

1 **Title:** Predation by protists influences the temperature response of microbial communities

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10 **Running Title:** Protists influence microbial communities

12 **Author Contributions**

13 JDR and JPG conceived the study. JDR, AY and JPG designed and conducted the experiments.
14 JPG, AY, and MS processed and analyzed the microbial biomass, respiration, and protist trait
15 data JDR and MS processed and analyzed the microbial community data. JDR and JPG wrote
16 the manuscript with significant input from all other authors.

17 **Conflict of Interest**

18 The contributors declare no conflict(s) of interest.

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26 **Abstract**

27 Temperature strongly influences microbial community structure and function, which in turn
28 contributes to the global carbon cycle that can fuel further warming. Recent studies suggest that
29 biotic interactions amongst microbes may play an important role in determining the temperature
30 responses of these communities. However, how microbial predation regulates these communities
31 under future climates is still poorly understood. Here we assess whether predation by one of the
32 most important bacterial consumers globally – protists – influences the temperature response of
33 a freshwater microbial community structure and function. To do so, we exposed these microbial
34 communities to two cosmopolitan species of protists at two different temperatures, in a month-
35 long microcosm experiment. While microbial biomass and respiration increased with temperature
36 due to shifts in microbial community structure, these responses changed over time and in the
37 presence of protist predators. Protists influenced microbial biomass and function through effects
38 on community structure, and predation actually reduced microbial respiration rate at elevated
39 temperature. Indicator species and threshold indicator taxa analyses showed that these predation
40 effects were mostly determined by phylum-specific bacterial responses to protist density and cell
41 size. Our study supports previous findings that temperature is an important driver of microbial
42 communities, but also demonstrates that predation can mediate these responses to warming, with
43 important consequences for the global carbon cycle and future warming.

44

45 **Keywords**

46 Predation, temperature, protist, microbiome, aquatic, TITAN, indic species, respiration, microbial
47 biomass.

48 INTRODUCTION

49 Understanding the biotic factors that influence global climate change is one of the most pressing
50 goals of ecology (Van der Putten et al., 2010). Doing so hinges on better understanding the biotic
51 and abiotic feedbacks that determine global carbon cycling (Jackson et al., 2017). While several
52 of the biotic mechanisms that lead to global releases and sequestration of carbon are well
53 documented (Nielsen et al., 2014; van den Hoogen et al., 2020), only a subset of those are
54 currently taken into account in predictive Earth System Models (Sulman et al., 2019).

55 Microbial organisms comprise 14% of all existing biomass on Earth (Bar-On et al., 2018;
56 Flemming & Wuertz, 2019), while the entirety of the Animal Kingdom, for comparison, only
57 represents 0.3% (Bar-On et al., 2018). Microbial decomposition is responsible for the recycling of
58 organic matter back into food webs, thus partly subsidizing the flux of energy and matter in all
59 ecosystems (Cordone et al., 2020; Mougi, 2020). Through respiration and decomposition of
60 existing carbon pools, microorganisms are largely regarded as one of the most important biotic
61 controls of the global carbon cycle (Bardgett et al., 2008; Gougoulias et al., 2014; Jansson &
62 Hofmockel, 2020; Schimel & Schaeffer, 2012; Wang, 2018). Additionally, respiration rates are
63 well-known to increase with temperature among ectotherms and unicellular organisms (Bond-
64 Lamberty et al., 2018; DeLong et al., 2017; Gillooly et al., 2001), potentially resulting in a scenario
65 where warming begets more warming. However, temperature-mediated increases in respiration
66 rates often plateau –or even decline– over time in microbial communities (Bradford, 2013;
67 Crowther & Bradford, 2013; Ye et al., 2020; Yergeau et al., 2012), although not always (Hartley
68 et al., 2008; Zimmermann et al., 2012). These diverse responses thus show there is much that
69 still needs to be understood about the processes regulating microbial respiration and function in
70 the wild.

71 Temperature often mediates ecological interactions (Bernhardt et al., 2018; Binzer et al.,
72 2012; Dell et al., 2014; Garzke et al., 2019; Uszko et al., 2017). The strength of feeding
73 interactions, in particular, increases with temperature, as feeding rates increase among

74 consumers to compensate for increasing metabolic demands (Dell et al., 2011; Gillooly et al.,
75 2001). Stronger predation in turn leads to declines in prey abundance and total biomass
76 (Barneche et al., 2021; DeLong & Lyon, 2020; Garzke et al., 2019; Gilbert et al., 2014). Because
77 gross respiration rates are determined by standing biomass, temperature effects on predation
78 may ultimately influence ecosystem-level processes such as community respiration rates
79 (O'Connor et al., 2009), and thus mediate the temperature response of microbial respiration rates
80 worldwide. In particular, bacterivory is a dominant factor leading to microbial biomass loss (Baltar
81 et al., 2016; Pedrós-Alió et al., 2000; Rgens & Massana, 2008), which has been proposed to
82 influence soil respiration rates (Gao et al., 2019), and shown to affect litter decomposition in soils
83 across temperatures (Geisen et al., 2021; Sulman et al., 2018).

84 Recent efforts have mapped the global distribution of nematodes – a major group of
85 microbial predators (Nielsen et al., 2014; van den Hoogen et al., 2019, 2020). These global maps
86 represent a step forward in clarifying the role of feeding interactions in the temperature responses
87 of microbial communities. However, with a global biomass 200 times larger than that of
88 nematodes (Bar-On et al., 2018), unicellular eukaryotes - collectively known as ‘protists’ - likely
89 play a major role in regulating microbial communities at global scales (Oliverio et al., 2020)
90 through bacterivory (Erktan et al., 2020; Gao et al., 2019). Ciliate protists, in particular, are well-
91 known bacterivores (Foissner & Berger, 1996), their population dynamics and feeding interactions
92 are strongly temperature-dependent (DeLong & Lyon, 2020), and they are present in all major
93 ecosystems (Foissner & Berger, 1996; Oliverio et al., 2020). As such, predation of
94 microorganisms by protists can mediate the temperature response of microbial communities (Gao
95 et al., 2019; Geisen et al., 2021), although this phenomenon has only been shown for one species
96 of protist in soils (Geisen et al., 2021). If general, this process has the potential to strongly
97 influence microbial respiration worldwide under warmer temperatures (Crowther et al., 2015;
98 Geisen et al., 2018). Additionally, microbial predators respond to environmental conditions
99 themselves in multiple ways, including changes in feeding rates (DeLong & Lyon, 2020; Englund

100 et al., 2011) and changes in the traits that influence predation (Atkinson et al., 2003; Dell et al.,
101 2011; Gibert et al., 2016), which add complexity to an already complex problem.

102 Here, we examine the potential interactive effects of protist predation and temperature on
103 microbial diversity, biomass, and total respiration rates, by incubating a microbial community from
104 a local ephemeral pond in the presence and absence of two cosmopolitan ciliate protists of
105 different size and at different temperatures. We ask: 1) how does temperature influence microbial
106 community biomass, structure, and function?, 2) how does protist presence influence the
107 temperature response of microbial community biomass, structure, and function?, and 3) are there
108 direct temperature responses of the protists influencing their effects on the microbial community
109 they feed upon?

110 We hypothesize that microbial biomass and function should increase with temperature,
111 although we expect that effect to plateau over time (Bradford, 2013; Crowther & Bradford, 2013;
112 Ye et al., 2020; Yergeau et al., 2012). We expect protist predation to decrease overall microbial
113 biomass (Glücksman et al., 2010; Hahn & Höfle, 2001), which could reduce total respiration rates.
114 We also hypothesize that predation effects should be dependent on protist size, as feeding rates
115 are well-known to increase with body size (Zaoli et al., 2019). While little is known about the exact
116 diet of these protists, we expect them to differ, at least minimally because of gape-limitation
117 (Glücksman et al., 2010): larger protists should be able to consume the same species that smaller
118 protists do, plus some biofilm or colony-making microbial taxa. Consequently, we hypothesize
119 that differential consumption of microbial species by different protist species should result in
120 changes in microbial composition (Glücksman et al., 2010; Hahn & Höfle, 2001), that may lead to
121 changes in community structure and function. Last, we predict that protists themselves may
122 respond to the imposed treatments by decreasing body size with temperature (temperature-size
123 rule; (D. Atkinson, 1994; Atkinson et al., 2006). These changes may in turn influence how they
124 interact with the microbial community.

125

126 **METHODS**

127 *Water collection, microcosm setup and incubation*

128 We collected 40 L of surface water from an ephemeral freshwater pond at Duke Forest (Gate 9,
129 36.019139, -78.987698, Durham, NC). To isolate the aquatic microbial community used in our
130 experiment, we filtered the entire water sample through autoclaved filters (11 μ m pore size,
131 Whatman) to remove debris, metazoans, and larger protists; then we filtered through sterile GF/A
132 filters (1.6 μ m pore size, Whatman) to remove flagellates and other smaller organisms. Smaller
133 microbes were retained in the filtrate. Removal of protists and metazoans from the source pond
134 microbial community was confirmed by visual inspection using a stereomicroscope (Leica
135 M205C), then re-confirmed on control microcosms at the end of the experiment using fluid
136 imaging (detailed below). The microbial communities were incubated in 250mL acid-washed and
137 autoclaved borosilicate jars filled with a mixture of pond water filtrate (2/3, or 133mL), and Carolina
138 Biological Protist culture medium (1/3, or 67mL) plus two wheat seeds to serve as a carbon source
139 ((Altermatt et al., 2015), for a total of 140 replicate microcosms. We included a negative control
140 (n=1), containing the same volume of sterile protist media, to confirm axenic conditions throughout
141 the incubation and subsequent processing. All microcosms were incubated in Percival AL-22L2
142 growth chambers (Percival Scientific, Perry, Iowa) at 22°C, 10% light intensity (1700 lux), 75%
143 humidity, and a 16:8 hr day-night cycle (day length at time of collection). After a seven day pre-
144 incubation period, to allow equilibration of the microbial communities, we harvested 20
145 microcosms as positive controls to assess the effects of incubation on microbial composition,
146 relative to the original pond microbial community. The negative control was extracted for genomic
147 DNA alongside these 20 samples (*detailed below*).

