

# 1 Mortality causes universal changes in microbial community composition

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## 6 **Abstract**

7 All organisms are sensitive to the abiotic environment, and a deteriorating  
8 environment can lead to extinction. However, survival in a multispecies  
9 community also depends upon inter-species interactions, and some species may  
10 even be favored by a harsh environment that impairs competitors. A  
11 deteriorating environment can thus cause surprising transitions in community  
12 composition. Here, we combine theory and laboratory microcosms to develop a  
13 predictive understanding of how simple multispecies communities change under  
14 added mortality, a parameter that represents environmental harshness. In order  
15 to explain changes in a multispecies microbial system across a mortality gradient,  
16 we examine its members' pairwise interactions. We find that increasing mortality  
17 favors the faster grower, confirming a prediction of simple models. Furthermore,  
18 if the slower grower outcompetes the faster grower in environments with low or  
19 no added mortality, the competitive outcome can reverse as mortality increases.  
20 We find that this tradeoff between growth rate and competitive ability is indeed  
21 prevalent in our system, allowing for striking pairwise outcome changes that  
22 propagate up to multispecies communities. These results argue that a bottom-up  
23 approach can provide insight into how communities will change under stress.

## 24 **Introduction**

25 Ecological communities are defined by their structure, which includes  
26 species composition, diversity, and interactions<sup>1</sup>. All such properties are  
27 sensitive to the abiotic environment, which influences both the growth of  
28 individual species and the interactions between them. The structure of  
29 multispecies communities can thus vary in complex ways across environmental  
30 gradients<sup>2-7</sup>. A major challenge is therefore to predict how a changing  
31 environment affects competition outcomes and alters community structure. In  
32 particular, environmental deterioration can radically change community structure.  
33 Instances of such deterioration include antibiotic use on gut microbiota<sup>8</sup>, ocean  
34 warming in reef communities<sup>9</sup>, overfishing in marine ecosystems<sup>10</sup>, and habitat  
35 loss in human-modified landscapes<sup>11</sup>. Such disturbances can affect community  
36 structure in several ways, such as allowing for the spread of invasive species<sup>12</sup>,  
37 causing biodiversity loss and mass extinction<sup>13,14</sup>, or altering the interactions  
38 between the remaining community members<sup>15,16</sup>. For example, a stable  
39 ecosystem can be greatly disrupted by the removal of a single keystone species,  
40 potentially affecting species with which it does not directly interact<sup>17-19</sup>.

41 A common form of environmental deterioration is increased mortality,  
42 which can be implemented in the laboratory in a simple way. In fact, the  
43 standard method of cultivating and competing bacteria involves periodic dilution

44 into fresh media, a process that necessarily discards cells from the population.  
45 The magnitude of the dilution determines the fraction of cells discarded and  
46 therefore the added mortality rate, making environmental harshness easy to tune  
47 experimentally.

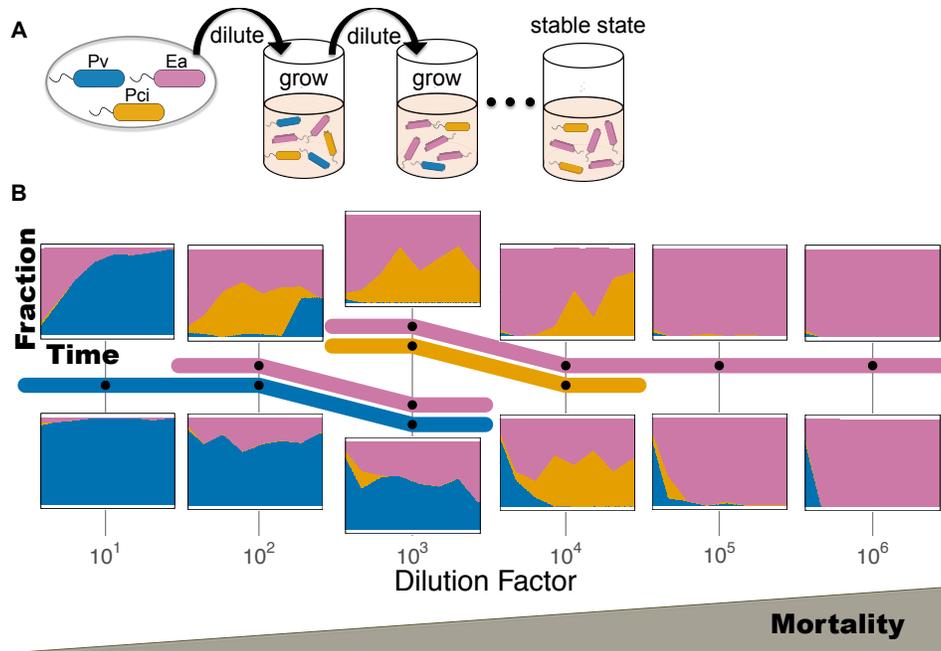
48 The choice of dilution factor often receives little attention, yet theoretical  
49 models predict that an increased mortality rate experienced equally by all species  
50 in the community can have dramatic effects on community composition. In  
51 particular, it is predicted that such a global mortality will favor the faster-growing  
52 species in pairwise competition, potentially reversing competition outcomes from  
53 dominance of the slow grower to dominance of the fast grower<sup>1,20,21</sup>. Indeed,  
54 there is some experimental support for competitive reversals in chemostat  
55 competition experiments between microbial species with different growth rates<sup>22–</sup>  
56 <sup>24</sup>. A less-explored prediction is that if a high mortality rate causes a competitive  
57 reversal, the competition will also result in either coexistence or bistability (where  
58 the winner depends on the starting fraction) at some range of intermediate  
59 mortality<sup>25–27</sup>. In addition, little is known about how mortality will alter the  
60 composition of multispecies communities.

