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3 **Unpredictable soil conditions can affect the prevalence of a microbial**
4 **symbiosis**

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23 *discoideum*, *Paraburkholderia*, microbiome

24 **Abstract**

25 The evolution of symbiotic interactions may be affected by unpredictable
26 conditions. However, a link between prevalence of these conditions and symbiosis
27 has not been widely demonstrated. We test for these associations using
28 *Dictyostelium discoideum* social amoebae and their bacterial endosymbionts. *D.*
29 *discoideum* commonly hosts endosymbiotic bacteria from three taxa:
30 *Paraburkholderia*, *Amoebophilus* and *Chlamydiae*. Three species of facultative
31 *Paraburkholderia* endosymbionts are the best studied and give hosts the ability to
32 carry prey bacteria through the dispersal stage to new environments. *Amoebophilus*
33 and *Chlamydiae* are obligate endosymbiont lineages with no measurable impact on
34 host fitness. We tested whether the frequency of both single infections and
35 coinfections of these symbionts were associated with the unpredictability of their
36 soil environments by using symbiont presence-absence data from *D. discoideum*
37 isolates from 21 locations across the eastern United States. We found that symbiosis
38 across all infection types, symbiosis with *Amoebophilus* and *Chlamydiae* obligate
39 endosymbionts, and symbiosis involving coinfections were not associated with any
40 of our measures. However, unpredictable precipitation was associated with
41 symbiosis in two species of *Paraburkholderia*, suggesting a link between
42 unpredictable conditions and symbiosis.

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46

47 **Introduction**

48 The evolution of cooperation varies with ecological unpredictability (Scott,
49 2023; Scott et al., 2023b). For example, the prevalence of cooperative breeding in
50 birds is associated with unpredictable environmental conditions (Jetz & Rubenstein,
51 2011; Griesser et al., 2017). Cooperative breeding is thought to allow organisms to
52 invade unpredictable environments (Cornwallis et al., 2017) or buffer against times
53 when conditions are harsh (Capilla-Lasheras et al., 2021). So far studies on the
54 relationship between ecological unpredictability and cooperation have focused on
55 interactions between members of the same species (Jetz & Rubenstein, 2011;
56 Sheehan et al., 2015; Griesser et al., 2017; Firman et al., 2020). Cooperative
57 associations between different species in a symbiosis, or mutualism, has been
58 suggested to have similar benefits in unpredictable environments (Lekberg & Koide,
59 2014; Veresoglou et al., 2021; Scott, Queller & Strassmann, 2022a) and may thus be
60 associated with them. However, this association has not been tested.

61 We investigated whether symbiosis was associated with unpredictable
62 conditions using the microbiome of *Dictyostelium discoideum*. *D. discoideum* is a
63 social amoeba that spends part of its lifecycle as a single cell eating bacteria in the
64 soil (Raper, 1937). After exhausting edible bacteria, individual amoebae come
65 together and form a multicellular structure called a fruiting body to disperse
66 resistant spores (Kessin, 2001). Inside some fruiting bodies in the wild, different
67 species of bacteria have been identified (Brock et al., 2018; Sallinger, Robeson &
68 Haselkorn, 2021; Steele et al., 2023). Most of these bacteria appear to be regular soil

69 bacteria that happen to be in the matrix of the spore-containing part of the fruiting
70 body. Many of these bacteria are even edible by *D. discoideum* (Brock et al., 2018).

71 A subset of the bacteria that are found in *D. discoideum* fruiting bodies appear
72 to be prevalent symbionts. The first symbionts to be discovered were three species
73 of facultatively endosymbiotic *Paraburkholderia* bacteria (Brock et al., 2011;
74 DiSalvo et al., 2015). The life histories of these *Paraburkholderia* bacteria in their
75 natural soil habitats are unknown, but they can be cultured outside of their hosts in
76 the lab (DiSalvo et al., 2015; Brock et al., 2020) and one species has been shown to
77 be horizontally transferred in the lab (Noh et al., 2024). Two of these
78 *Paraburkholderia* species, *P. hayleyella* and *P. bonniea*, may have a longer history of
79 host association as shown by their reduced genomes, while *P. agricolaris* may be a
80 newer symbiont (Noh et al., 2022).