148

149 *Experimental treatments*

150 After the initial seven-day incubation period, microcosms were randomly assigned to
151 treatments in a fully factorial experimental design with two levels of temperature (22°C, i.e., the

152 water temperature on the day of collection; or 25°C, a warming scenario simulating a +3°C
153 increase in temperature), and three levels of protist predation (no protist, presence of
154 *Tetrahymena pyriformis*, or presence of *Colpidium sp.*). We used *Tetrahymena pyriformis*
155 (hereafter *Tetrahymena*) and *Colpidium sp.* (hereafter *Colpidium*), due to their putative generalist
156 bacterivore habits (Foissner & Berger, 1996), their cosmopolitan distribution (Elliott, 1970), and,
157 hence, their likelihood of playing a pivotal role in mediating the temperature response of microbial
158 communities worldwide. Also, these protists have a large size difference (20-70 μm for
159 *Tetrahymena* vs 60-120 μm of *Colpidium*) which theory predicts should lead to differences in
160 feeding and interaction strengths with their bacterial prey (Englund et al., 2011; Rall et al., 2012;
161 Zaoli et al., 2019).

162 Protists were introduced by pipetting 0.5mL of well-mixed protist stock cultures into
163 experimental microcosms. To control for the introduction of the microbes already occurring in the
164 protist cultures, we also added the same volume of a homogenized protist stock media, filtered of
165 *Tetrahymena* and *Colpidium* cells, into all microcosms. The microcosms were thus assigned to
166 one of 6 possible treatments: 1) 22°C, no protists; 2) 25°C, no protists; 3) 22°C, *Tetrahymena*; 4)
167 25°C, *Tetrahymena*; 5) 22°C, *Colpidium*; 6) 25°C, *Colpidium*. Half of the microcosms in each
168 treatment were harvested at Day 12 and the remaining half at Day 24, to assess whether observed
169 responses changed over time in systematic ways.

170

171 *Microbial Biomass and Community Respiration*

172 We quantified total microbial biomass, microbial diversity, and total community respiration to
173 assess the joint impacts of temperature, time, and protist predation on microbial community
174 structure and function. As a proxy for total biomass, we measured the optical density at 600nm
175 wavelength (or OD600; (Beal et al., 2020) of each microcosm (1/3 dilutions), using a Jenway 3505
176 UV Spectrophotometer (Cole-Parmer, Vernon-Hills, IL, USA). Larger OD600 values (higher
177 absorbance+scattering) indicate higher total microbial biomass (Beal et al., 2020).

178 We determined total community respiration using an optode-based real time OXY-4 SMA
179 respirometer (PreSens, Regensburg, Germany; (Altermatt et al., 2015; DeLong & Vasseur, 2012).
180 Respiration rate was measured on 22 mL subsamples for 30 minutes, after a 30 minute
181 acclimation period, on a subset of all microcosms (n=72). This was done at their original
182 experimental temperature and the cross-treatment temperature (n=36 microcosms, with two
183 measurements each) to disentangle long term temperature effects from short-term impacts.
184 Respiration rates were estimated as the rate of change (slope) of the estimated oxygen
185 concentration over time (in $\mu\text{mol O}_2/\text{min}$, Figures S1, S2, Appendix 1). Respiration rates did not
186 differ significantly between the two temperatures at which they were measured (effect = -
187 $0.01 \pm 0.12\text{SE}$, $p=0.96$), so readings for both temperatures from a single microcosm were
188 averaged for subsequent analyses. To assess whether total biomass or community respiration
189 changed with experimental treatment, we used linear models with protist presence (no protist,
190 *Tetrahymena* or *Colpidium*), time (12 or 24 days), and temperature (22 or 25°C) as explanatory
191 variables (and their possible interactions), and either biomass or respiration rates as response
192 variables in R v4.0.2; R Core Team, 2013). All measures of biomass, function and microbial
193 community structure were measured at days 12 and 24.

194

195 *Protist abundances and traits*

196 To disentangle potential effects of protist presence and abundance on microbial communities, we
197 estimated protist population sizes through fluid imaging of 3 mL subsamples out of four
198 microcosms from each treatment using a FlowCam (Fluid Imaging Technologies, Scarborough,
199 ME, USA). Fluid imaging also yields high-resolution measurements of multiple cell traits like
200 cellular volume and shape, and optical properties of the cells (Gibert et al., 2017). We used
201 ensuing trait data to assess potential responses of the protists to imposed experimental conditions
202 as well as potential responses of the microbial communities to both protist traits and densities
203 (detailed below). We focused on nine different phenotypic characteristics: five measurements of

204 shape and size (length, area, volume, circularity, and aspect ratio) and four measurements of
205 optical properties of the cells (sigma-intensity and three components of hue: Red/Green, Red/Blue
206 and Blue/Green ratios). These measurements were taken on days 12, and 24. We assessed
207 whether protist population counts changed with either temperature or time using linear models,
208 and we assessed whether protist phenotypes responded over time and with temperature using
209 perMANOVA (Anderson, 2001, 2017) using the *vegan* package in R (v2.5.6; (Oksanen et al.,
210 2019).

211

212 *Amplicon Sequence Data Processing and Microbial Community Structure Analysis*

213 We used 16S rRNA amplicon sequencing to examine the impacts of temperature, time, and
214 protists, on microbial community structure. After the incubation period (12 or 24 days), we
215 collected the microbial communities by filtering 200mL from each microcosm onto gamma-
216 irradiated 0.2µm nitrocellulose membranes (Advantec, Taipei, Taiwan) and stored the filters at -
217 20°C until DNA extraction. Total genomic DNA was extracted from each filter using DNeasy
218 PowerWater DNA Extraction Kits (Qiagen, Hilden, Germany), modified with a heating step (60°C)
219 before the initial vortexing step to maximize lysis across different microbial cell types. We
220 fluorometrically quantified the genomic DNA concentrations with Qubit (Thermo Fisher, Waltham,
221 MA, USA), and sent an equimolar set of genomic DNA samples to the Research Technology
222 Support Facility (RTSF) at Michigan State University for amplicon prep and sequencing. We
223 targeted the V4 hypervariable region of the 16S rRNA gene using the standard 515F/806R
224 universal primers with 12 bp Golay barcodes (Caporaso et al., 2011). RTSF sequenced our
225 samples with Illumina MiSeq (PE 250 bp, V2 chemistry), and returned 9,069,268 raw reads
226 (average/sample: 62,981 reads), publicly available at EMBL-ENA under project accession
227 number: PRJEB44142 (ERS6200133 - ERS6200276).

228 We processed the raw fastq sequence data through Dada2 (v1.16.0; (Callahan et al.,
229 2016) in R (v4.0.2; R Core Team, 2013), to trim and filter low quality sequence reads and calculate

230 error rates for denoising and merging the pair-ends into 3801 non-chimeric representative
231 amplicon sequence variants, or ASVs. These representative ASVs were further curated with Lulu
232 to reduce artificially inflated diversity due to amplification and sequencing errors, resulting in 1423
233 representative ASVs (Frøslev et al., 2017).

234 We taxonomically identified chloroplast and mitochondrial 16S rRNA sequences using the
235 Silva 138 reference taxonomy (Quast et al., 2013), removing 315 ASVs for a final 16S rRNA
236 representative set of 1108 ASVs. This final representative ASV set was aligned to the Silva 138
237 NR full-length 16S rRNA alignment with MAFFT (Katoh & Frith, 2012) using default settings, and
238 subsequently trimmed and masked to the V4 region. We then updated the trimmed V4 alignment
239 to estimate a phylogeny using the iterative algorithm of PASTA (Mirarab et al., 2015), and used
240 this final set of ASVs to update the corresponding sample ASV community table.

241 For alpha diversity estimates, we rarefied all microbial 16S rRNA samples to a sequencing
242 depth of 8600 to maximize sampling depth while retaining the majority of samples. We treated
243 the data as compositional for all other analyses by using a variance-stabilizing transformation
244 (VST) of the ASV community table without singleton ASVs (Gloor et al., 2017), using DESeq2
245 (v1.12.3; (McMurdie & Holmes, 2013). We calculated a comprehensive range of alpha-diversity
246 indices, from observed ASV richness and Shannon-Weiner to Pielou's evenness index and
247 abundance-weighted phylogenetic diversity (weighted Unifrac) on each rarefied sample using
248 'core-metrics-phylogenetic' in Qiime2 (v2020.8; (Bolyen et al., 2019). We used ANOVA to test for
249 individual and interactive effects of experimental treatments on alpha diversity of the microbial
250 communities.

251 To examine the impacts of temperature, incubation time, and protists on the overall
252 structure of the microbial communities, we used principal component analysis on an abundance-
253 weighted bray-curtis distance matrix of the VST table in *vegan* R (v2.5-6; (Oksanen et al., 2019).
254 We tested for individual and interactive treatment effects with a perMANOVA using the adonis()
255 function in *vegan* R (v2.5-6; (Oksanen et al., 2019). We performed multilevel pairwise

256 comparisons of the community data using the pairwise.adonis() function in the pairwiseAdonis R
257 package (v0.0.1; (Martinez Arbizu, 2017). We also examined differences among group community
258 variation –or spread in ordination space– using the betadisper() function (PERMDISP2;
259 (Anderson et al., 2006) in *vegan* R (v2.5-6; (Oksanen et al., 2019), which uses multivariate
260 homogeneity of group dispersions, or the multivariate form of a Levene's test (Anderson, 2006;
261 O'Neill & Mathews, 2000).

262 For treatments imposing significant changes in microbial community structure, we also
263 identified potential positive or negatively responding microbes (ASVs). We employed two
264 distinctive methods of indicator taxa analysis: categorical *indicspecies* in R (De Cáceres &
265 Legendre, 2009) and a direct gradient analysis, threshold indicator taxa analysis (TITAN) in R
266 (Baker & King, 2010). With *indicspecies*, we identified ASVs with significant differential abundance
267 patterns by treatment level using multi-level pattern analysis with the multipatt() function (De
268 Cáceres & Legendre, 2009). In contrast, with TITAN, we identified microbial ASVs significantly
269 associated with changes in measured protist phenotypic traits, specifically protist size, and protist
270 abundance, by separately regressing each microbial ASV against each protist trait. TITAN outputs
271 provided pure and reliable positive and negative indicator ASVs (75% purity and reliability
272 thresholds), as well as individual and community-level abundance thresholds, for each protist trait
273 gradient. All data and code used for these analyses, can be accessed at
274 https://github.com/JPGibert/Microbial_Responses_Prots_Temp, unless otherwise stated.