61 In this paper, we report experimental results that expand upon the prior  
62 literature regarding pairwise competition, and we use the pairwise outcomes to  
63 develop a predictive understanding of how multispecies community composition  
64 changes with increased mortality. First, experimental pairwise competition of five  
65 bacterial species confirmed that 1) increased mortality favors the fast grower in a  
66 competition, and can reverse the winner of the competition from slow grower to  
67 fast grower, and 2) at intermediate dilution rates, either coexistence or bistability  
68 occurs. Interestingly, we find that a pervasive tradeoff between growth rate and  
69 competitive ability in our system favors slow growers in high-density, low-  
70 mortality environments, enabling striking changes in outcomes as mortality  
71 increases. Second, to bridge the pairwise results to three- and four-species  
72 communities, we employed simple predictive pairwise assembly rules<sup>28</sup>, where  
73 we find that the pairwise outcomes such as coexistence and bistability propagate  
74 up to the multispecies communities. Our results highlight that the seemingly  
75 complicated states a community adopts across a mortality gradient can be traced  
76 back to a predictable pattern in the outcomes of its constituent pairs.

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## 79 **Results**



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**Figure 1: Increasing dilution causes striking shifts in a three-species community.** **A)** To probe how added mortality changes community composition, we competed three soil bacteria over a range of dilution rates. Cells were inoculated and allowed to grow for 24 hours before being diluted into fresh media. This process was continued for seven days, until a stable equilibrium was reached. The magnitude of the dilution factor (10 to 10<sup>6</sup>) determines the fraction of cells discarded, and thus the amount of added mortality. **B)** We began with a three-species community (*Enterobacter aerogenes* (*Ea*), *Pseudomonas citronellolis* (*Pci*), and *Pseudomonas veronii* (*Pv*)), initialized from four starting fractions at each dilution factor. The outcomes of two of the starting fractions are shown, along with a “subway” map, where survival of species is represented with colors assigned to each species. Black dots indicate where data was collected, while colors indicate the range over which a given species is inferred to survive. Species *Pv* dominates at the lowest dilution factor, and *Ea* dominates at the highest dilution factors. The stacking of two colors represents coexistence of two species, whereas the two levels at dilution factor 10<sup>3</sup> indicate bistability, where both coexisting states, *Ea-Pv* and *Ea-Pci*, are stable and the starting fraction determines which stable state the community reaches.

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To probe how a changing environment affects community composition, we employed an experimentally tractable system of soil bacteria competitions subject to daily growth/dilution cycles across six dilution factors (Fig. 1A). We selected five species of soil bacteria: *Enterobacter aerogenes* (*Ea*), *Pseudomonas aurantiaca* (*Pa*), *Pseudomonas citronellolis* (*Pci*), *Pseudomonas putida* (*Pp*), and *Pseudomonas veronii* (*Pv*). These species have been used in previous experiments by the group, which did not vary dilution factor<sup>28,29</sup>. All five species grow well in our defined media containing glucose as the primary carbon source (see Methods) and have distinct colony morphology that allows for measuring species abundance by plating and colony-counting on agar.

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We began by competing three of the five species, *Ea*, *Pci*, and *Pv*, for seven 24-hour cycles under six different dilution factor regimes. To assay for alternative stable states, each dilution factor condition was initialized by four different starting fractions (equal abundance as well as prevalence of one species in a 90-5-5% split). Despite the simplicity of the community and the experimental perturbation, we observed five qualitatively different outcomes corresponding to different combinations of the species surviving at equilibrium

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99 (Fig. 1B). At the highest and lowest dilution factors, one species excludes the  
100 others at all starting fractions ( $Pv$  at low dilution,  $Ea$  at high dilution). Two  
101 coexisting states ( $Ea-Pv$  and  $Ea-Pci$ ) occur at medium low ( $10^2$ ) and medium  
102 high ( $10^4$ ) dilution factors, again independent of the starting fractions of the  
103 species. However, at intermediate dilution factor ( $10^3$ ), we found that the  
104 surviving species depended upon the initial abundances of the species. At this  
105 experimental condition, the system displays bistability between the two different  
106 coexisting states ( $Ea-Pv$  and  $Ea-Pci$ ) that were present at neighboring dilution  
107 factors. These three species therefore display a surprisingly wide range of  
108 community compositions as the mortality rate is varied.

109 To make sense of these transitions in community composition, we decided  
110 to first focus on two-species competitions, not only because they should be  
111 simpler, but also because prior work from our group gives reason to believe that  
112 pairwise outcomes are sufficient for predicting multispecies states<sup>28</sup>. Accordingly,  
113 we used a simple two-species Lotka-Volterra competition model with an added  
114 mortality term  $\delta N_i$  experienced equally by both species<sup>21</sup>:

$$115 \quad \dot{N}_i = r_i N_i (1 - N_i - \alpha_{ij} N_j) - \delta N_i$$

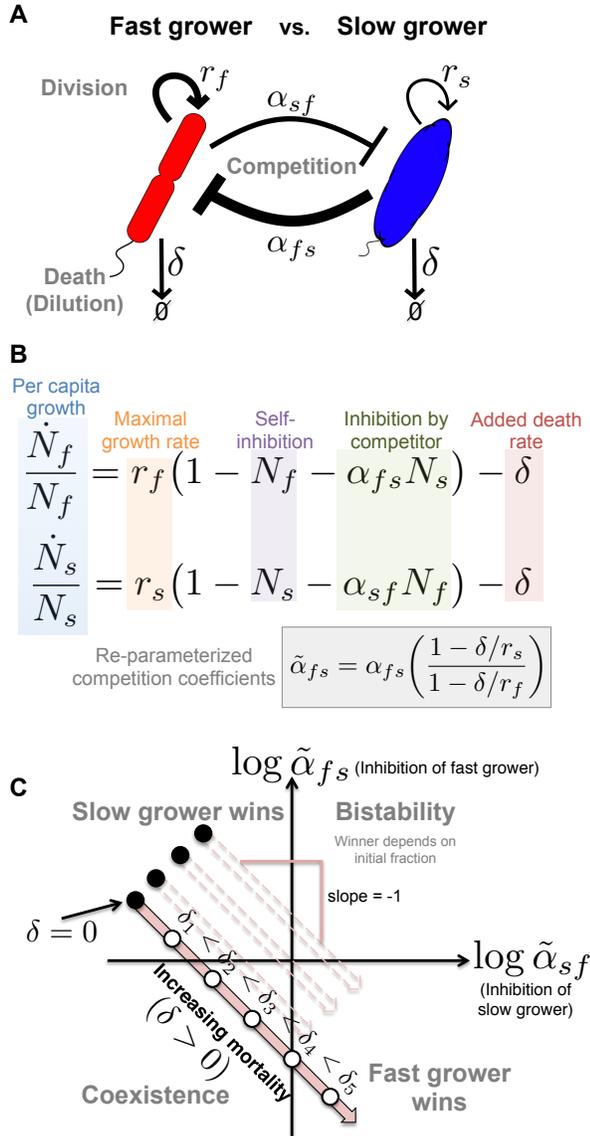
116 where  $N_i$  is the density of species  $i$  (normalized to its carrying capacity),  $r_i$  is the  
117 maximum growth rate of species  $i$ , and the competition coefficient  $\alpha_{ij}$  is a  
118 dimensionless constant reflecting how strongly species  $i$  is inhibited by species  $j$   
119 (Fig. 2). This model can be re-parameterized into the Lotka-Volterra model with  
120 no added mortality, where the new competition coefficients  $\tilde{\alpha}_{ij}$  now depend upon  
121  $r_i$  and  $\delta$  (see S2 for derivation):