81 All three *Paraburkholderia* species increase host fitness by allowing hosts to
82 carry other species of edible bacteria along with *Paraburkholderia* inside the spore-
83 containing part of the fruiting body called a sorus (Khojandi et al., 2019; Brock et al.,
84 2020). *Paraburkholderia* are often carried inside spores while prey bacteria are
85 carried outside of the spores in the sorus (Khojandi et al., 2019). Carriage allows
86 host amoebae to seed out populations of prey bacteria that hosts can then eat
87 (Brock et al., 2011). However, the ability to carry comes at the cost of reduced spore
88 production when edible bacteria are common (DiSalvo et al., 2015; Scott, Queller &
89 Strassmann, 2022b). The source of this fitness cost for hosts is unknown, though
90 there is some evidence that *Paraburkholderia* itself harms hosts. For example, the
91 density of *Paraburkholderia* tends to be associated with lower host spore

92 production (Scott, Queller & Strassmann, 2022a,b; Noh et al., 2024) and
93 *Paraburkholderia* infection interferes with host immune cells that develop during
94 the multicellular stage (Scott et al., 2023a).

95 *D. discoideum* also harbors endosymbiotic bacteria that are obligate: one
96 from the genus *Amoebophilus* and different haplotypes from the phylum
97 Chlamydiae. These obligate endosymbionts cannot be cultured outside of their
98 hosts. Both *Amoebophilus* and Chlamydiae have not been found to measurably affect
99 host fitness, even when they occur as coinfections with *Paraburkholderia*
100 (Haselkorn et al., 2021). We will refer to these obligate endosymbionts as
101 *Amoebophilus* and Chlamydiae.

102 Environmental sampling has found that *Paraburkholderia* prevalence is
103 about 25% of sampled hosts but varies by sampling location (Haselkorn et al., 2019)
104 and over time (DuBose et al., 2022). Obligate endosymbionts are found in about
105 40% of sampled hosts (Haselkorn et al., 2021). *Paraburkholderia* and *Amoebophilus*
106 coinfections are more common than expected due to chance (Haselkorn et al., 2021).

107 A key source of unpredictability in the soil environment of *D. discoideum* that
108 has not been studied is precipitation. Precipitation can drastically shift the soil
109 environment because of the complex structure and physical properties of the soil
110 (Or et al., 2007). Such shifts are known to affect the abundance of microbes in the
111 soil (Zeglin et al., 2013). When precipitation is unpredictable, it is likely to impact
112 the availability of soil bacteria for *D. discoideum* to eat. We hypothesize that hosts
113 that have *Paraburkholderia* symbionts may be buffered from unpredictable changes

114 in prey abundance because they can carry prey bacteria (Scott, Queller &
115 Strassmann, 2022a).

116 Other soil characteristics may also be important for the prevalence of
117 symbiosis. pH has already been shown to affect the *D. discoideum* microbiome
118 (Sallinger, Robeson & Haselkorn, 2021). Temperature can have strong effects on
119 host amoebae that could shape their interactions with symbionts (Shu et al., 2020).
120 Soil nutrients (usually measured by the ratio of carbon to nitrogen in the soil) have
121 not been studied in this symbiosis but are known to affect other symbiotic
122 interactions (Johnson et al., 2010) and to affect soil bacteria (Bahram et al., 2018)
123 that are potential prey of *D. discoideum*. Here we test how unpredictability and
124 other soil characteristics affect the symbiosis between *D. discoideum* and its
125 symbionts.

126

127 **Materials and Methods**

128 *Presence of text from preprinted thesis chapter*

129 Portions of the text in this manuscript were previously published as a preprint
130 (Scott et al., 2023b) and as part of a thesis (Scott, 2023).

131

132 *Data Acquisition and Processing*

133 To measure the frequency of symbiosis, we used data from prior
134 environmental sampling (Haselkorn et al., 2019, 2021). The first study (Haselkorn et
135 al., 2019) tested *D. discoideum* isolates from 21 locations in the United States (one
136 location was sampled two separate times) for the presence of the three species of

137 *Paraburkholderia* symbionts (Brock et al., 2020) using *Paraburkholderia* specific 16S
138 rRNA sequencing. The second study (Haselkorn et al., 2021) tested a similar set of *D.*
139 *discoideum* isolates for *Amoebophilus* and Chlamydiae using symbiont specific 16S
140 rRNA sequencing, but also included samples from a few additional countries. For
141 this study, we focused only on the United States samples because sites from other
142 countries were not well sampled and could skew the results. We used these data to
143 construct a presence (1)-absence (0) variable for each *D. discoideum* clones for
144 whether they were infected with any of the three species of *Paraburkholderia*, or
145 *Amoebophilus*, or Chlamydiae. We also generated a presence-absence measure for
146 total symbiosis (having any symbiont across all the tested taxa) and for coinfections
147 between the five different symbiont types (*P. agricolaris*, *P. hayleyella*, *P. bonniea*,
148 *Amoebophilus*, and Chlamydiae).

