein presented are the same as in Fig. 3B – the only difference
 499 is that here the simulation box is half the linear size (1/4 the area). Simulations were performed to
 500 measure the probability distribution for the number of surviving species under four conditions (1,000
 501 each): high and low competitive asymmetry and high and low structural disorder. The structural scale was
 502 held fixed. We used a maximum likelihood estimator (MLE) to measure the ensemble average survival
 503 probability (α) under those four conditions. Without competitive asymmetry (red and green X's), the
 504 number of surviving species was heavily weighted toward the maximum possible number (8). With high
 505 competitive asymmetry, the probability distributions spread across all possible numbers of species with
 506 relatively little distinction between ordered and disordered systems (cyan and purple X's). In all instances,
 507 the corresponding MLE fits are shown as solid lines. These results support the hypothesis that, regardless
 508 of structural scale, smaller environments hinder long-term species coexistence. In all simulations $L = 75$,
 509 $\langle P \rangle = 0.25$, and $\Delta x/R = 3.5$.



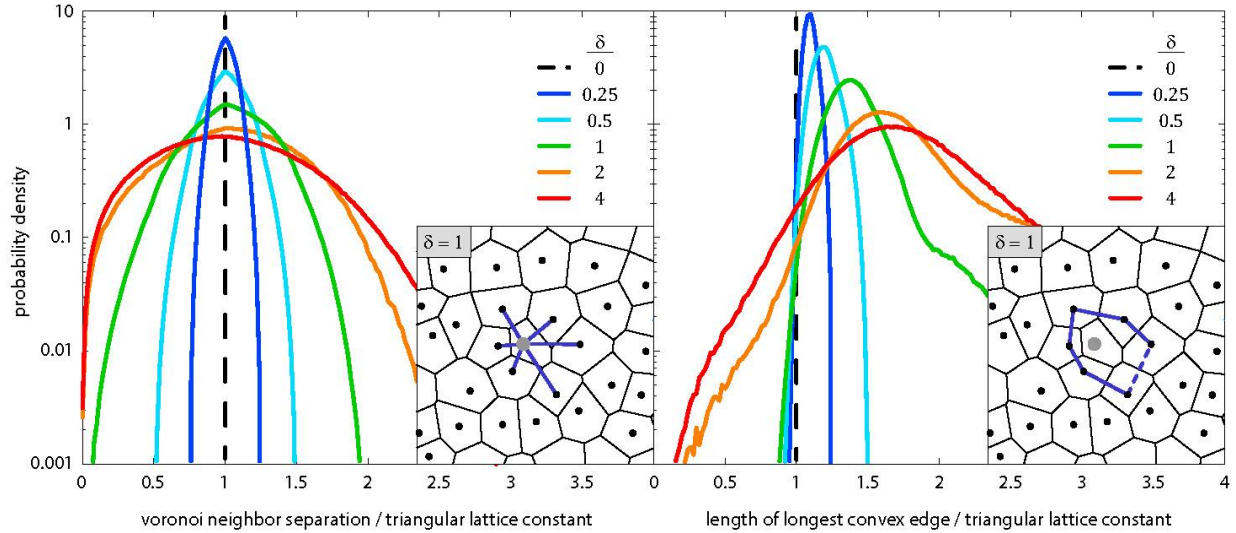
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511 **SI Figure 4.** To determine the impact of steric disorder on the mean number of surviving species,
512 independent of the effect of competitive asymmetry, we correlated each row of Fig. 3D with every other
513 row of the same figure (55 unique correlations). All of those correlations were greater than 0.928, and the
514 mean of all of those correlations was 0.969, meaning that over a range of steric disorder the relationship
515 between mean number of surviving species and competitive asymmetry was quantitatively similar.



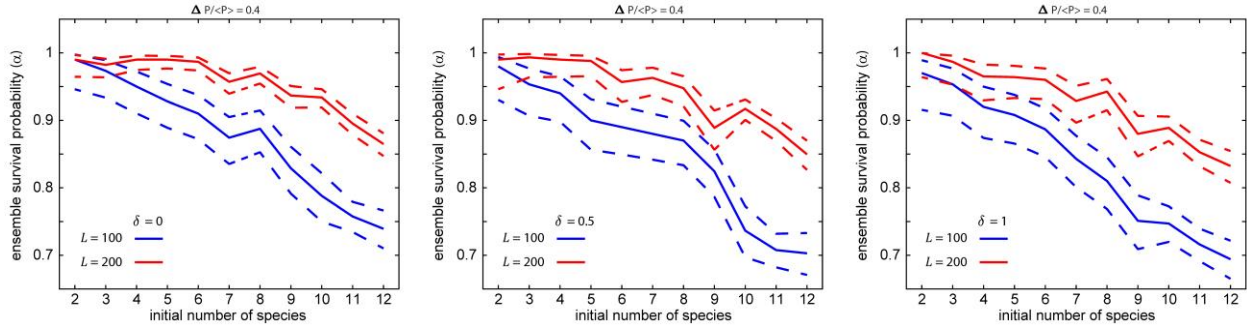
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517 **SI Figure 5.** Using the same 4,000 simulations from Fig. 3, we examined the density of interspecies
518 boundaries under those four conditions. **(A)** A sample image of 8 competing species in a disordered steric
519 environment. Species establish spatial domains (solid colors) with dark boundaries between those
520 domains where active competition takes places. **(B)** Across all simulations (though here for the same
521 image as A), custom image analysis software examined the positions of each pillar (white) and the
522 corresponding Voronoi tessellation (magenta tessellation) that indicates which pillars are Voronoi nearest
523 neighbors. Image analysis algorithms segmented the interspecies boundaries between pillars and
524 classified them according to how many pillars a boundary connected (blue = 2, green = 3, orange = 4).
525 Approximately 2% of all connections were not Voronoi nearest neighbors (data not shown), and thus these
526 connections were not used in this analysis. Boundaries that made contact with the edge of the simulation
527 (gray) were not used in this analysis. **(C)** For each set of conditions, here shown as four colors (same colors
528 as in Fig. 3B), we calculated the number of connections made by boundaries between Voronoi nearest
529 neighbors as compared to the maximum possible number of boundaries (boundaries between all Voronoi
530 nearest neighbors). While there is a notable difference between ordered and disordered connection
531 density when competition is balanced (red and green), the salient difference is between balanced (red /
532 green) and asymmetric (cyan / purple) competition. Systems with asymmetric competition have
533 significantly fewer connections between objects, consistent with their higher abundance variability, and
534 thus there is effectively less competition (i.e. fewer interfaces) in asymmetric systems.