$$122 \quad \tilde{N}_i = \tilde{r}_i \tilde{N}_i (1 - \tilde{N}_i - \tilde{\alpha}_{ij} \tilde{N}_j)$$

$$123 \quad \tilde{\alpha}_{ij} = \alpha_{ij} \frac{\left(1 - \frac{\delta}{r_j}\right)}{\left(1 - \frac{\delta}{r_i}\right)}$$

124 The outcome of competition—dominance, coexistence, or bistability—simply  
125 depends upon whether each of the  $\tilde{\alpha}$  are greater or less than one, as in the basic  
126 Lotka-Volterra competition model<sup>21</sup>.

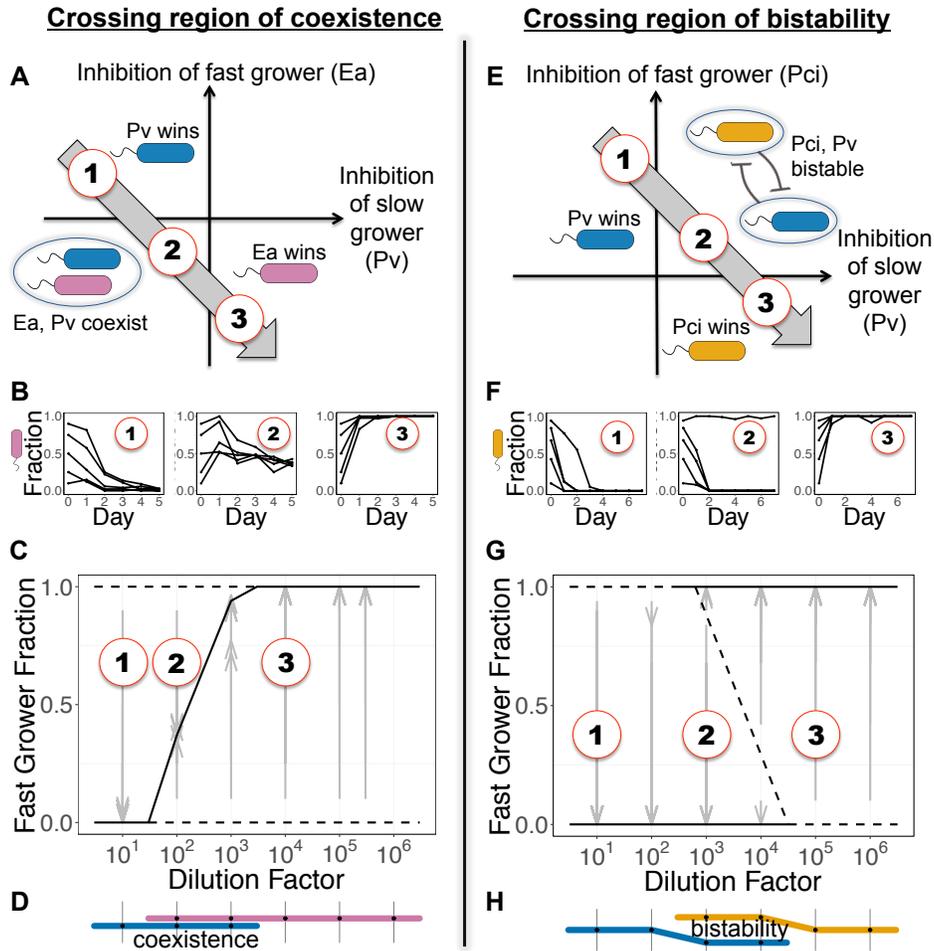
127 In this model, it is possible for a slow grower ( $N_s$ ) to outcompete a fast  
128 grower ( $N_f$ ) if the slow grower is a strong competitor ( $\alpha_{fs} > 1$ ) and the fast  
129 grower is a weak competitor ( $\alpha_{sf} < 1$ ) (Fig. 2). However, the competition  
130 coefficients change with increasing mortality  $\delta$  in a way that favors the fast  
131 grower:  $\tilde{\alpha}_{fs}$  shrinks and  $\tilde{\alpha}_{sf}$  grows, eventually leading the fast grower to  
132 outcompete the slow grower. A powerful way to visualize this change is to plot  
133 the outcomes, as determined by the competition coefficients (Fig 2C); increasing  
134 mortality causes the outcome to traverse a 45° trajectory through the phase  
135 space, leading to the fast grower winning at high mortality. At intermediate  
136 mortality, the model predicts the two species will either coexist or be bistable.  
137 This model therefore makes very clear predictions regarding how pairwise  
138 competition will change under increased mortality, given the aforementioned slow  
139 grower advantage at low mortality.