149 To investigate the role of environmental predictability on the *Dictyostelium*-
150 *Paraburkholderia* symbiosis, we acquired data on long-term precipitation. We also
151 acquired data on soil pH, soil organic carbon, nitrogen, and temperature for each
152 sample location from online databases (detailed below). These variables are known
153 to affect the abundance of bacteria in the soil (Bahram et al., 2018). For each
154 location, we collected monthly precipitation data from 1901 to 2020 from the
155 climate research unit database version 4.05 (Harris et al., 2020). To measure the
156 predictability of precipitation across these monthly measures, we calculated
157 Colwell's P (Colwell, 1974) using the *Colwell's* function in the hydrostats package
158 (Bond & Bond, 2022) with 12 bins corresponding to months and with log-
159 transformed precipitation measures as in Table 2 in Colwell (Colwell, 1974).

160 Colwell's P ranges from completely unpredictable (0) to completely predictable (1).
161 To better capture ecologically relevant timescales, we tested two P measures meant
162 to capture long-term and recent predictability: (1) calculated with precipitation data
163 from 1901 to the year that a sample was collected and (2) calculated from
164 precipitation data from 5 years before the sample was taken.

165 We collected mean soil pH, mean nitrogen, and mean organic carbon data
166 from the SoilGrids database version 2.0 (de Sousa et al., 2020). SoilGrids are soil
167 predictions based on empirical soil measurements and are generated at 250-meter
168 scales. We collected mean soil temperature variables from Lembrechts et al. (2022)
169 that were generated by predicting deviations of soil temperatures from air
170 temperatures at 0 to 5 cm and 5-15 cm depths. We used 0-5 cm depths for soilGrids
171 and soil temperature data because *D. discoideum* typically resides in the top layers
172 of soil.

173

174 *Statistical methods*

175 To test for coinfections across locations, we used mixed effect logistic
176 regression from the *lme4* package (Bates, 2010) in R version 4.1.2 (R Core Team,
177 2013). We tested for possible coinfections between all five of the symbiont types
178 that we investigated. To account for multiple observations at a location, we used
179 location as a random effect. We treated the location that was sampled twice
180 (Mountain Lake Biological Station) as two separate locations because soil samples
181 were taken from different areas within Mountain Lake Biological Station and
182 because samples were collected 14 years apart.

183 As a follow up to our logistic regression results across locations, we tested
184 whether coinfections involving different *Paraburkholderia* species were random in
185 specific locations using Fisher's exact tests (SI Tables). To perform Fisher's exact
186 tests, we constructed a 2x2 contingency table for each sampling location in which at
187 least 2 of the investigated 3 *Paraburkholderia* symbionts were present. To correct
188 for multiple comparisons, we adjusted p-values using Benjamini-Hochberg's
189 correction.

190 To test for associations between soil characteristics and prevalence of
191 individual symbionts or coinfections, we fit a set of mixed effect logistic regression
192 models using lme4 (Bates, 2010) as above. In these models, we tested the effect of
193 soil characteristics on each of our five symbiont types individually. We also tested
194 the effect of soil characteristics on the prevalence of symbiosis regardless of the
195 type and on the prevalence of coinfections between *P. hayleyella* and *Amoebophilus*
196 as these coinfections were more common than expected by chance. We tested
197 models that were derived from a full model that included the precipitation
198 predictability (Collwell's P) since 1901 and for a five year period before samples
199 were collected, mean annual temperature (MAT), carbon to nitrogen ratio (C/N),
200 mean annual precipitation (MAP), and soil pH. To reduce the risk of overfitting, we
201 only compare models with two or fewer total predictors. To identify top models
202 among the set derived from the full model, we used AICc values (Burnham &
203 Anderson, 2004) and examined effect sizes of model estimates. We identify
204 uninformative models if the model does not differ from an intercept only (null)
205 model in terms of AICc. We identify informative models if the model AICc is less than

206 the null model by 2 or more. For multiple models that fit better than the null model,
207 we examined models within two AICc units of the best fitting model and looked for
208 variables that were consistently in top models. To test for spatial autocorrelation in
209 our models, we performed a Moran's I test on simulated residuals using the
210 *DHARMA* package in R (Hartig, 2020). All models were free of spatial
211 autocorrelation.