275

276 **RESULTS**

277 *Temperature and time affect microbial biomass, function, and structure*

278 Temperature and incubation time had interactive effects on total microbial biomass: warmer
279 temperature resulted in larger OD600, but that effect disappeared over time (Fig 1a, $\text{effect}_{\text{Temp}} = 0.08 \pm 0.04 \text{SE}$, $p=0.08$; $\text{effect}_{\text{Time}} = 0.10 \pm 0.04 \text{SE}$, $p=0.019$; $\text{effect}_{\text{Temp} \times \text{Time}} = -0.14 \pm 0.06 \text{SE}$,
280 $p=0.02$, more details in Appendix 2). Respiration rate also showed significant interactive effects

282 of time and temperature similar to those found for bacterial biomass: respiration increased with
283 temperature at first, but that effect was reversed over time (Fig 1b, $\text{effect}_{\text{Temp}} = 0.62 \pm 0.29\text{SE}$,
284 $p=0.036$; $\text{effect}_{\text{Time}} = 0.46 \pm 0.20\text{SE}$, $p=0.025$; $\text{effect}_{\text{Temp} \times \text{Time}} = -0.90 \pm 0.29\text{SE}$, $p=0.003$, Appendix
285 2).

286 Temperature and time, but not their interaction, influenced microbial community structure,
287 with increased alpha- and beta-diversity with elevated temperature and with time. (Fig 1c,
288 Appendix 3). Mimicking biomass and respiration results, microbial community structure was
289 significantly affected by temperature, time, and their interaction (Fig 1d). The microbial
290 communities were primarily structured by incubation time, with 13.3% of the variation explained
291 by community shifts from Day 12 to Day 24 harvest ($p=.001$). Temperature (22°C vs. 25°C)
292 explained 5.5% of the community variation across all harvesting time points ($p=.001$, Fig 1d),
293 while the interaction of temperature and time explained 3.2% of the variation in microbial
294 community structure ($p=.001$, Fig 1d). Post-hoc tests revealed that all four treatment combinations
295 resulted in significantly distinct groupings of microbial community structure ($p.\text{adj}=.006$). Finally,
296 increased temperature and incubation time imposed significant increases to beta-dispersion
297 (temp: $p.\text{adj}=.003$, time: $p.\text{adj}=.001$), with wider spread in group dispersion at the warmer
298 temperature in the early harvested microbiomes ($p.\text{adj}=.045$) (Fig 1d).

299

300 *Effects of protist predation on the microbial function and community structure*

301 The larger protist (*Colpidium*) significantly reduced OD600 biomass relative to the no protist
302 treatment, while the smaller *Tetrahymena* did not (Fig 2a, $\text{effect}_{\text{Colp}} = -0.09 \pm 0.04\text{SE}$, $p=0.015$;
303 $\text{effect}_{\text{Tetra}} = -0.05 \pm 0.04\text{SE}$, $p=0.19$). Protist effects on OD600 biomass did not interact with time or
304 temperature (Table S1, Fig S3, Appendix 2). *Tetrahymena* had no noticeable effect on microbial
305 respiration rate either (Fig 2b, $\text{effect}_{\text{Tetra}} = -0.05 \pm 0.04\text{SE}$, $p=0.19$). However, *Colpidium* had a
306 significant effect on respiration that interacted with temperature: in the presence of *Colpidium*,

307 total respiration was lower at 25°C than at 22°C ($\text{effect}_{\text{Colp}} = 0.99 \pm 0.25\text{SE}$, $p < 0.01$; $\text{effect}_{\text{Colp} \times \text{Temp}} =$
308 $-0.87 \pm 0.36\text{SE}$, $p = 0.017$; Fig 2b).

309 Predator presence had no significant effects on any of the measured alpha diversity
310 indices of the microbial communities (ASV richness, $p = 0.6$; phylogenetic diversity, $p = 0.8$;
311 Shannon-Wiener diversity, $p = 0.5$; or community evenness, $p = 0.4$, Fig 2c, Appendix 3).
312 However, both protists significantly affected microbial community composition (Fig 2d), although
313 neither one interacted with temperature or time (protist and temperature interaction: $p = 0.22$;
314 protist and time interaction: $p = 0.25$; protist, time and temperature interaction: $p = 0.60$). Protist
315 treatments explained 6.7% of the variation in microbial community structure ($p = .001$). Microbial
316 communities exposed to either protist species significantly differed from the no protist microbial
317 communities (*Tetrahymena*: $p.\text{adj} = .001$; *Colpidium*: $p.\text{adj} = .001$), and also differed between the
318 two protist species treatments ($p.\text{adj} = .004$). Group dispersion analysis of beta diversity revealed
319 no differences in the degree of group variation in community structure among protist treatment
320 levels ($p.\text{adj} = .239$).

321

322 *Feedbacks on protist abundance and traits*

323 Protist abundance increased over time (Fig 3a $\text{effect}_{\text{Colp}} = 172.05 \pm 46.77\text{SE}$, $p = 0.002$; $\text{effect}_{\text{Tetra}} =$
324 $344.9 \pm 132.9\text{SE}$, $p = 0.02$), as expected, but final abundance was independent from temperature
325 (Fig 3b; $\text{effect}_{\text{Colp}} = -16.43 \pm 66.66\text{SE}$, $p = 0.89$; $\text{effect}_{\text{Tetra}} = 120.9 \pm 160.3\text{SE}$, $p = 0.46$). This indicates
326 that temperature effects on protist abundances are unlikely to explain, alone, observed effects on
327 microbial communities and respiration rate. Both time and temperature influenced protist traits
328 independently and interactively (Fig 3c-f, Tables S4-S7, Appendix 4), but each species responded
329 in slightly different ways. Contrary to the temperature-size rule, *Colpidium* sp. responded to
330 increasing temperatures by becoming larger and more elongated (Fig 3c, perMANOVA $p < 0.01$,
331 Table S4, S5, Appendix 4). On the other hand, *Tetrahymena* response was consistent with a
332 temperature-size rule, becoming smaller and rounder with temperature (Fig 3e, perMANOVA

333 $p<0.01$, Table S6, S7, Appendix 4). Over time, however, *Colpidium* got smaller and shorter (Fig
334 3d, perMANOVA $p<0.01$, Table S4, S5, Appendix 4), while temperature effects on *Tetrahymena*
335 were exacerbated over time (Fig 3f, perMANOVA $p<0.01$, Table S6, S7, Appendix 4). Both protists
336 showed changes in optical properties as time went by (Fig 3d, e, perMANOVA $p<0.01$),
337 suggestive of changes in cellular contents.

338

339 *Density- and Trait Effects of Protists on Taxa-specific Responses*

340 The observed changes in overall bacterial community structure were likely driven by the 113
341 ASVs that exhibited significant changes in relative abundance (8% of 1423 total ASVs) to the
342 imposed experimental treatments (Fig 4, Appendix 5). Of these responders, 91 ASVs
343 responded significantly to temperature, with 76.9% positively responding to increased
344 temperature and 23.1% showing decreased relative abundance with elevated treatment (Fig
345 4a). The ASVs flourishing under elevated temperature were largely clustered into several
346 phyla: Verrucomicrobia (12 ASVs), Proteobacteria (10 ASVs), the basal Patescibacteria (9
347 ASVs), Bacteroidota (7 ASVs) and Spirochaetota (7 ASVs); while the other 25 'warm
348 responders' were spread across ten additional bacterial phyla. In contrast, ASVs thriving
349 under ambient temperatures (21 ASVs) were distributed across the entire bacterial phylogeny
350 (Fig 4a).

351 Of the 113 responding ASVs, 23.9% (27 ASVs) exhibited significant shifts in relative
352 abundance to the presence, or absence, of the predator protists (Fig 4b). The presence of
353 *Colpidium* resulted in more responding ASVs (11 ASVs) compared to *Tetrahymena* (7 ASVs) or
354 the no protist treatment (9 ASVs). Responders were distributed throughout the bacterial domain.
355 With TITAN analysis, we also identified 47 ASVs as indicators to gradients of protist cell density
356 and body size (Fig 4b). Seven indicators were negatively associated with *Tetrahymena* body size,
357 while two ASVs positively responded to increased cell size. The density of *Tetrahymena* density

358 corresponded to five positive and five negative responders, distributed across five phyla. Two
359 ASVs responded consistently to cell density and size: a negative indicator ASV_45, identified as
360 *Paenibacillus* spp. (Chitinophagaceae), and a positive responder, ASV_269 in
361 Selenomonadaceae. *Colpidium* cell density and body size resulted in 82% more responding ASVs
362 than to *Tetrahymena* traits. Most of the responders were impacted by *Colpidium* density (21
363 ASVs), of which the bulk (15 ASVs) responded negatively to more *Colpidium* cells. No ASVs
364 responded to both *Colpidium* density and cell size, but one responder (ASV 78), in the genus
365 *Afipia*, positively responded to the density of both predators (Fig 4, Appendix 5). ASVs from
366 Proteobacteria, Bacteroidota and Verrucomicrobiota seemed to respond to both protists, while
367 ASVs from Gemmatimonadota and Actinobacteria only responded to *Colpidium* (Fig 4), thus
368 suggesting some level of specificity to predation by protists, but also to protist species.

369

370 **DISCUSSION**

371 Microbes strongly influence the global carbon cycle through respiration and assimilation of both
372 labile and recalcitrant forms of carbon (Jackson et al., 2017). Understanding how changes in
373 environmental temperature may influence microbial community function in general, and
374 respiration rates, in particular, is crucial to hone our ability to forecast future warming trends
375 (REFS). Our study shows how temperature determines both community structure and function in
376 a temperate pond microbial community (Fig 1). We also show how predation by one of the most
377 important consumers of microorganisms worldwide, protist ciliates (Gao et al., 2019; Oliverio et
378 al., 2020), mediate temperature effects on function (Fig 2, 3-4), through Phylum-specific bacterial
379 responses to protist density and size (Fig 4).

380 Our results show that temperature directly influences community function, owing, in part,
381 to shifts in community structure over time and across temperatures (Fig 2). However, the effects
382 of temperature on function were reversed over time (Fig 2c), which is consistent with other studies
383 showing that while total microbial respiration increases with temperature at first, that effect is short

384 lived or even fully reversed as time elapses (Bradford, 2013; Crowther & Bradford, 2013; Ye et
385 al., 2020; Yergeau et al., 2012). To explain these changes, previous studies have invoked shifts
386 in carbon use efficiency (Frey et al., 2013). While we cannot rule out the possibility of decreased
387 availability of labile carbon within our microcosms, we have attempted to control for that by adding
388 wheat seeds, which provided a slow-release of labile carbon to the incubated communities over
389 time (Altermatt et al., 2015). On the other hand, both temperature and time led to large shifts and
390 increased variability in community structure (Fig 2d), with the warmer temperature leading to a
391 higher relative abundance of some microbial taxa over others (Fig 4), suggesting some degree of
392 phylogenetically conserved responses (Isobe et al., 2020; Martiny et al., 2013). These results thus
393 suggest a possible causal relationship between changes in community structure and function, as
394 proposed by others (Hall et al., 2018), and despite such changes being rarely observed (Fang et
395 al., 2020; Graham et al., 2016; Rocca et al., 2015). While changes in carbon use efficiency have
396 been recently accounted for in state-of-the-art forecasting models (Allison et al., 2010;
397 Sinsabaugh et al., 2013), changes in microbial community structure have not (Sulman et al.,
398 2018). Our results therefore emphasize the need to take such changes into account to improve
399 our predictive models of climate change.