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**Figure 2: An increasing global mortality rate is predicted to favor the fast grower. A-B)** Here we illustrate the parameters of the Lotka-Volterra (LV) interspecific competition model with added mortality: population density  $N$ , growth  $r$ , death  $\delta$  (subscript  $f$  for fast grower and  $s$  for slow grower), and the strengths of inhibition  $\alpha_{sf}$  and  $\alpha_{fs}$ . The width of arrows in (A) corresponds to an interesting case that we observe experimentally, in which the fast grower is a relatively weak competitor. **C)** The outcomes of the LV model without mortality depend solely upon the competition coefficients  $\alpha$ , and the phase space is divided into one quadrant per outcome. If it is a strong competitor, the slow grower can exclude the fast grower. Imposing a uniform mortality rate  $\delta$  on the system, however, favors the faster grower by making the re-parameterized competition coefficients  $\tilde{\alpha}$  depend on  $r$  and  $\delta$ . Given that a slow grower dominates at low or no added death, the model predicts that coexistence or bistability will occur at intermediate added death rates before the outcome transitions to dominance of the fast grower at high added death (see S2 for derivation).

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**Figure 3: In pairwise competition experiments, increasing dilution favors the faster grower, and coexistence or bistability occur at intermediate dilution.** **A)** Experimental results are shown from a competition between *Pv* (blue) and *Ea* (pink). **B) Left panel:** Despite its slow growth rate, *Pv* excludes faster grower *Ea* at the lowest dilution factor. **Middle panel:** Increasing death rate causes the outcomes to traverse the coexistence region of the phase space. **Right panel:** As predicted, fast-growing *Ea* dominates at high dilution factor. **C)** An experimental bifurcation diagram shows stable points with a solid line, and unstable points with a dashed line. The stable fraction of coexistence shifts in favor of the fast grower as dilution increases. Gray arrows show experimentally measured time trajectories, beginning at the starting fraction and ending at the final fraction. **D)** A “subway map” denotes survival/extinction of a species at a particular dilution factor with presence/absence of the species color. **E-F)** *Pv* outcompeted another fast grower *Pci* (yellow) at low dilution factors, but the pair became bistable instead of coexisting as dilution increased; the unstable fraction can be seen to shift in favor of the fast grower (**G**). **H)** Two levels in the subway map show bistability.

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145 To test these predictions in the laboratory, we performed all pairwise  
 146 competitions at multiple dilution factors and starting fractions of our five bacterial  
 147 species: *Pp*, *Ea*, *Pci*, *Pa*, *Pv* (listed in order from fast to slow growing species).

148 We find that these pairwise competitive outcomes change as expected from the  
 149 LV model, where increased dilution favors the fast grower (Fig S1). For example,

150 in *Ea-Pv* competition we find that *Pv*, despite being the slower grower, is able to  
 151 exclude *Ea* at low dilution rates (Fig 3B, left panel). From the standpoint of the

152 LV model, *Pv* is a strong competitor despite being a slow grower in this

environment. However, as predicted by the model, at high dilution rates the slow-

153 growing *Pv* is excluded by the fast-growing *Ea* (Fig 3B, right panel). Importantly,  
154 *Pv* is competitively excluded at a dilution factor of  $10^4$ , an experimental condition  
155 at which it could have survived in the absence of a competitor. Finally, and again  
156 consistent with the model, at intermediate dilution rates we find that the *Ea-Pv*  
157 pair crosses a region of coexistence, where the two species reach a stable  
158 fraction over time that is not a function of the starting fraction (Fig 3B, middle  
159 panel). The *Ea-Pv* pair therefore displays the transitions through the LV phase  
160 space in the order predicted by our model (Fig 3A-D).

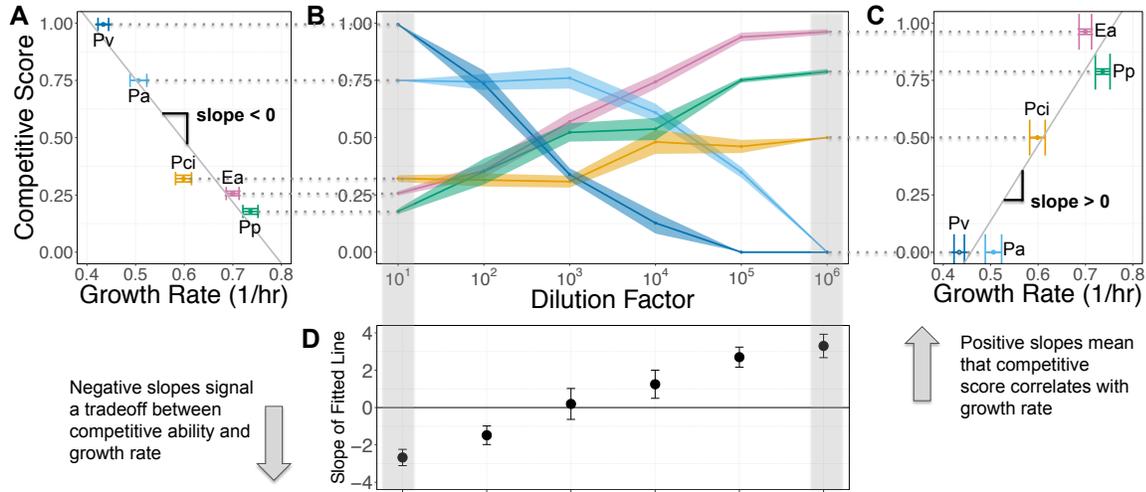
161 The LV model predicts that other pairs will cross a region of bistability  
162 rather than coexistence, and indeed this is what we observe experimentally with  
163 the *Pci-Pv* pair (Fig 3E-H). Once again, the slow-growing *Pv* dominates at low  
164 dilution factor yet is excluded at high dilution factor. However, at intermediate  
165 dilution factors this pair crosses a region of bistability, in which the final outcome  
166 depends upon the starting fractions of the species. The Lotka-Volterra model  
167 with added mortality therefore provides powerful insight into how real microbial  
168 species compete, despite the many complexities of the growth and interaction  
169 that are necessarily neglected in a simple phenomenological model.

170 Indeed, a closer examination of the trajectory through the LV phase space  
171 of the *Pci-Pv* pair reveals a violation of the simple outcomes allowed within the  
172 LV model. In particular, at dilution factor  $10^2$  we find that when competition is  
173 initiated from high initial fractions of *Pci* that *Pv* persists at low fraction over time  
174 (Fig. 3G). This outcome, a bistability of coexistence and exclusion (rather than of  
175 exclusion and exclusion), is not an allowed outcome within the LV model  
176 (modifications to the LV model can give rise to it, as shown by <sup>30</sup>). This subtlety  
177 highlights that the transitions (e.g. bifurcation diagrams in Fig 3C,G) can be more  
178 complex than what occurs in the LV model, but that nonetheless the transitions  
179 within the LV model represent a baseline to which quantitative experiments can  
180 be compared.