212 For models that showed an effect of unpredictable precipitation on *P.*
213 *hayleyella* and *P. agricolaris* prevalence, we ensured that these effects were not
214 solely due to the influence of the two largest sample locations (Mountain Lake
215 Biological Station in Virginia). To do this, we refit 1,000 models on subsets of the
216 data where Mountain Lake samples were no longer outliers in terms of the number
217 of sampled clones. To produce subsets, we randomly removed 350 clones from the
218 pool of clones from both locations. Using our fit models, we then estimated the effect
219 of unpredictable precipitation and compared these estimated effects to those
220 estimated from the full dataset.

221 To test whether *P. hayleyella* and *P. bonniea* inhabit soils that differ in their
222 precipitation unpredictability, we used a permutation tests. We randomly shuffled
223 host infection status (infected with *P. hayleyella* or infected with *P. bonniea*) from
224 hosts infected by either of these species without replacement and calculated sample
225 statistics for values of precipitation predictability across 10,000 samples. As sample
226 statistics, we investigated the differences between both the means and medians of
227 the two species after permutation. Both mean and median difference statistics gave
228 equivalent results. We report the median difference p-value in the main text.

229

230 **Results**

231 To test for relationships between soil characteristics and symbiont
232 prevalence, we used presence-absence data of symbionts that were collected from
233 22 collection trips to 21 locations (Figure 1A, Table 1) across the eastern United
234 States (Haselkorn et al., 2019, 2021). Because some coinfections are known to be
235 more common than expected (Haselkorn et al., 2021), we first tested all screened
236 hosts for non-random coinfections that may also vary with the soil environment
237 using logistic regression. *Paraburkholderia* coinfections were not more common
238 than expected (Figure 1B) even when we tested for coinfections at individual
239 locations using Fisher's exact tests (SI Tables). Generally, *Paraburkholderia* and
240 *Amoebophilus* coinfections are more common than expected with *P. hayleyella* and
241 *Amoebophilus* coinfections being the most enriched (Figure 1B). This extends prior
242 findings that focused on a subset of locations (Haselkorn et al., 2021). *Amoebophilus*
243 and Chlamydiae coinfections are less common than expected across our sampled
244 sites.

245 To identify associations with symbiont prevalence, we used logistic
246 regression models. To measure precipitation unpredictability, we calculated
247 Colwell's P (see Table 2 in Colwell, 1974) using monthly precipitation data for each
248 location since 1901 (Figure 2A). Rainfall was generally unpredictable as Colwell's P
249 ranged from 0.25 to 0.42. To make sure that more recent unpredictability did not
250 deviate from long-term predictability, we also calculated Colwell's P for the last five
251 years before collection at each location (Figure 2B). Colwell's P ranges from 0 to 1,

252 with 0 being unpredictable and 1 being perfectly predictable (Colwell, 1974). Along
253 with our measures of unpredictability, we collected mean annual precipitation
254 (Figure 2C), soil pH (Figure 2D), soil mean annual temperature (Figure 2E), soil
255 carbon to nitrogen ratio data (Figure 2F). Correlations between these variables
256 tended to be low with the exception of mean annual temperature being correlated
257 with pH and long-term Colwell's P (Figure S1).

258 We found that the frequencies of the two *Paraburkholderia* species with
259 reduced genomes, *P. hayleyella* and *P. bonniea*, were associated with unpredictable
260 precipitation, but in opposite directions (Figure 3A&B). Other variables measuring
261 mean soil characters were not associated with prevalence unless also included with
262 unpredictable precipitation (SI Tables). *P. hayleyella* prevalence was higher in more
263 unpredictable environments (log-odds = -1.047, se = 0.545; Figure 3A) while *P.*
264 *bonniea* prevalence was higher in more predictable environments (log-odds = 1.181,
265 se = 0.442; Figure 3B). These opposite responses to the predictability of
266 precipitation remained even when we accounted for the influence of the two largest
267 sampling locations (Figure S2). Moreover, our data show (histograms in Figure 3)
268 that *P. hayleyella* is found where precipitation is relatively unpredictable (0.33.5 on
269 average) while *P. bonniea* is found where precipitation is more predictable (38.1 on
270 average; Permutation test: $p < 0.001$). For the other symbiont infections – *P.*
271 *agricolaris*, the obligate *Amoebophilus* and Chlamydiae endosymbionts, *P. hayleyella*-
272 *Amoebophilus* coinfections, and even symbiosis overall – prevalence was not
273 associated with unpredictable precipitation or mean soil characteristics (SI Tables).