400 Secondly, we show that predation by larger protists, like *Colpidium* sp., mediates the
401 impacts of temperature on microbial community function (Fig 2a, b). Indeed, protist predation
402 resulted in changes in total biomass (Fig 2a), microbial respiration that interacted with
403 temperature (Fig 2b) Predation by the larger *Colpidium* sp. actually led to a reversal of the
404 temperature effect on respiration rate (Fig 2b). Interestingly, a recent paper showed that soil
405 decomposition rates increased in the presence of the protist *Physarum polycephalum* at low
406 temperatures, but that effect disappeared at a warmer temperature (Geisen et al., 2021). Our
407 results confirm –and extend– those of Geisen and collaborators to a different protist system, and
408 to a freshwater microbial community, thus suggesting this might be a more general pattern rather
409 than an idiosyncratic effect. If further confirmed, this may also indicate that predation by protists

410 could reduce total microbial respiration in warmer climates, thus representing a poorly understood
411 but potentially important biotic control on the global carbon cycle that ultimately sets the pace of
412 future warming.

413 Thirdly, protist effects on total microbial biomass (Fig 2a) and function (Fig 2b) were, as
414 hypothesized, size-dependent (Fig 3a,b, Fig 4b). Further analysis also revealed that these effects
415 on microbial communities were likely due to individual bacterial taxa differentially responding to
416 protist density and size (Fig 4b), thus confirming that strong size-dependencies may be at play.
417 Previous studies have shown that protist predation can select for bacterial size (Erktan et al.,
418 2020; Hahn & Höfle, 2001; Pernthaler, 2005), and both negative and positive associations with
419 different protists have also been shown (Oliverio et al., 2020). In addition to the direct predator
420 effects on responding microbial taxa, we cannot rule out indirect effects of the predator presence,
421 due to higher order interactions to explain the abundance shifts of certain responding microbes
422 (Karakoç et al., 2018; Mickalide & Kuehn, 2019). Our results add to this growing literature by
423 mechanistically linking changes in protist density and size to specific bacterial responders (Fig
424 4b). By showing that cell size and density-dependencies are at play, our experimental results
425 suggest that consumer-resource models that take into account size-dependencies on predation
426 and foraging rates (DeLong et al., 2015; Gauzens et al., 2020; Gilbert et al., 2014) could be used
427 to improve on current Earth System Models once microbial interactions are accounted for.

428 Lastly, our results showed that the traits of both protist predators also responded to
429 imposed experimental conditions, albeit in different ways. While size is well-known to influence
430 consumer-resource interactions (DeLong et al., 2015; Gauzens et al., 2020; Gilbert et al., 2014),
431 protist size and shape can and often do respond to foraging (Atkinson et al., 2006; DeLong et al.,
432 2014; Gilbert et al., 2017; Tan et al., 2021), thus potentially resulting in a feedback between
433 predator and prey phenotypes. Since the microbial communities themselves changed in structure
434 with time and temperature, this study cannot tease apart the direct effects of temperature on
435 protist responses from those mediated by microbial community temperature responses. However

436 understanding how these reciprocal effects may lead to shifts in the function of microbial
437 communities as temperature increases is an exciting avenue for future research.

438 While our results uncovered interesting patterns about predation influence on the
439 temperature response of microbial communities, there also are shortcomings to our findings that
440 need to be accounted for to fully understand the full scope of these results. For example, the
441 incubation of the microbial communities led to significant departures, in terms of composition,
442 from the original pond microbial communities (Fig S7). One possibility is that our microcosms
443 were artificially awash with nutrients, thus selecting for a microbial composition that would not
444 naturally prevail in more oligotrophic pond conditions. To better understand how common the
445 results shown here may actually be, these abiotic and biotic treatments should also be studied in
446 mesocosms or other semi-natural experimental settings. Our experimental temperature
447 treatments also did not account for diurnal and seasonal temperature fluctuations, nor could they
448 inform us about any broader effects of seasonal changes in temperature. Seasonality, in
449 particular, is likely also shifting as temperatures rise globally (Easterling et al., 2000; Meehl &
450 Tebaldi, 2004; Rahmstorf & Coumou, 2011; Rummukainen, 2012), but whether those effects differ
451 from those of changes in mean temperatures, as shown here, is unknown. Last, the short-term
452 nature of our experimental manipulations necessarily reduce the possible scope of our inference,
453 even though both the nature and magnitude of the effects reported here seem large enough to
454 be of importance beyond our specific set up.

455 Our results emphasize the dynamic nature of temperature effects on microbial community
456 structure and function as well as how a neglected biological factor (protist predation) influences
457 such responses. We show how protist predation can mediate temperature effects on microbial
458 communities, how such impacts are dependent on the body-size and density of the predator, and
459 how microbial responses to temperature may in turn influence the traits of these microbial
460 consumers. Our study suggests novel and surprising mechanisms that future forecasting models
461 may need to account for to accurately predict biological controls on the global carbon cycle.