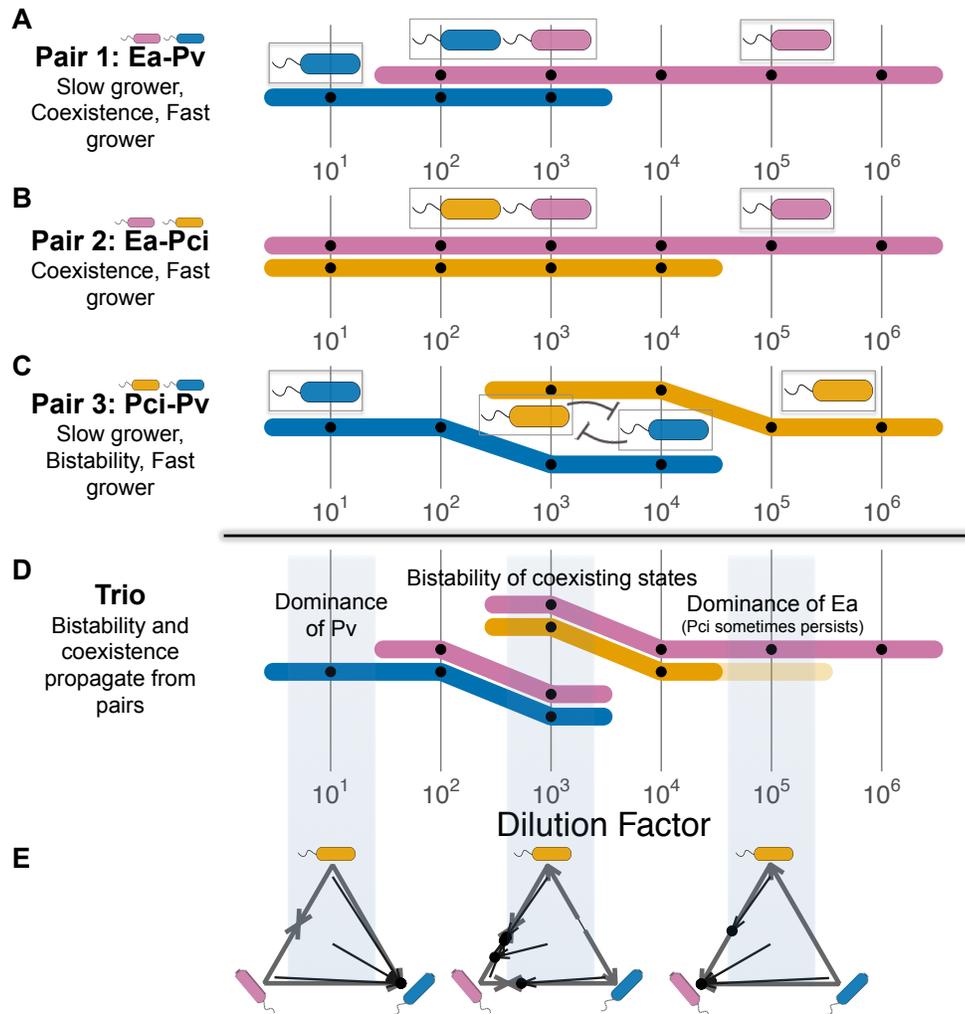
181 The model predicts that mortality will reverse competition outcomes if and  
182 only if a slow grower outcompetes a fast grower at low or no added death,  
183 exhibiting a tradeoff between growth and competitive ability. Changes in  
184 outcome are therefore most dramatic when a strongly competing slow grower  
185 causes the trajectory to begin in the upper left quadrant of the phase space (Fig.  
186 3A, E), allowing it to move through other quadrants as mortality increases.  
187 Indeed, in the pairwise competitions described above, the slowest-growing  
188 species, *Pv*, is a strong competitor at low dilution factor. To probe this potential  
189 tradeoff more extensively, we compared the growth rates of our five species in  
190 monoculture (Fig. S3) to their competitive performance at low dilution factor. In  
191 seven of the ten pairs, the slower grower excluded the faster grower, and the  
192 other three pairs coexisted (Fig. S1). We therefore find that our five species  
193 display a pervasive tradeoff between growth rate and competitive ability, possibly  
194 because the slower-growing species fare better in high-density environments that  
195 reach saturation.

196 To visualize how competitive success changes with dilution factor, we  
197 defined the competitive score of each species to be its mean fraction after  
198 reaching equilibrium in all pairs in which it competed. The aforementioned

199 tradeoff can be seen as an inverse relationship between growth rate and  
 200 competitive score at the lowest dilution factor (Fig. 4A). As predicted, the  
 201 performance of the fast-growing species increases monotonically with increasing  
 202 dilution factors (Fig. 4B). Competitive superiority of the slowest grower (*Pv*) at  
 203 low dilution rates transitions to the next-slowest (*Pa*) at intermediate rates, before  
 204 giving rise to dominance of the fastest growers (*Pci*, *Ea*, *Pp*) at maximum rates  
 205 (Fig 4B-D). We therefore find that the mortality rate largely determines the  
 206 importance of a species' growth rate to competitive performance in pairwise  
 207 competition.  
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**Figure 4: In experimental competition of five bacterial species in pairs, a tradeoff between growth and competitive ability leads to strong dependence of outcome on dilution factor.** The LV model predicts that increasing dilution will favor faster-growing species over slower-growing ones. If fast growers dominate at low dilution factors, though, no changes in outcome will be expected. Changes in outcome are therefore most dramatic when slow growers are strong competitors at low dilution, exhibiting a tradeoff between growth rate and competitive ability. **A)** This tradeoff was pervasive in our system: slower growth rates resulted in higher competitive scores at the lowest dilution factor. Growth rate was calculated with OD600 measurements of the time taken to reach a threshold density within the exponential phase; error bars represent the SEM of replicates ( $n \sim 20$  replicates) (Fig. S3). Competitive score was calculated by averaging fraction of a given species across all pairwise competitive outcomes; error bars were calculated by bootstrapping, where replicates of mean experimental outcomes of a given pair were sampled with replacement. **B)** The competitive scores in **A)** are extended to all dilution factors. The slowest grower's score monotonically decreases with dilution, while the fast growers' scores increase, and an intermediate grower peaks at intermediate dilution factor. **C)** At high dilution factors, the order of scores is reversed. **D)** At low dilution factors  $10^1$  and  $10^2$ , competitive ability is negatively correlated with growth rate; the correlation becomes positive above dilution factor  $10^3$ . Error bars are the standard error coefficients given by the linear regression function `lm` in R.