274

275 **Discussion**

276 Our finding that *P. hayleyella* prevalence increases in unpredictable
277 conditions supports our hypothesis that symbiosis may buffer hosts during times
278 when conditions are unpredictable. However, our finding for the relatively less
279 common *P. bonniea* is in the opposite direction of this hypothesis.

280 One explanation for why unpredictability differently affects *P. hayleyella* and
281 *bonniea* prevalence is that these sister species (Brock et al., 2020) compete and are
282 partitioning their niches within hosts based on unpredictable precipitation. Indeed,
283 *P. hayleyella* and *P. bonnieae* were found on different ends of our measure of the
284 predictability of precipitation. Some additional support for niche partitioning
285 comes from a previous finding that *P. hayleyella* and *P. bonniea* differ on which
286 sugars they can metabolize (Brock et al., 2020). One argument against niche
287 partitioning within hosts is that the prevalence of these symbionts may not be high
288 enough for strong competition within hosts. Instead, competition in the soil could
289 drive niche partitioning between these symbionts. In this case, interactions with
290 other members of the *D. discoideum* microbiome that were not included here may be
291 involved. Another possibility is that life history characteristics of *P. hayleyella* and *P.*
292 *bonniea* affect the ability of these bacteria to survive in soils with different levels of
293 unpredictable precipitation.

294 In addition to the role of unpredictability, we also identified new associations
295 between different symbionts in *D. discoideum* hosts. We found that *P. hayleyella* and
296 *Amoebophilus* coinfections are more common than expected and *Amoebophilus* and
297 Chlamydiae coinfections are less common than expected (Figure 1B). The

298 association between *P. hayleyella* and *Amoebophilus* suggests that the abundance of
299 both may be driven by the same environmental conditions. Another possibility is
300 that *P. hayleyella* and *Amoebophilus* are mutualists that have increased survival
301 when together in the same host. The rarity of *Amoebophilus* and Chlamydiae
302 coinfections may indicate competitive exclusion inside *D. discoideum* hosts. Another
303 explanation is that *Amoebophilus* or Chlamydiae actively prevent each other's
304 colonization. Chlamydial endosymbionts have been shown to reduce the success of
305 other endosymbionts in other species of amoebae (König et al., 2019; Arthofer et al.,
306 2022).

307 Our results provide suggestive evidence of the role of unpredictability
308 driving symbiosis that should be followed up in future studies. However, our study
309 is limited in several ways due to data constraints. First, our samples were not
310 replicated over time, so our results do not capture the variation in *Paraburkholderia*
311 symbiosis over time. This may be an important factor as other soil sampling studies
312 have found that symbiosis with *Paraburkholderia* may vary over time in some
313 locations (DuBose et al., 2022). Second, our soil and climate measures do not
314 capture within site heterogeneity that is important in many microbial systems
315 (Nannipieri et al., 2019). For this reason, our study should inspire future fieldwork
316 with better sampling to better understand the drivers of symbiosis in this system.

317 This study demonstrates that the frequency of a microbial symbiosis can be
318 associated with unpredictable environmental conditions. Unpredictable conditions
319 may be an important driver of cooperation between members of the same species
320 and between different species.

321

322 **Data Availability**

323 Data and code are available at [https://gitlab.com/treyjscott/symbiont prevalence](https://gitlab.com/treyjscott/symbiont_prevalence).

324

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485 **Tables and Table Legends**

486 Table 1: Counts (and percent) of individual endosymbiont types, the total number of
 487 screened hosts, and the year of collection for each sampling location used in this
 488 study. Percents need not sum to 100 because of the presence of coinfections.