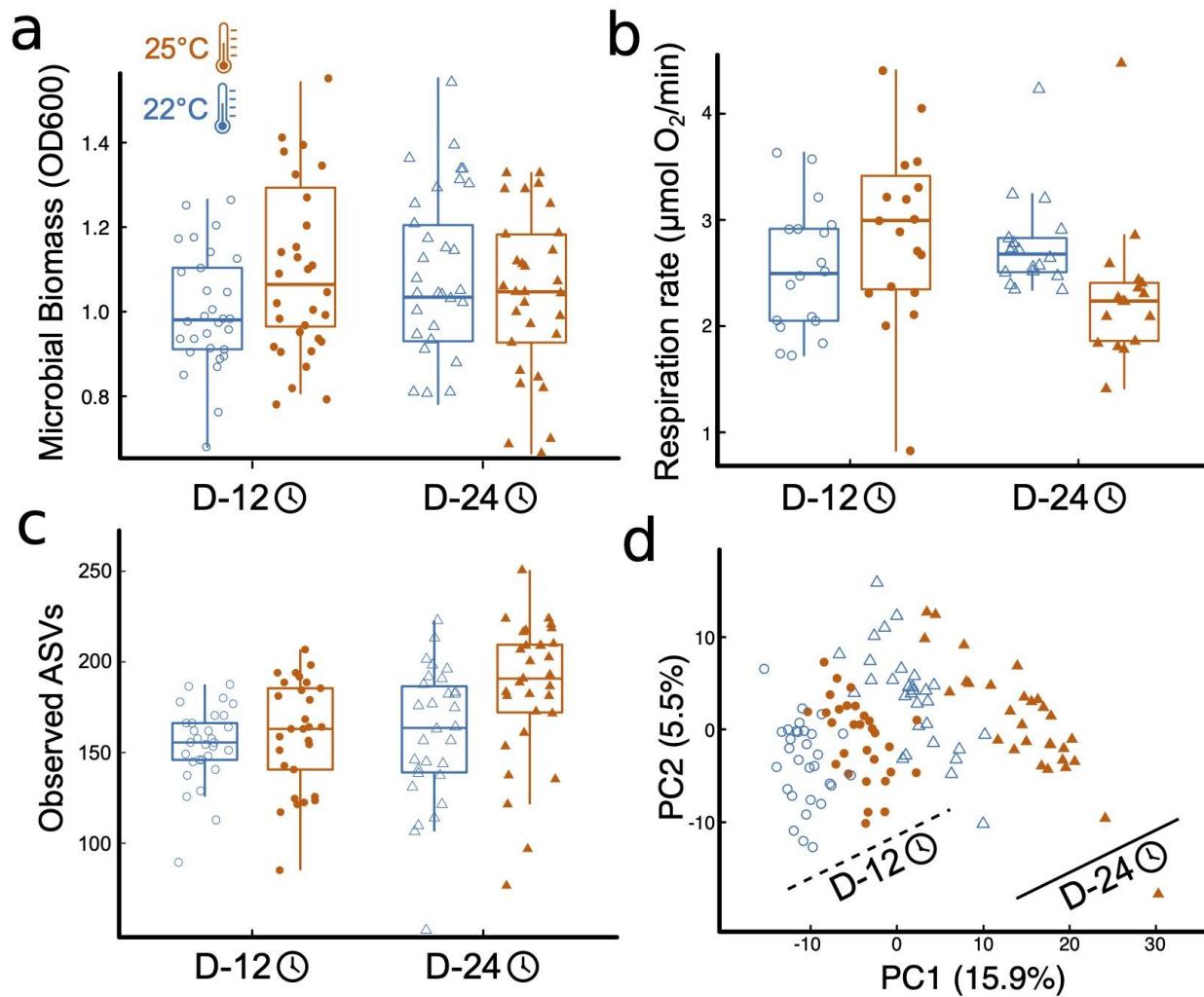
462

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468 **TABLES and FIGURES**

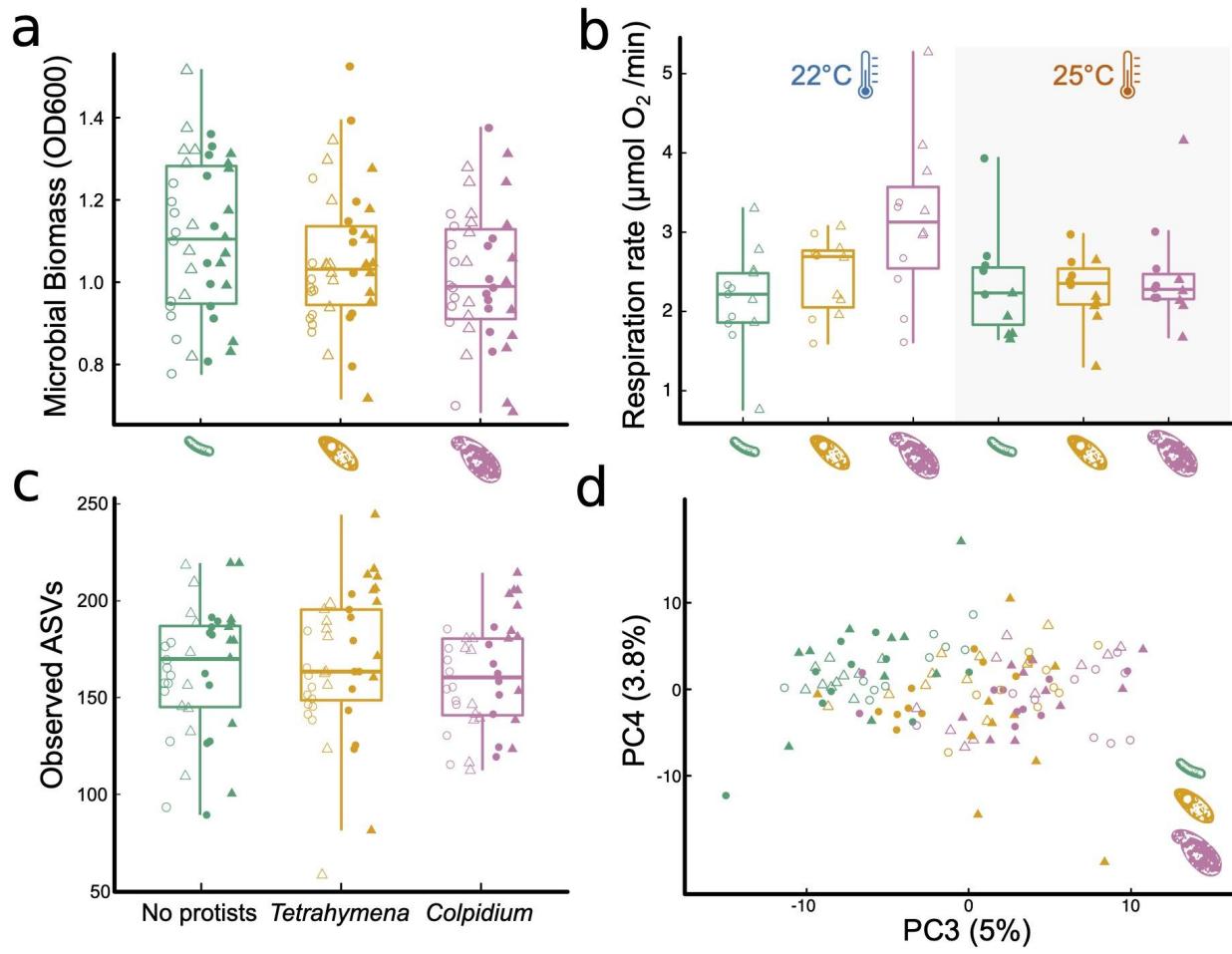
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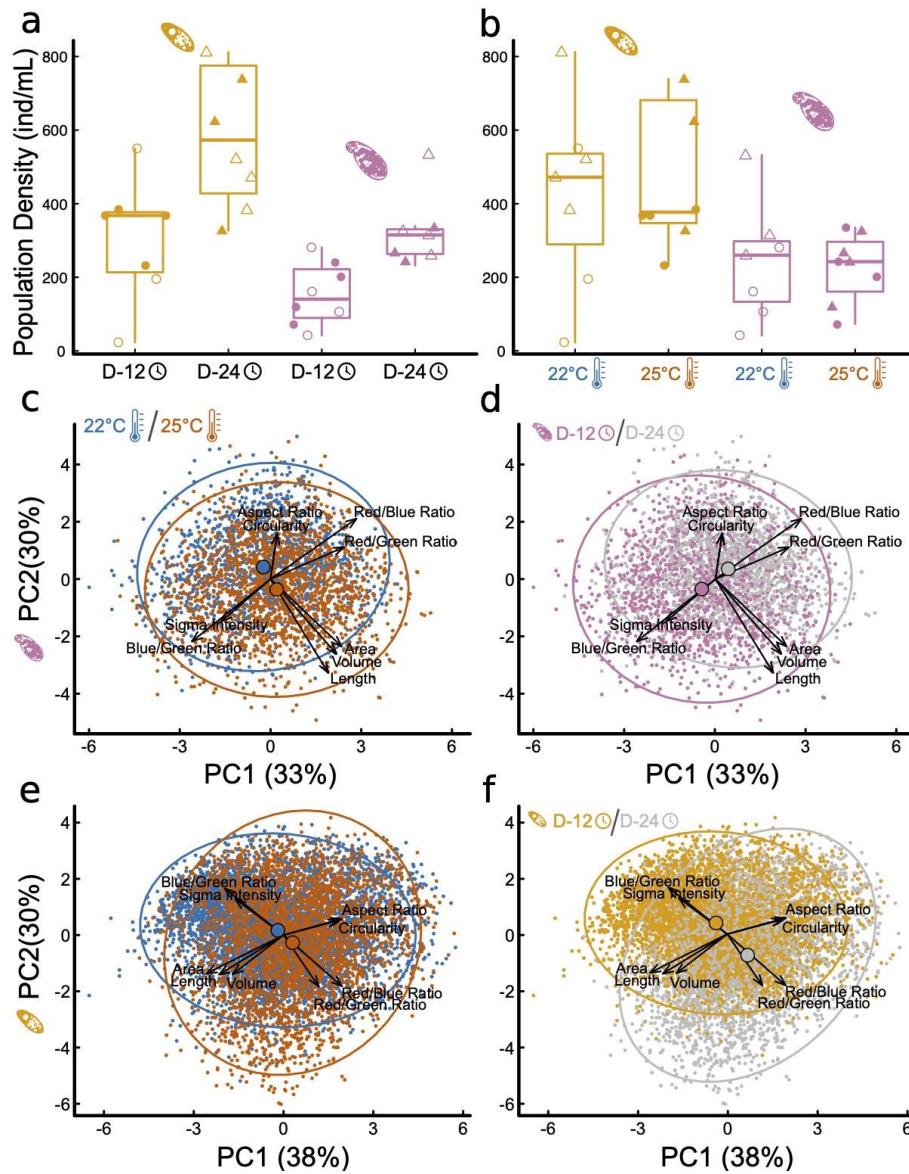
471 **Figure 1. Temperature impacts on microbial function and community structure.** (a) Boxplots
472 of the treatment effects on total microbial biomass, (b) the effects on total microbial respiration,
473 here as oxygen consumption, (c) the effects on microbial community richness, here observed
474 ASVs, and (d) the effects of temperature and time on the microbial community structure. Shapes
475 represent incubation time: Day12 - circles, Day 24 - triangles; and temperature marked by point
476 fill: 22°C - empty point, 25°C - color filled point.

477



478

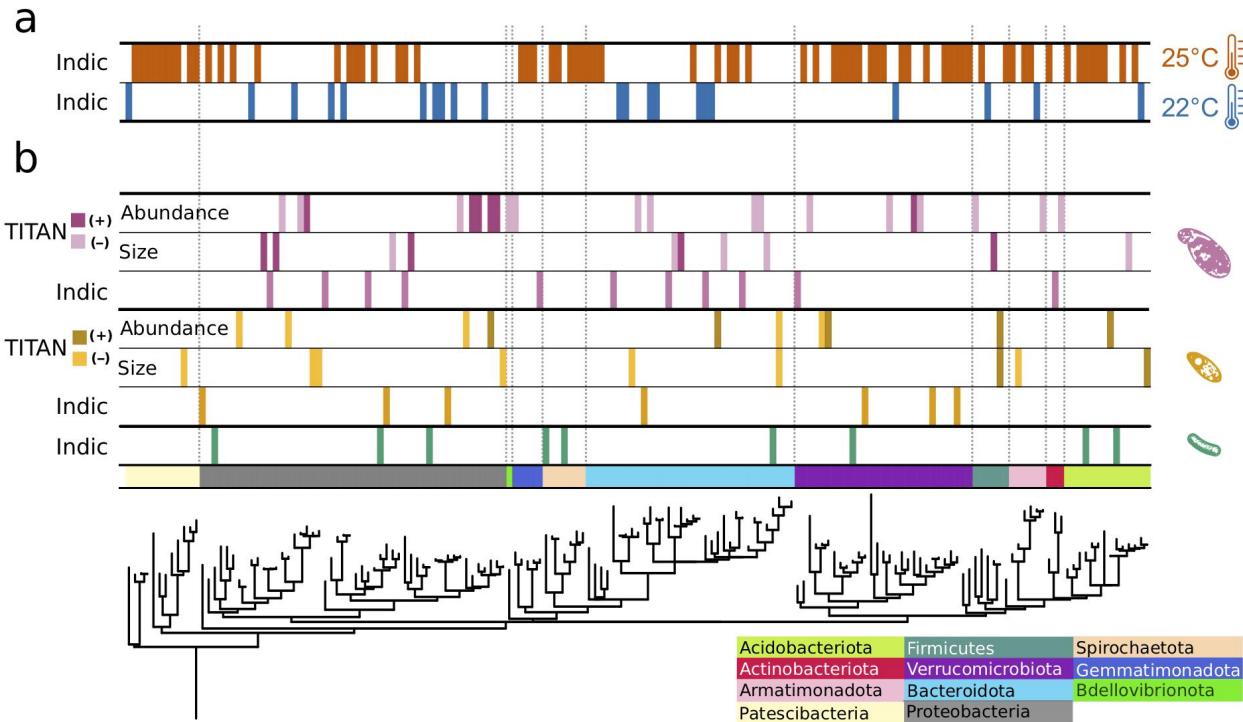
479 **Figure 2. Influence of protist presence and species on pond microbial community function**
480 **and community structure.** The effect of the absence of protists (green), *Tetrahymena* (yellow)
481 or *Colpidium* (fuchsia) on: (a) optical density (600nm) as a proxy for total microbial biomass, (b)
482 total microbial respiration (O_2 consumption rate), (c) microbial community richness (observed
483 ASVs), and (d) a principal component analysis of microbial community structure. Shapes
484 represent incubation time: Day12 - circles, Day 24 - triangles; and temperature marked by point
485 fill: 22°C - empty point, 25°C - color filled point.



486

487 **Figure 3. Impact of temperature treatments and incubation time on protist density and**
488 **morphology.** The effect of incubation time (A) and temperature treatment (B) on *Tetrahymena*
489 (yellow) and *Colpidium* (pink) density (cells/mL) in the microcosms; and principal component
490 analysis of multivariate protist phenotypes (C-F): *Colpidium* (C, D) and *Tetrahymena* (E, F),
491 colored by temperature (C, E) and by time (D, F). Vectors represent the principal components
492 loadings of each measured phenotypic characteristic, including: shape, size, optical depth, and
493 hue.

494



495

496 **Figure 4: Phylogenetic distribution of treatment impacts on individual bacterial ASVs.**

497 Responder ASVs showing consistent change in relative abundance, to temperature (a) and protist
498 (b) treatments. Data strips labeled, "Indic", represent ASVs positively correlated with a particular
499 temperature treatment level, generated from multi-level pattern analysis output; data strips
500 labeled, "TITAN", show responding ASVs to changes in specific protist species' traits, analyzed
501 with direct gradient analysis.