**Figure 5: Coexistence and bistability propagate from pair to trio, as predicted by assembly rules.** **A-C)** “Subway maps” show pairwise competition outcome trajectories across changing dilution factor, as explained in Figs. 1 and 3. The fast grower’s line is always plotted above the slow grower’s line. Of the three pairs that make up the community *Ea-Pci-Pv*, two are coexisting (**A**, **B**) and one is bistable (**C**). **D)** The pairwise assembly rules state that a species will survive in a community if it survives in all corresponding pairs. At dilution factor 10, *Ea* and *Pci* coexist, but both are excluded by *Pv*. The rules correctly predict that *Pv* will dominate in the trio. Because both species can be excluded in a bistable pair, a bistable pairwise outcome propagates to the trio as more than one allowed state. Each of the bistable species can be seen separately coexisting with *Ea* at dilution factor  $10^3$ , as they do in pairs. The assembly rules failed at  $10^5$  for one out of four starting conditions: *Pci* coexists with *Ea* when it should go extinct (Fig. S8). **E)** Three-species competition results are shown in simplex plots. Arrows begin and end at initial and final fractions, respectively. Edges represent pairwise results, and black dots represent trio results.

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Now that we have an understanding of how pairwise competitive outcomes shift in response to increased mortality, we return to the seemingly complicated set of outcomes observed in our original three-species community (Fig. 1). In a previous study<sup>28</sup>, we developed community assembly rules that allow for prediction of species survival in multispecies competition from the corresponding pairwise competition outcomes. These rules state that in a multispecies competition, a species will survive if and only if it coexists with all other surviving species in pairwise competition. If one or more bistable pairs is involved in a multispecies community, the assembly rules allow for either of the

220 stable states. We see that the seemingly complicated trio outcomes follow from  
 221 these assembly rules applied to our corresponding pairwise outcomes at all  
 222 dilution factors (Fig. 5). For example, at the lowest dilution factor (10), *Ea-Pci*  
 223 coexist, but each of these species is excluded by *Pv* in pairwise competition, thus  
 224 leading to the (accurate) prediction that only *Pv* will survive in the trio competition.  
 225 In addition, we observe that the bistability of *Pci-Pv* at dilution factor  $10^3$   
 226 propagates up to lead to bistability in the trio, but with each stable state  
 227 corresponding to coexistence of two species. The only trio outcome not  
 228 successfully predicted by the rules is the occasional persistence of *Pci* at a  
 229 dilution factor of  $10^5$  (Figs. 5D, S8). Our analysis of pairwise shifts under  
 230 increased mortality therefore provides a predictive understanding of the complex  
 231 shifts observed within a simple three-species bacterial community.

232 To determine whether our analysis of community shifts under mortality is  
 233 more broadly applicable, we combined our five species into various three- and  
 234 four-species subsets, similar to the *Ea-Pci-Pv* competition (Fig. 5). In total, we  
 235 competed five three-species communities and three four-species communities at  
 236 all six dilution factors. Overall, a quantitative generalization of our assembly  
 237 rules (see Methods) predicted the equilibrium fractions with an error of 14%,  
 238 significantly better than the 39% error that results from predictions obtained from  
 239 monoculture carrying capacity (Table 1, Fig. S2). These results indicate that  
 240 pairwise outcomes are good predictors of multispecies states in the presence of  
 241 increased mortality.

Estimate Type	Errors: Trios	Quads	Overall
Carrying Capacities (Monocultures)	0.385	0.395	<b>0.39</b>
Pairwise Outcomes	0.093	0.190	<b>0.14</b>

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**Table 1: Errors of pairwise assembly rules are much lower than errors of estimates using monoculture carrying capacity.** We made quantitative predictions of the relative fractions in multispecies competition outcomes using both monoculture carrying capacities as well as the pairwise assembly rules. Errors of quantitative predictions are the L2 norm of the distance between predicted fixed point and observed fixed point (see Methods and Fig. S2). The values shown are mean error normalized by the maximum error.

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## Discussion

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The question of how community composition will change in a deteriorating environment is essential, as climate change, ocean acidification, and deforestation infringe upon many organisms' habitats, increasing mortality either directly, by decimating populations, or indirectly, by making the environment less hospitable to them. We used an experimentally tractable microbial microcosm to tune mortality through dilution rate, and found a pervasive tradeoff between growth rate and competitive ability (Fig. 4). This tradeoff causes slow growers to outcompete fast growers in high-density, low-dilution environments. Increasing mortality favors fast growers, in line with model predictions. We observed coexistence and bistability at intermediate dilution factors in pairwise experiments

255 (Fig. 3), and found that such coexistence and bistability propagated up to three-  
256 and four-species communities (Fig. 5). Coexistence was more common than  
257 bistability, which is in line with expectations of optimal foraging theory<sup>1</sup>. We were  
258 able to explain seemingly complicated multispecies states with pairwise results,  
259 which traversed all possible competition outcomes allowed by the two-species  
260 model.

261 The aforementioned tradeoff made for striking transitions in the  
262 communities that we studied. Without the tradeoff, the model would be less  
263 useful. If a fast grower outcompetes a slow grower at low dilution rates, the  
264 model predicts no change in outcome at higher dilution rates. Our results at low  
265 dilution are consistent with previous experimental evidence of a tradeoff between  
266 growth and competitive ability among different mutants of the same bacterial  
267 strain<sup>31</sup> and protozoa<sup>32</sup>. Additionally, data show that antibiotic resistance, despite  
268 its clear competitive benefit, imposes a fitness cost on bacteria<sup>33</sup>. There is also  
269 evidence that seed-producing plants exhibit a growth/competition tradeoff; plants  
270 that produce larger seeds necessarily produce fewer of them, but were found to  
271 have better seedling establishment when competing with smaller-seeded  
272 plants<sup>34,35</sup>.