Location	P. <i>hayleyella</i>	P. <i>agricolaris</i>	P. <i>bonniea</i>	Amoebophilus	Chlamydiae	Total Scree Hosts
Arkansas- Forest City	3 (33.3%)	0 (0%)	0 (0%)	0 (0%)	1 (11.1%)	
Georgia- Cooper Creek	0 (0%)	0 (0%)	0 (0%)	0 (0%)	10 (71.4%)	
Illinois- Effingham	0 (0%)	2 (28.6%)	0 (0%)	0 (0%)	0 (0%)	
Indiana- Bloomington (Lobelia)	9 (50%)	0 (0%)	0 (0%)	1 (5.6%)	3 (16.7%)	
Indiana- Patoka Lake	8 (61.5%)	4 (30.8%)	0 (0%)	1 (7.7%)	3 (23.1%)	
Kentucky- Land Between the Lakes	6 (60%)	6 (60%)	0 (0%)	0 (0%)	4 (40%)	
Massachusetts- Mt. Greylock	1 (8.3%)	4 (33.3%)	0 (0%)	0 (0%)	1 (8.3%)	
Massachusetts-Boston	0 (0%)	0 (0%)	0 (0%)	0 (0%)	5 (55.6%)	
Missouri- St. Louis	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (7.7%)	
North Carolina- Linville Falls	0 (0%)	10 (41.7%)	0 (0%)	0 (0%)	0 (0%)	
North Carolina- Little Butts Gap	0 (0%)	1 (4.2%)	3 (12.5%)	1 (4.2%)	3 (12.5%)	
Tennessee- Indian Gap	0 (0%)	2 (20%)	1 (10%)	0 (0%)	1 (10%)	
Tennessee- Rhodo Thicket	0 (0%)	3 (42.9%)	0 (0%)	1 (14.3%)	3 (42.9%)	
Tennessee- Road	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	
Tennessee- Sugarlands	0 (0%)	0 (0%)	2 (33.3%)	1 (16.7%)	0 (0%)	
Texas- Armand Bayou	0 (0%)	0 (0%)	0 (0%)	2 (28.6%)	0 (0%)	
Texas- Carthage	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	