502 **REFERENCES**

503 Allison, S. D., Wallenstein, M. D., & Bradford, M. A. (2010). Soil-carbon response to warming
504 dependent on microbial physiology. In *Nature Geoscience*. <https://doi.org/10.1038/ngeo846>

505 Altermatt, F., Fronhofer, E. A., Garnier, A., Giometto, A., Hammes, F., Klecka, J., Legrand, D.,
506 Mächler, E., Massie, T. M., Pennekamp, F., Plebani, M., Pontarp, M., Schtickzelle, N.,
507 Thuillier, V., & Petchey, O. L. (2015). Big answers from small worlds: a user's guide for
508 protist microcosms as a model system in ecology and evolution. *Methods in Ecology and*
509 *Evolution / British Ecological Society*, 6(2), 218–231. <https://doi.org/10.1111/2041-210X.12312>

510

511 Anderson, M. J. (2001). A new method for non-parametric multivariate analysis of variance.
512 *Austral Ecology*, 26(1), 32–46. <https://doi.org/10.1111/j.1442-9993.2001.01070.pp.x>

513 Anderson, M. J. (2006). Distance-Based Tests for Homogeneity of Multivariate Dispersions. In
514 *Biometrics* (Vol. 62, Issue 1, pp. 245–253). <https://doi.org/10.1111/j.1541-0420.2005.00440.x>

515

516 Anderson, M. J. (2017). Permutational Multivariate Analysis of Variance (PERMANOVA). In
517 *Wiley StatsRef: Statistics Reference Online* (pp. 1–15).
518 <https://doi.org/10.1002/9781118445112.stat07841>

519 Anderson, M. J., Ellingsen, K. E., & McArdle, B. H. (2006). Multivariate dispersion as a measure
520 of beta diversity. *Ecology Letters*, 9(6), 683–693. <https://doi.org/10.1111/j.1461-0248.2006.00926.x>

521

522 Atkinson, D. (1994). Temperature and Organism Size—A Biological Law for Ectotherms? In
523 *Advances in Ecological Research* (pp. 1–58). [https://doi.org/10.1016/s0065-2504\(08\)60212-3](https://doi.org/10.1016/s0065-2504(08)60212-3)

524

525 Atkinson, D., Ciotti, B. J., & Montagnes, D. J. S. (2003). Protists decrease in size linearly with
526 temperature: ca. 2.5% degrees C(-1). *Proceedings. Biological Sciences / The Royal*

527 Society, 270(1533), 2605–2611. <https://doi.org/10.1098/rspb.2003.2538>

528 Atkinson, D., Morley, S. A., & Hughes, R. N. (2006). From cells to colonies: at what levels of
529 body organization does the “temperature-size rule” apply? *Evolution & Development*, 8(2),
530 202–214. <https://doi.org/10.1111/j.1525-142X.2006.00090.x>

531 Baker, M. E., & King, R. S. (2010). A new method for detecting and interpreting biodiversity and
532 ecological community thresholds. In *Methods in Ecology and Evolution* (Vol. 1, Issue 1, pp.
533 25–37). <https://doi.org/10.1111/j.2041-210x.2009.00007.x>

534 Baltar, F., Palovaara, J., Unrein, F., Catala, P., Horňák, K., Šimek, K., Vaqué, D., Massana, R.,
535 Gasol, J. M., & Pinhassi, J. (2016). Marine bacterial community structure resilience to
536 changes in protist predation under phytoplankton bloom conditions. *The ISME Journal*,
537 10(3), 568–581. <https://doi.org/10.1038/ismej.2015.135>

538 Bardgett, R. D., Freeman, C., & Ostle, N. J. (2008). Microbial contributions to climate change
539 through carbon cycle feedbacks. *The ISME Journal*, 2(8), 805–814.
540 <https://doi.org/10.1038/ismej.2008.58>

541 Barneche, D. R., Hulatt, C. J., Dossena, M., Padfield, D., Woodward, G., Trimmer, M., & Yvon-
542 Durocher, G. (2021). Warming impairs trophic transfer efficiency in a long-term field
543 experiment. *Nature*, 592(7852), 76–79. <https://doi.org/10.1038/s41586-021-03352-2>

544 Bar-On, Y. M., Phillips, R., & Milo, R. (2018). The biomass distribution on Earth. *Proceedings of
545 the National Academy of Sciences of the United States of America*, 115(25), 6506–6511.
546 <https://doi.org/10.1073/pnas.1711842115>

547 Beal, J., Farny, N. G., Haddock-Angelli, T., Selvarajah, V., Baldwin, G. S., Buckley-Taylor, R.,
548 Gershater, M., Kiga, D., Marken, J., Sanchania, V., Sison, A., Workman, C. T., & iGEM
549 Interlab Study Contributors. (2020). Robust estimation of bacterial cell count from optical
550 density. *Communications Biology*, 3(1), 512. <https://doi.org/10.1038/s42003-020-01127-5>

551 Bernhardt, J. R., Sunday, J. M., & O'Connor, M. I. (2018). Metabolic Theory and the
552 Temperature-Size Rule Explain the Temperature Dependence of Population Carrying

553 Capacity. *The American Naturalist*, 192(6), 687–697. <https://doi.org/10.1086/700114>

554 Binzer, A., Guill, C., Brose, U., & Rall, B. C. (2012). The dynamics of food chains under climate
555 change and nutrient enrichment. *Philosophical Transactions of the Royal Society of*
556 *London. Series B, Biological Sciences*, 367(1605), 2935–2944.
557 <https://doi.org/10.1098/rstb.2012.0230>

558 Bolyen, E., Rideout, J. R., Dillon, M. R., Bokulich, N. A., Abnet, C. C., Al-Ghalith, G. A.,
559 Alexander, H., Alm, E. J., Arumugam, M., Asnicar, F., Bai, Y., Bisanz, J. E., Bittinger, K.,
560 Brejnrod, A., Brislawn, C. J., Brown, C. T., Callahan, B. J., Caraballo-Rodríguez, A. M.,
561 Chase, J., ... Caporaso, J. G. (2019). Reproducible, interactive, scalable and extensible
562 microbiome data science using QIIME 2. *Nature Biotechnology*, 37(8), 852–857.
563 <https://doi.org/10.1038/s41587-019-0209-9>

564 Bond-Lamberty, B., Bailey, V. L., Chen, M., Gough, C. M., & Vargas, R. (2018). Globally rising
565 soil heterotrophic respiration over recent decades. *Nature*, 560(7716), 80–83.
566 <https://doi.org/10.1038/s41586-018-0358-x>

567 Bradford, M. A. (2013). Thermal adaptation of decomposer communities in warming soils.
568 *Frontiers in Microbiology*, 4, 333. <https://doi.org/10.3389/fmicb.2013.00333>

569 Callahan, B. J., McMurdie, P. J., Rosen, M. J., Han, A. W., Johnson, A. J. A., & Holmes, S. P.
570 (2016). DADA2: High-resolution sample inference from Illumina amplicon data. In *Nature*
571 *Methods* (Vol. 13, Issue 7, pp. 581–583). <https://doi.org/10.1038/nmeth.3869>

572 Caporaso, J. G., Lauber, C. L., Walters, W. A., Berg-Lyons, D., Lozupone, C. A., Turnbaugh, P.
573 J., Fierer, N., & Knight, R. (2011). Global patterns of 16S rRNA diversity at a depth of
574 millions of sequences per sample. *Proceedings of the National Academy of Sciences of the*
575 *United States of America*, 108 Suppl 1, 4516–4522.
576 <https://doi.org/10.1073/pnas.1000080107>

577 Cordone, G., Salinas, V., Marina, T. I., Doyle, S. R., Pasotti, F., Saravia, L. A., & Momo, F. R.
578 (2020). Green vs brown food web: Effects of habitat type on multidimensional stability

579 proxies for a highly-resolved Antarctic food web. *Food Webs*, 25, e00166.

580 <https://doi.org/10.1016/j.fooweb.2020.e00166>

581 Crowther, T. W., & Bradford, M. A. (2013). Thermal acclimation in widespread heterotrophic soil

582 microbes. *Ecology Letters*, 16(4), 469–477. <https://doi.org/10.1111/ele.12069>

583 Crowther, T. W., Thomas, S. M., Maynard, D. S., Baldrian, P., Covey, K., Frey, S. D., van

584 Diepen, L. T. A., & Bradford, M. A. (2015). Biotic interactions mediate soil microbial

585 feedbacks to climate change. *Proceedings of the National Academy of Sciences of the*

586 *United States of America*, 112(22), 7033–7038. <https://doi.org/10.1073/pnas.1502956112>

587 De Cáceres, M., & Legendre, P. (2009). Associations between species and groups of sites:

588 indices and statistical inference. *Ecology*, 90(12), 3566–3574. <https://doi.org/10.1890/08-1823.1>

589

590 Dell, A. I., Pawar, S., & Savage, V. M. (2011). Systematic variation in the temperature

591 dependence of physiological and ecological traits. *Proceedings of the National Academy of*

592 *Sciences of the United States of America*, 108(26), 10591–10596.

593 <https://doi.org/10.1073/pnas.1015178108>

594 Dell, A. I., Pawar, S., & Savage, V. M. (2014). Temperature dependence of trophic interactions

595 are driven by asymmetry of species responses and foraging strategy. *The Journal of*

596 *Animal Ecology*, 83(1), 70–84. <https://doi.org/10.1111/1365-2656.12081>

597 DeLong, J. P., Gibert, J. P., Luhring, T. M., Bachman, G., Reed, B., Neyer, A., & Montooth, K. L.

598 (2017). The combined effects of reactant kinetics and enzyme stability explain the

599 temperature dependence of metabolic rates. *Ecology and Evolution*, 7(11), 3940–3950.