273 The mechanism for the competitive ability of the slow growers in our  
274 system is not easily explained; supernatant experiments, in which fast growers  
275 were placed in slow growers' filtered spent media showed little or no inhibition of  
276 growth compared to controls (Fig. S6). Furthermore, in monocultures the slow  
277 growers exhibited higher lag times than the fast growers (Fig. S5), which would  
278 seem to be disadvantageous in low-dilution, high-density conditions where  
279 resources could be quickly consumed by a competitor with a shorter lag<sup>36</sup>. The  
280 frequency of the tradeoff in other systems is a question worthy of further  
281 investigation, in particular because natural microbial systems, such as soil  
282 communities or the gut microbiome, are better represented with a low dilution  
283 rate than a high dilution rate<sup>37,38</sup>.

284 We employed a set of simple pairwise assembly rules<sup>28</sup> to predict the  
285 states of three- and four-species communities (Table 1, Fig. S2). The rules'  
286 success is in line with recent microbial experiments suggesting that pairwise  
287 interactions play a key role in determining multispecies community assembly<sup>28,39</sup>  
288 and community-level metabolic rates<sup>40</sup>; in contrast, some theory and empirical  
289 evidence supports the notion of pervasive and strong higher-order interactions<sup>41-  
290 44</sup>. Our results provide support for a bottom-up approach to simple multispecies  
291 communities, and show that pairwise interactions alone can generate  
292 multispecies states that appear nontrivial. In the model, this happens because  
293 up to three qualitative regimes of pairwise competition translate to more possible  
294 combinatorial multispecies outcomes.

295 Here we found that the LV model with added mortality provided useful  
296 guidance for how experimental competition would shift under increased dilution,  
297 but resource-explicit models may in some cases provide additional mechanistic  
298 insight<sup>45,46</sup>. In particular, various resource-explicit models can recapitulate the  
299 qualitative changes predicted by the LV model with added mortality. For  
300 example, the  $R^*$  rule states the species that can survive on the lowest equilibrium

301 resource concentration will dominate other species<sup>1</sup>. The equilibrium  
302 concentration increases with the dilution rate, thus favoring the species with the  
303 highest maximal growth rate (see S4). However, a species with a low maximal  
304 rate may dominate under low dilution if it can grow more efficiently at low  
305 resource concentrations. Resource explicit models are most commonly used for  
306 simple environments, whereas here we worked with media containing three  
307 carbon sources. In addition, we have found that complex media with many  
308 dozens of carbon sources yields similar changes in pairwise outcomes with  
309 dilution and multispecies communities that could be predicted by the pairwise  
310 assembly rules (Figs. S2,7). Further work is necessary to explore the  
311 circumstances in which phenomenological or resource-explicit models should be  
312 used<sup>47–49</sup>.

313 It is also important to note that not all deteriorating environments will  
314 cause such simple and uniform increases in mortality. Antibiotics, and in  
315 particular  $\beta$ -lactam antibiotics, might selectively attack fast growers over slow  
316 growers<sup>50</sup>. Overfishing might target certain species of fish. Climate change  
317 might affect growth rate rather than death rate by increasing temperature, which  
318 usually increases growth rates<sup>51</sup>. In such a case, it is not certain whether  
319 environmental deterioration in the form of warming would favor slow growers or  
320 fast growers. An important direction for future research is to determine whether  
321 other changes to the environment will have similarly simple consequences for the  
322 composition of microbial communities. In this study, we have seen how a simple  
323 prediction about a simple perturbation in pairwise competition—increased  
324 mortality will favor the faster-growing species—allowed us to interpret seemingly  
325 nontrivial outcomes in multispecies communities.

326

## 327 **Methods**

328

### 329 **Species and media**

330 The soil bacterial species used in this study were *Enterobacter aerogenes* (Ea,  
331 ATCC#13048), *Pseudomonas aurantiaca* (Pa, ATCC#33663), *Pseudomonas*  
332 *citronellolis* (Pci, ATCC#13674), *Pseudomonas putida* (Pp, ATCC#12633) and  
333 *Pseudomonas veronii* (Pv, ATCC#700474). All species were obtained from  
334 ATCC. Two types of growth media were used: one was complex and undefined,  
335 while the other was minimal and defined. All results presented in the main text  
336 are from the defined media. All species grew in monoculture in both media. The  
337 complex medium was 0.1X LB broth (diluted in water). The minimal medium was  
338 S medium, supplemented with glucose and ammonium chloride. It contains 100  
339 mM sodium chloride, 5.7 mM dipotassium phosphate, 44.1 mM monopotassium  
340 phosphate, 5 mg/L cholesterol, 10 mM potassium citrate pH 6 (1 mM citric acid  
341 monohydrate, 10 mM tri-potassium citrate monohydrate), 3 mM calcium chloride,  
342 3 mM magnesium sulfate, and trace metals solution (0.05 mM disodium EDTA,  
343 0.02 mM iron sulfate heptahydrate, 0.01 mM manganese chloride tetrahydrate,  
344 0.01 mM zinc sulfate heptahydrate, 0.01 mM copper sulfate pentahydrate), 0.93  
345 mM ammonium chloride, 10 mM glucose. 1X LB broth was used for initial  
346 inoculation of colonies. For competitions involving more than two species,

347 plating was done on 10 cm circular Petri dishes containing 25 ml of nutrient agar  
348 (nutrient broth (0.3% yeast extract, 0.5% peptone) with 1.5% agar added). For  
349 pairwise competitions, plating was done on rectangular Petri dishes containing  
350 45 ml of nutrient agar, onto which diluted 96-well plates were pipetted at 10 ul per  
351 well.