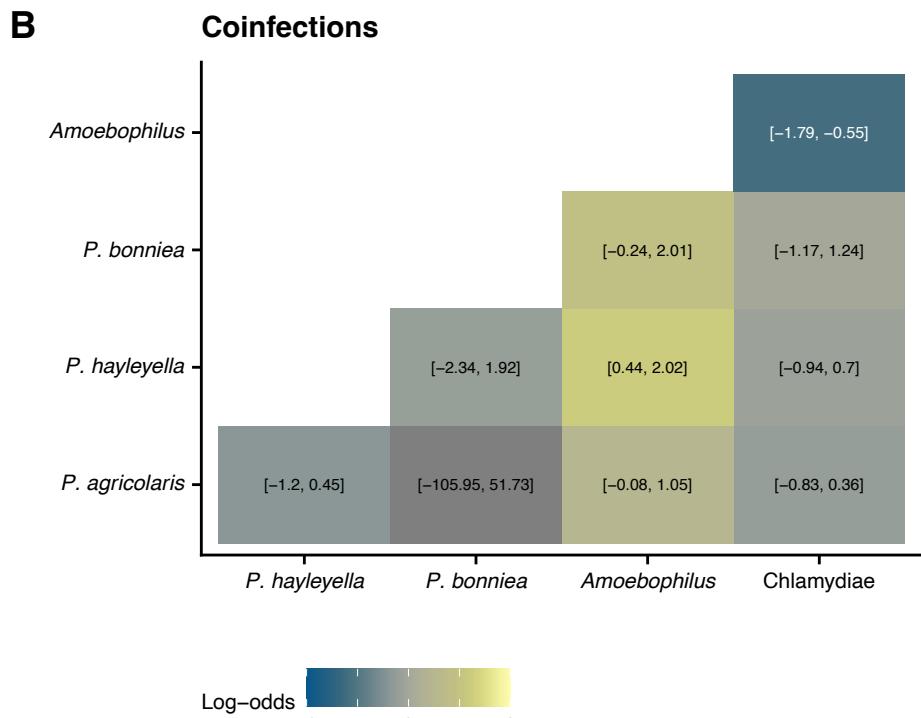
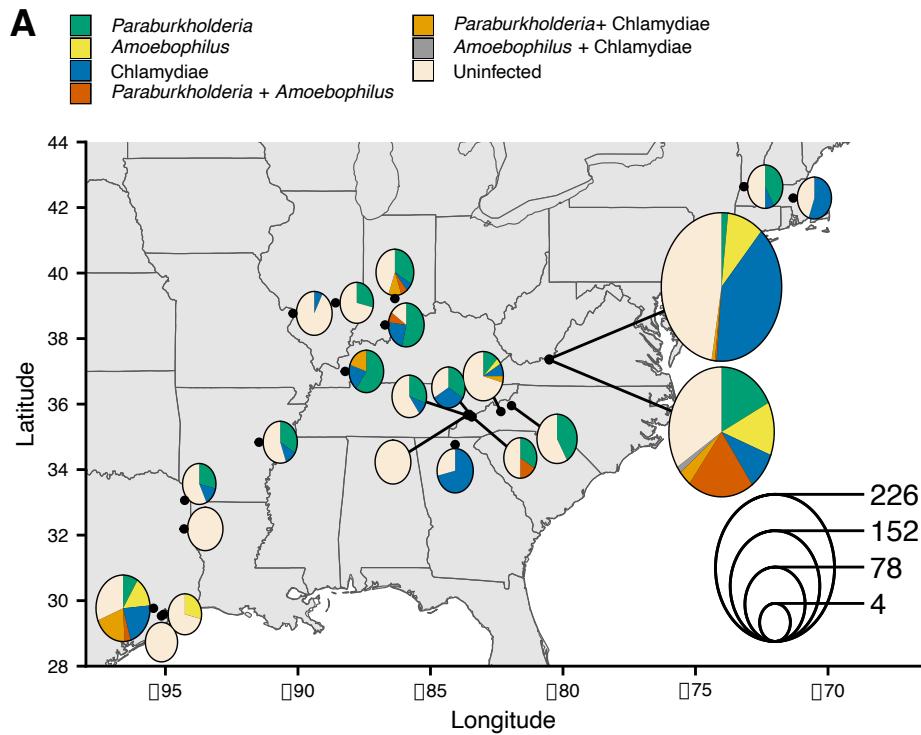
	Texas- Houston Arboretum	2 (3.4%)	19 (32.2%)	0 (0%)	14 (23.7%)	27 (45.8%)
	Texas- Linden	1 (14.3%)	1 (14.3%)	0 (0%)	0 (0%)	1 (14.3%)
	Texas- Webster	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	Virginia- Mountain Lake Biological Station	0 (0%)	3 (1.3%)	4 (1.8%)	23 (10.2%)	92 (40.7%)
	Virginia- Mountain Lake Biological Station	26 (13.8%)	48 (25.5%)	8 (4.3%)	70 (37.2%)	33 (17.6%)
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511 **Figures and Figure Legends**



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513 **Figure 1:** *D. discoideum* sample locations and patterns of endosymbiont infection.

514 (A) Map of *D. discoideum* sample locations. Black points show locations. Pie charts

515 show the frequencies of symbionts in screened hosts. Relative pie chart size
516 indicates the number of sampled hosts at a location. (B) Patterns of coinfection for
517 different symbiont pairs from logistic regressions. Color shows the estimated log
518 odds (95% confidence intervals are shown in the boxes). *P. agricolaris*-*P. bonnieae*
519 coinfection mean is not colored because it is an outlier due to the lack of any
520 coinfections (confidence intervals are still shown). Map was generated with the sf
521 package in R (Pebesma, 2018).