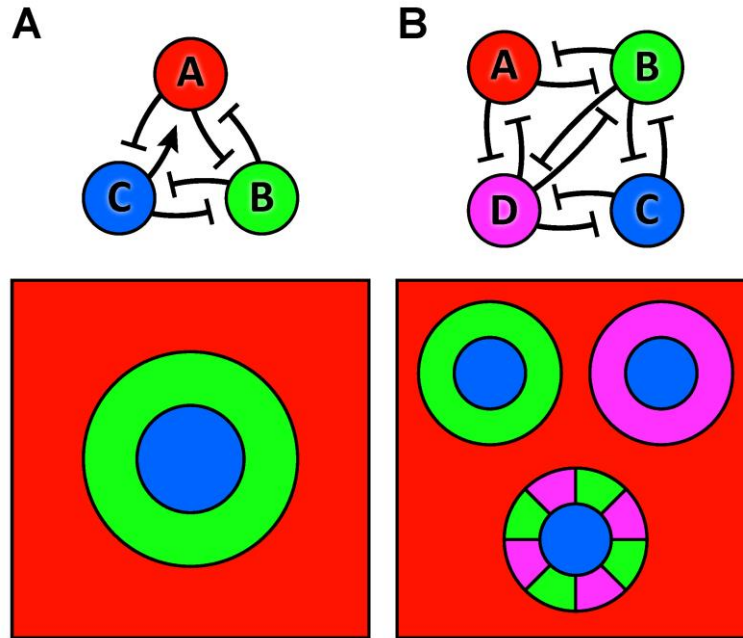
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536 **SI Figure 6.** Local statistics of Voronoi tessellation as a function of the structural disorder. **(left)**
537 Distributions of distances between Voronoi nearest neighbors. In a perfect triangular lattice this
538 distribution is a delta-function (black dashed line). As disorder increases the distribution of nearest
539 neighbor distances spreads out and a significant fraction of neighbors are found closer together than in a
540 triangular lattice of the same overall density. The vast majority of interspecies boundaries are between
541 Voronoi nearest neighbors. Thus widening of the distribution impacts whether a particular interspecies
542 boundary is stable, because the maximum curvature and hence maximum competitive asymmetry that is
543 stable at a boundary is set by the distance between the objects that the boundary connects. The inset
544 shows an example of a Voronoi neighborhood and the local distances being measured (dark blue lines).
545 **(right)** We examined hypothetical domains defined by the convex polygon around a steric object (see
546 inset) – this defines a consistent region inside of which a competitor could stably exist (many other
547 polygons could also be drawn). Across a large number of such polygon domains, we measured the
548 distribution of longest edge lengths as a function of structural disorder. If the longest edge is less than the
549 triangular lattice constant with the same overall density, then this domain is guaranteed to be more stable
550 to competitive asymmetry than the corresponding ordered polygon. As disorder increases, the fraction of
551 all such polygons that meet this more stringent stability condition increases, supporting the hypothesis
552 that disorder should have a stabilizing effect when competition is asymmetric, contingent on there being
553 a sufficiently large area and hence sufficient opportunities for such domains to exist.



554

555 **SI Figure 7.** Same exact data as shown in Fig. 4B in the text, separated by value of δ and shown with 95%
556 confidence intervals (dashed lines) determined by maximum-likelihood estimation. Variations caused by
557 differences in δ are not significant, but variations caused by system-size differences are significant.



558

559 **SI Figure 8.** Spatial arrangements of species that support stability in non-all-to-all graphs. **(A)** The simplest
560 example of a non-ATA graph (top) for which species abundances are stable in a structured environment –
561 a single matrix element (arrow from C to A) breaks the ATA condition. The schematic (bottom) shows an
562 arrangement of species that is stable, even though an interspecies boundary between A and C is not stable
563 in any structured environment; this is the only arrangement that can stably support all three species for
564 the graph shown. **(B)** A second, more complex example where four species can be arranged to yield stable
565 abundances of all species, regardless of the interaction between species A and C (no connection shown).
566 This graph admits three arrangements that allow A and C to coexist regardless of their interaction.

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