## 352 **Growth rate measurements**

353 Growth curves were captured by measuring the optical density of monocultures  
354 (OD 600 nm) in 15-minute intervals over a period of ~50 hours (Fig. S3). Before  
355 these measurements, species were grown in 1X LB broth overnight, and then  
356 transferred to the experimental medium for 24 hours. The OD of all species was  
357 then equalized. The resulting cultures were diluted into fresh medium at factors  
358 of  $10^{-8}$  to  $10^{-3}$  of the equalized OD. Growth rates were measured by assuming  
359 exponential growth to a threshold of OD 0.1, and averaging across many starting  
360 densities and replicates ( $n = 19$  for *Pci*,  $n = 22$  for all other species). This time-  
361 to-threshold measurement implicitly incorporates lag times, because a species  
362 with a time lag will take longer to reach the threshold OD than another species  
363 with the same exponential rate but no lag time. We also estimated lag times and  
364 exponential rates explicitly (Fig. S4). We used these measurements to develop  
365 an alternative to the time-to-threshold rates, which also incorporated lag time. To  
366 estimate this effective growth rate, we multiplied the exponential rate by a factor  
367 depending on lag time and time between daily dilutions (Fig. S5B, S4). This  
368 method does change growth rate estimates slightly, but does not change the  
369 order of growth rates among the five species, and thus the qualitative predictions  
370 of the model (Fig. S5A-B). For this reason, we preferred to use the time-to-  
371 threshold method, because it involved only one measurement, rather than two,  
372 and had a lower error.

## 373 **Competition experiments**

374 Frozen stocks of individual species were streaked out on nutrient agar Petri  
375 dishes, grown at room temperature for 48 h and then stored at 4 °C for up to two  
376 weeks. Before competition experiments, single colonies were picked and each  
377 species was grown separately in 50 ml Falcon tubes, first in 5 ml LB broth for 24  
378 h and next in 5 ml of the experimental media for 24 h. During the competition  
379 experiments, cultures were grown in 500  $\mu$ l 96-well plates (BD Biosciences), with  
380 each well containing a 200- $\mu$ l culture. Plates were incubated at 25°C and shaken  
381 at 400 rpm, and were covered with an AeraSeal film (Sigma-Aldrich). For each  
382 growth–dilution cycle, the cultures were incubated for 24 h and then serially  
383 diluted into fresh growth media. Initial cultures were prepared by equalizing OD  
384 to the lowest density measured among competing species, mixing by volume to  
385 the desired species composition, and then diluting mixtures by the factor to which  
386 they would be diluted daily (except for dilution factor  $10^{-6}$ , which began at  $10^{-5}$  on  
387 Day 0, to avoid causing stochastic extinction of any species). Relative  
388 abundances were measured by plating on nutrient agar plates. Each culture was  
389 diluted in phosphate-buffered saline prior to plating. For competitions involving  
390 more than two species, plating was done on 10 cm circular Petri dishes. For

391 pairwise competitions, plating was done on 96-well-plate-sized rectangular Petri  
392 dishes containing 45 ml of nutrient agar, onto which diluted 96-well plates were  
393 pipetted at 10 ul per well. Multiple replicates of the latter dishes were used to  
394 ensure that enough colonies could be counted. Colonies were counted after 48 h  
395 incubation at room temperature. The mean number of colonies counted, per  
396 plating, per experimental condition, was 42.

### 397 **Assembly rule predictions and accuracy**

398 In order to make predictions about three- and four-species states, we used the  
399 qualitative and quantitative outcomes of pairwise competition. The two types of  
400 pairwise outcomes allowed for two types of predictions. First, the qualitative  
401 outcomes (dominance/exclusion, coexistence, or bistability) of the pairs were  
402 used to predict whether a species would be present or absent from a community.  
403 These outcomes are shown in the “subway maps” of Fig. S1, where the presence  
404 of a species is noted by the presence of its assigned color. Coexistence is  
405 shown by two stacked colors, and bistability is shown by two separated colors.  
406 The qualitative error rate is the percentage of species, out of the total number of  
407 species (three for trios, four for quads), that are incorrectly predicted to be  
408 present or absent (Table 1, Fig. S2-A,B). The qualitative success rate is the  
409 percentage of species that are correctly predicted as present or absent (Fig. S2-  
410 D).

411 Second, the quantitative outcomes of the pairs were used to predict the  
412 quantitative outcomes of three- and four-species communities. These outcomes  
413 are shown in the fraction plots of Fig. S1, where equilibrium points are indicated  
414 by the black dots. When two or more species coexist in pairs, the assembly rules  
415 predicts they will coexist in multispecies communities, provided that an additional  
416 species does not exclude them. The predicted equilibrium coexisting fraction of  
417 two species is the same in a community as it is in a pair, while the fractions of  
418 more than two coexisting species are predicted with the weighted geometric  
419 mean of pairwise coexisting fractions. For example, in a three-species coexisting  
420 community, the fraction of species 1 depends on its coexisting fractions with the  
421 other two species in pairs:

$$422 \quad f_1 = (f_{12}^{w_2} f_{13}^{w_3})^{\frac{1}{w_2+w_3}}$$

423 where  $f_{12}$  is the fraction of species 1 after reaching equilibrium in competition  
424 with species 2,  $w_2 = \sqrt{f_{21}f_{23}}$  and  $w_3 = \sqrt{f_{31}f_{32}}$ . Finally, these predictions are  
425 normalized by setting  $f_1^* = \frac{f_1}{f_1+f_2+f_3}$ . The quantitative error of a particular  
426 community outcome is the distance of the predicted fractions from the observed  
427 community fractions, measured with the L2 norm. The maximum error, for any  
428 number of species, is  $\sqrt{2}$ , which occurs when a species that was predicted to go  
429 extinct in fact dominates:

430 
$$\sqrt{\sum((1,0, \dots, 0) - (0,1, \dots, 0))^2} = \sqrt{2}$$

431 To calculate the overall quantitative errors (Table 1, Fig. S2-C), we divided each  
432 error by  $\sqrt{2}$  and took the mean.

433 Finally, we also predicted multispecies states using carrying capacities as  
434 measured in monocultures. We assumed that in competition, each species  
435 would grow to a density proportionate to its carrying capacity. In other words, the  
436 monoculture prediction assumes that all species always coexist. The error from  
437 the prediction to the observed data was calculated with the L2 norm, as above.

#### 438 **Code availability**

439 The code used for analyzing data is available from the first author upon request.

#### 440 **Data availability**

441 Access to the data is publicly available at TBD.

442

443

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