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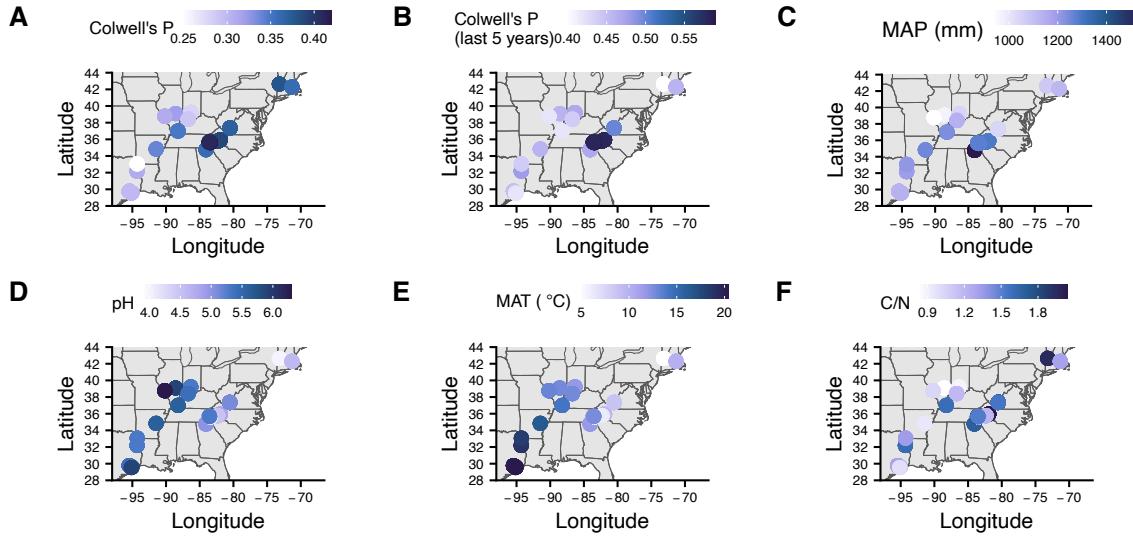
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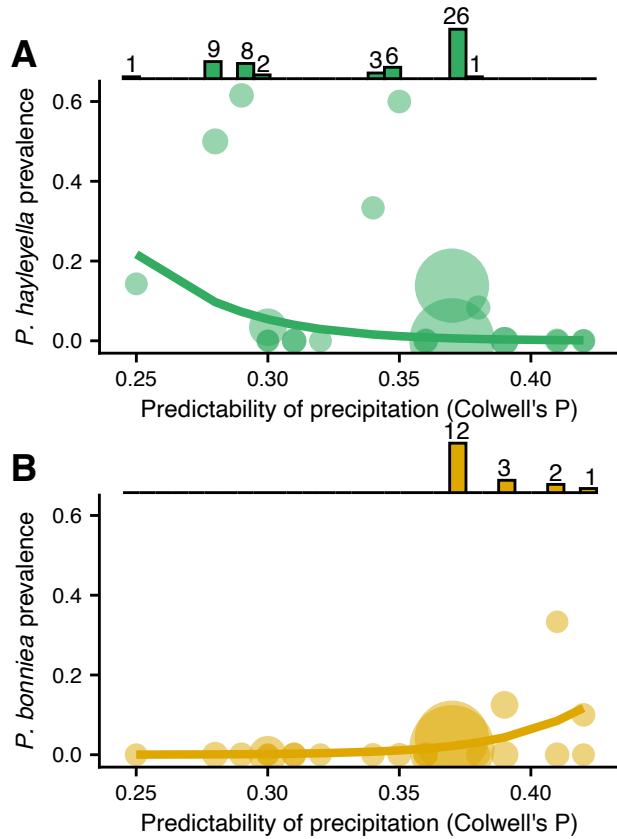
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532 **Figure 2:** Maps of soil characteristics from sample locations. (A) Colwell's P for
 533 precipitation from 1901 to the year of sampling. (B) Colwell's P from the five years
 534 before sampling. (C) Mean annual precipitation (MAP) calculated from 1901 to the
 535 year of sampling. (D) pH of soil. (E) Mean annual temperature (MAT) of soil. (F)
 536 Carbon to nitrogen ratio (C/N) of soil. Map was generated with the sf package in R
 537 (Pebesma, 2018).

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540 **Figure 3:** *P. hayleyella* and *P. bonniea* are differently affected by and inhabit
 541 different areas of precipitation predictability. The prevalence of *P. hayleyella* (A) and
 542 *P. bonniea* (B) with different values of predictability of precipitation across locations
 543 (samples per site is indicated by the size of the point). Prevalence is the fraction of
 544 screened hosts that were found with a given endosymbiont. Logistic regression fits
 545 are shown as lines. *P. hayleyella* and *P. bonniea* inhabit different soils in terms of
 546 their precipitation predictability as shown by histograms on top of panels (note
 547 that *P. bonniea* is only found at predictability values above 0.37 while *P. hayleyella* is
 548 found almost exclusively at or below this value). Numbers above bars in histogram
 549 are the number of symbionts found in screened hosts for a given value of
 550 precipitation predictability.