600 <https://doi.org/10.1002/ece3.2955>

601 DeLong, J. P., Gilbert, B., Shurin, J. B., Savage, V. M., Barton, B. T., Clements, C. F., Dell, A. I.,

602 Greig, H. S., Harley, C. D. G., Kratina, P., McCann, K. S., Tunney, T. D., Vasseur, D. A., &

603 O'Connor, M. I. (2015). The body size dependence of trophic cascades. *The American*

604 *Naturalist*, 185(3), 354–366. <https://doi.org/10.1086/679735>

605 DeLong, J. P., Hanley, T. C., & Vasseur, D. A. (2014). Predator-prey dynamics and the plasticity
606 of predator body size. In *Functional Ecology* (Vol. 28, Issue 2, pp. 487–493).
607 <https://doi.org/10.1111/1365-2435.12199>

608 DeLong, J. P., & Lyon, S. (2020). Temperature alters the shape of predator–prey cycles through
609 effects on underlying mechanisms. *PeerJ*, 8, e9377. <https://doi.org/10.7717/peerj.9377>

610 DeLong, J. P., & Vasseur, D. A. (2012). A dynamic explanation of size-density scaling in
611 carnivores. *Ecology*, 93(3), 470–476. <https://doi.org/10.1890/11-1138.1>

612 Easterling, D. R., Meehl, G. A., Parmesan, C., Changnon, S. A., Karl, T. R., & Mearns, L. O.
613 (2000). Climate extremes: observations, modeling, and impacts. *Science*, 289(5487),
614 2068–2074. <https://doi.org/10.1126/science.289.5487.2068>

615 Elliott, A. M. (1970). *The Distribution of Tetrahymena pyriformis* 1.
616 <https://deepblue.lib.umich.edu/bitstream/handle/2027.42/72276/j.1550-7408.1970.tb02348.x.pdf?sequence=1>

618 Englund, G., Ohlund, G., Hein, C. L., & Diehl, S. (2011). Temperature dependence of the
619 functional response. *Ecology Letters*, 14(9), 914–921. <https://doi.org/10.1111/j.1461-0248.2011.01661.x>

621 Erktan, A., Rillig, M. C., Carminati, A., Jousset, A., & Scheu, S. (2020). Protists and
622 collembolans alter microbial community composition, C dynamics and soil aggregation in
623 simplified consumer–prey systems. *Biogeosciences* , 17(20), 4961–4980.
624 <https://bg.copernicus.org/articles/17/4961/2020/>

625 Fang, C., Ke, W., Campioli, M., Pei, J., Yuan, Z., Song, X., Ye, J.-S., Li, F., & Janssens, I. A.
626 (2020). Unaltered soil microbial community composition, but decreased metabolic activity in
627 a semiarid grassland after two years of passive experimental warming. *Ecology and
628 Evolution*, 10(21), 12327–12340. <https://doi.org/10.1002/ece3.6862>

629 Flemming, H.-C., & Wuertz, S. (2019). Bacteria and archaea on Earth and their abundance in
630 biofilms. *Nature Reviews. Microbiology*, 17(4), 247–260. <https://doi.org/10.1038/s41579-018-0043-1>

631 019-0158-9

632 Foissner, W., & Berger, H. (1996). A user-friendly guide to the ciliates (Protozoa, Ciliophora)
633 commonly used by hydrobiologists as bioindicators in rivers, lakes, and waste waters, with
634 notes on their ecology. In *Freshwater Biology* (Vol. 35, Issue 2, pp. 375–482).
635 <https://doi.org/10.1111/j.1365-2427.1996.tb01775.x>

636 Frey, S. D., Lee, J., Melillo, J. M., & Six, J. (2013). The temperature response of soil microbial
637 efficiency and its feedback to climate. *Nature Climate Change*, 3(4), 395–398.
638 <https://doi.org/10.1038/nclimate1796>

639 Frøslev, T. G., Kjøller, R., Bruun, H. H., Ejrnæs, R., Brunbjerg, A. K., Pietroni, C., & Hansen, A.
640 J. (2017). Algorithm for post-clustering curation of DNA amplicon data yields reliable
641 biodiversity estimates. *Nature Communications*, 8(1), 1–11. <https://doi.org/10.1038/s41467-017-01312-x>

643 Gao, Z., Karlsson, I., Geisen, S., Kowalchuk, G., & Jousset, A. (2019). Protists: Puppet Masters
644 of the Rhizosphere Microbiome. *Trends in Plant Science*, 24(2), 165–176.
645 <https://doi.org/10.1016/j.tplants.2018.10.011>

646 Garzke, J., Connor, S. J., Sommer, U., & O'Connor, M. I. (2019). Trophic interactions modify the
647 temperature dependence of community biomass and ecosystem function. *PLoS Biology*,
648 17(6), e2006806. <https://doi.org/10.1371/journal.pbio.2006806>

649 Gauzens, B., Rall, B. C., Mendonça, V., Vinagre, C., & Brose, U. (2020). Biodiversity of intertidal
650 food webs in response to warming across latitudes. *Nature Climate Change*, 10(3), 264–
651 269. <https://doi.org/10.1038/s41558-020-0698-z>

652 Geisen, S., Hu, S., Dela Cruz, T. E. E., & Veen, G. F. C. (2021). Protists as catalysts of
653 microbial litter breakdown and carbon cycling at different temperature regimes. *The ISME
654 Journal*, 15(2), 618–621. <https://doi.org/10.1038/s41396-020-00792-y>

655 Geisen, S., Mitchell, E. A. D., Adl, S., Bonkowski, M., Dunthorn, M., Ekelund, F., Fernández, L.
656 D., Jousset, A., Krashevská, V., Singer, D., Spiegel, F. W., Walochnik, J., & Lara, E.

657 (2018). Soil protists: a fertile frontier in soil biology research. *FEMS Microbiology Reviews*,
658 42(3), 293–323. <https://doi.org/10.1093/femsre/fuy006>

659 Gibert, J. P., Allen, R. L., Hruska, R. J., 3rd, & DeLong, J. P. (2017). The ecological
660 consequences of environmentally induced phenotypic changes. *Ecology Letters*, 20(8),
661 997–1003. <https://doi.org/10.1111/ele.12797>

662 Gibert, J. P., Chelini, M.-C., Rosenthal, M. F., & DeLong, J. P. (2016). Crossing regimes of
663 temperature dependence in animal movement. *Global Change Biology*, 22(5), 1722–1736.
664 <https://doi.org/10.1111/gcb.13245>

665 Gilbert, B., Tunney, T. D., McCann, K. S., DeLong, J. P., Vasseur, D. A., Savage, V., Shurin, J.
666 B., Dell, A. I., Barton, B. T., Harley, C. D. G., Kharouba, H. M., Kratina, P., Blanchard, J. L.,
667 Clements, C., Winder, M., Greig, H. S., & O'Connor, M. I. (2014). A bioenergetic framework
668 for the temperature dependence of trophic interactions. *Ecology Letters*, 17(8), 902–914.
669 <https://doi.org/10.1111/ele.12307>

670 Gillooly, J. F., Brown, J. H., West, G. B., Savage, V. M., & Charnov, E. L. (2001). Effects of Size
671 and Temperature on Metabolic Rate. *Science*, 293(5538), 2248–2251.
672 <https://doi.org/10.1126/science.1061967>

673 Gloor, G. B., Macklaim, J. M., Pawlowsky-Glahn, V., & Egozcue, J. J. (2017). Microbiome
674 Datasets Are Compositional: And This Is Not Optional. *Frontiers in Microbiology*, 8, 2224.
675 <https://doi.org/10.3389/fmicb.2017.02224>

676 Glücksman, E., Bell, T., Griffiths, R. I., & Bass, D. (2010). Closely related protist strains have
677 different grazing impacts on natural bacterial communities. *Environmental Microbiology*,
678 12(12), 3105–3113. <https://doi.org/10.1111/j.1462-2920.2010.02283.x>

679 Gougoulias, C., Clark, J. M., & Shaw, L. J. (2014). The role of soil microbes in the global carbon
680 cycle: tracking the below-ground microbial processing of plant-derived carbon for
681 manipulating carbon dynamics in agricultural systems. In *Journal of the Science of Food and Agriculture* (Vol. 94, Issue 12, pp. 2362–2371). <https://doi.org/10.1002/jsfa.6577>

683 Graham, E. B., Knelman, J. E., Schindlbacher, A., Siciliano, S., Breulmann, M., Yannarell, A.,
684 Beman, J. M., Abell, G., Philippot, L., Prosser, J., Foulquier, A., Yuste, J. C., Glanville, H.
685 C., Jones, D. L., Angel, R., Salminen, J., Newton, R. J., Bürgmann, H., Ingram, L. J., ...
686 Nemergut, D. R. (2016). Microbes as Engines of Ecosystem Function: When Does
687 Community Structure Enhance Predictions of Ecosystem Processes? *Frontiers in*
688 *Microbiology*, 7, 214. <https://doi.org/10.3389/fmicb.2016.00214>

689 Hahn, M. W., & Höfle, M. G. (2001). Grazing of protozoa and its effect on populations of aquatic
690 bacteria. *FEMS Microbiology Ecology*, 35(2), 113–121. <https://doi.org/10.1111/j.1574-6941.2001.tb00794.x>

692 Hall, E. K., Bernhardt, E. S., Bier, R. L., Bradford, M. A., Boot, C. M., Cotner, J. B., Del Giorgio,
693 P. A., Evans, S. E., Graham, E. B., Jones, S. E., Lennon, J. T., Locey, K. J., Nemergut, D.,
694 Osborne, B. B., Rocca, J. D., Schimel, J. P., Waldrop, M. P., & Wallenstein, M. D. (2018).
695 Understanding how microbiomes influence the systems they inhabit. *Nature Microbiology*,
696 3(9), 977–982. <https://doi.org/10.1038/s41564-018-0201-z>

697 Hartley, I. P., Hopkins, D. W., Garnett, M. H., Sommerkorn, M., & Wookey, P. A. (2008). Soil
698 microbial respiration in arctic soil does not acclimate to temperature. *Ecology Letters*,
699 11(10), 1092–1100. <https://doi.org/10.1111/j.1461-0248.2008.01223.x>

700 Isobe, K., Bouskill, N. J., Brodie, E. L., Suderth, E. A., & Martiny, J. B. H. (2020). Phylogenetic
701 conservation of soil bacterial responses to simulated global changes. *Philosophical
702 Transactions of the Royal Society of London. Series B, Biological Sciences*, 375(1798),
703 20190242. <https://doi.org/10.1098/rstb.2019.0242>

704 Jackson, R. B., Lajtha, K., Crow, S. E., Hugelius, G., Kramer, M. G., & Piñeiro, G. (2017). The
705 Ecology of Soil Carbon: Pools, Vulnerabilities, and Biotic and Abiotic Controls. *Annual
706 Review of Ecology, Evolution, and Systematics*, 48(1), 419–445.
707 <https://doi.org/10.1146/annurev-ecolsys-112414-054234>

708 Jansson, J. K., & Hofmockel, K. S. (2020). Soil microbiomes and climate change. *Nature*

709 *Reviews. Microbiology*, 18(1), 35–46. <https://doi.org/10.1038/s41579-019-0265-7>

710 Karakoç, C., Radchuk, V., Harms, H., & Chatzinotas, A. (2018). Interactions between predation
711 and disturbances shape prey communities. *Scientific Reports*, 8(1), 2968.
712 <https://doi.org/10.1038/s41598-018-21219-x>

713 Katoh, K., & Frith, M. C. (2012). Adding unaligned sequences into an existing alignment using
714 MAFFT and LAST. *Bioinformatics*, 28(23), 3144–3146.
715 <https://doi.org/10.1093/bioinformatics/bts578>

716 Martinez Arbizu, P. (2017). pairwiseAdonis: Pairwise multilevel comparison using adonis. *R*
717 *Package Version 0. 0, 1.*

718 Martiny, A. C., Treseder, K., & Pusch, G. (2013). Phylogenetic conservatism of functional traits
719 in microorganisms. *The ISME Journal*, 7(4), 830–838.
720 <https://doi.org/10.1038/ismej.2012.160>

721 McMurdie, P. J., & Holmes, S. (2013). phyloseq: an R package for reproducible interactive
722 analysis and graphics of microbiome census data. *PLoS One*, 8(4), e61217.
723 <https://doi.org/10.1371/journal.pone.0061217>

724 Meehl, G. A., & Tebaldi, C. (2004). More intense, more frequent, and longer lasting heat waves
725 in the 21st century. *Science*, 305(5686), 994–997. <https://doi.org/10.1126/science.1098704>

726 Mickalide, H., & Kuehn, S. (2019). Higher-Order Interaction between Species Inhibits Bacterial
727 Invasion of a Phototroph-Predator Microbial Community. In *Cell Systems* (Vol. 9, Issue 6,
728 pp. 521–533.e10). <https://doi.org/10.1016/j.cels.2019.11.004>

729 Mirarab, S., Nguyen, N., Guo, S., Wang, L.-S., Kim, J., & Warnow, T. (2015). PASTA: Ultra-
730 Large Multiple Sequence Alignment for Nucleotide and Amino-Acid Sequences. *Journal of*
731 *Computational Biology: A Journal of Computational Molecular Cell Biology*, 22(5), 377–386.
732 <https://doi.org/10.1089/cmb.2014.0156>

733 Mougi, A. (2020). Coupling of green and brown food webs and ecosystem stability. *Ecology and*
734 *Evolution*, 10(17), 9192–9199. <https://doi.org/10.1002/ece3.6586>

735 Nielsen, U. N., Ayres, E., Wall, D. H., Li, G., Bardgett, R. D., Wu, T., & Garey, J. R. (2014).
736 Global-scale patterns of assemblage structure of soil nematodes in relation to climate and
737 ecosystem properties: Global-scale patterns of soil nematode assemblage structure. *Global
738 Ecology and Biogeography: A Journal of Macroecology*, 23(9), 968–978.
739 <https://doi.org/10.1111/geb.12177>

740 O'Connor, M. I., Piehler, M. F., Leech, D. M., Anton, A., & Bruno, J. F. (2009). Warming and
741 resource availability shift food web structure and metabolism. *PLoS Biology*, 7(8),
742 e1000178. <https://doi.org/10.1371/journal.pbio.1000178>

743 Oksanen, J., Blanchet, F. G., Friendly, M., Kindt, R., Legendre, P., McGlinn, D., Minchin, P. R.,
744 O'Hara, R. B., Simpson, G. L., Solymos, P., & Others. (2019). *vegan: Community Ecology
745 Package. R package version 2.5-6. 2019.*

746 Oliverio, A. M., Geisen, S., Delgado-Baquerizo, M., Maestre, F. T., Turner, B. L., & Fierer, N.
747 (2020). The global-scale distributions of soil protists and their contributions to belowground
748 systems. *Science Advances*, 6(4), eaax8787. <https://doi.org/10.1126/sciadv.aax8787>

749 O'Neill, M. E., & Mathews, K. Y. (2000). Theory & methods: A weighted least squares approach
750 to Levene's test of homogeneity of variance. *Australian & New Zealand Journal of
751 Statistics*, 42(1), 81–100. 757 6496(00)00026-x">https://doi.org/10.1016/s0168-6496(00)00026-x

758 Pernthaler, J. (2005). Predation on prokaryotes in the water column and its ecological
759 implications. *Nature Reviews. Microbiology*, 3(7), 537–546.
760 <https://doi.org/10.1038/nrmicro1180>

761 Quast, C., Pruesse, E., Yilmaz, P., Gerken, J., Schweer, T., Yarza, P., Peplies, J., & Glöckner,
762 F. O. (2013). The SILVA ribosomal RNA gene database project: improved data processing
763 and web-based tools. *Nucleic Acids Research*, 41(Database issue), D590–D596.
764 <https://doi.org/10.1093/nar/gks1219>

765 Rahmstorf, S., & Coumou, D. (2011). Increase of extreme events in a warming world.
766 *Proceedings of the National Academy of Sciences of the United States of America*,
767 108(44), 17905–17909. <https://doi.org/10.1073/pnas.1101766108>

768 Rall, B. C., Brose, U., Hartvig, M., Kalinkat, G., Schwarzmüller, F., Vucic-Pestic, O., & Petchey,
769 O. L. (2012). Universal temperature and body-mass scaling of feeding rates. *Philosophical
770 Transactions of the Royal Society of London. Series B, Biological Sciences*, 367(1605),
771 2923–2934. <https://doi.org/10.1098/rstb.2012.0242>

772 Rgens, K. J., & Massana, R. (2008). Protistan grazing on marine bacterioplankton. In *Microbial
773 ecology of the oceans* (p. 383). Wiley Online Library.
774 <https://onlinelibrary.wiley.com/doi/pdf/10.1002/9780470281840#page=399>

775 Rocca, J. D., Hall, E. K., Lennon, J. T., Evans, S. E., Waldrop, M. P., Cotner, J. B., Nemergut,
776 D. R., Graham, E. B., & Wallenstein, M. D. (2015). Relationships between protein-encoding
777 gene abundance and corresponding process are commonly assumed yet rarely observed.
778 *The ISME Journal*, 9(8), 1693–1699. <https://doi.org/10.1038/ismej.2014.252>

779 Rummukainen, M. (2012). Changes in climate and weather extremes in the 21st century:
780 Changes in climate and weather extremes. *Wiley Interdisciplinary Reviews. Climate
781 Change*, 3(2), 115–129. <https://doi.org/10.1002/wcc.160>

782 Schimel, J. P., & Schaeffer, S. M. (2012). Microbial control over carbon cycling in soil. *Frontiers
783 in Microbiology*, 3, 348. <https://doi.org/10.3389/fmicb.2012.00348>

784 Sinsabaugh, R. L., Manzoni, S., Moorhead, D. L., & Richter, A. (2013). Carbon use efficiency of
785 microbial communities: stoichiometry, methodology and modelling. *Ecology Letters*, 16(7),
786 930–939. <https://doi.org/10.1111/ele.12113>

787 Sulman, B. N., Moore, J. A. M., Abramoff, R., Averill, C., Kivlin, S., Georgiou, K., Sridhar, B.,
788 Hartman, M. D., Wang, G., Wieder, W. R., Bradford, M. A., Luo, Y., Mayes, M. A., Morrison,
789 E., Riley, W. J., Salazar, A., Schimel, J. P., Tang, J., & Classen, A. T. (2018). Multiple
790 models and experiments underscore large uncertainty in soil carbon dynamics.
791 *Biogeochemistry*, 141(2), 109–123. <https://doi.org/10.1007/s10533-018-0509-z>

792 Sulman, B. N., Sheviakova, E., Brzostek, E. R., Kivlin, S. N., Malyshev, S., Menge, D. N. L., &
793 Zhang, X. (2019). Diverse mycorrhizal associations enhance terrestrial C storage in a
794 global model. *Global Biogeochemical Cycles*, 33(4), 501–523.
795 <https://doi.org/10.1029/2018gb005973>

796 Tan, H., Hirst, A. G., Atkinson, D., & Kratina, P. (2021). Body size and shape responses to
797 warming and resource competition. *Functional Ecology*, 1365-2435.13789.
798 <https://doi.org/10.1111/1365-2435.13789>

799 Uszko, W., Diehl, S., Englund, G., & Amarasekare, P. (2017). Effects of warming on predator-
800 prey interactions - a resource-based approach and a theoretical synthesis. In *Ecology*
801 *Letters* (Vol. 20, Issue 4, pp. 513–523). <https://doi.org/10.1111/ele.12755>

802 van den Hoogen, J., Geisen, S., Routh, D., Ferris, H., Traunspurger, W., Wardle, D. A., de
803 Goede, R. G. M., Adams, B. J., Ahmad, W., Andriuzzi, W. S., Bardgett, R. D., Bonkowski,
804 M., Campos-Herrera, R., Cares, J. E., Caruso, T., de Brito Caixeta, L., Chen, X., Costa, S.
805 R., Creamer, R., ... Crowther, T. W. (2019). Soil nematode abundance and functional group
806 composition at a global scale. *Nature*, 572(7768), 194–198. <https://doi.org/10.1038/s41586-019-1418-6>

808 van den Hoogen, J., Geisen, S., Wall, D. H., Wardle, D. A., Traunspurger, W., de Goede, R. G.
809 M., Adams, B. J., Ahmad, W., Ferris, H., Bardgett, R. D., Bonkowski, M., Campos-Herrera,
810 R., Cares, J. E., Caruso, T., de Brito Caixeta, L., Chen, X., Costa, S. R., Creamer, R., da
811 Cunha E Castro, J. M., ... Crowther, T. W. (2020). A global database of soil nematode
812 abundance and functional group composition. *Scientific Data*, 7(1), 103.

813 <https://doi.org/10.1038/s41597-020-0437-3>

814 Van der Putten, W. H., Macel, M., & Visser, M. E. (2010). Predicting species distribution and
815 abundance responses to climate change: why it is essential to include biotic interactions
816 across trophic levels. *Philosophical Transactions of the Royal Society of London. Series B,
817 Biological Sciences*, 365(1549), 2025–2034. <https://doi.org/10.1098/rstb.2010.0037>

818 Wang, L. (2018). Microbial control of the carbon cycle in the ocean. *National Science Review*,
819 5(2), 287–291. <https://doi.org/10.1093/nsr/nwy023>

820 Ye, J., Bradford, M. A., Maestre, F. T., Li, F., & García-Palacios, P. (2020). Compensatory
821 thermal adaptation of soil microbial respiration rates in global croplands. *Global
822 Biogeochemical Cycles*, 34(6). <https://doi.org/10.1029/2019gb006507>

823 Yergeau, E., Bokhorst, S., Kang, S., Zhou, J., Greer, C. W., Aerts, R., & Kowalchuk, G. A.
824 (2012). Shifts in soil microorganisms in response to warming are consistent across a range
825 of Antarctic environments. *The ISME Journal*, 6(3), 692–702.
826 <https://doi.org/10.1038/ismej.2011.124>

827 Zaoli, S., Giometto, A., Marañón, E., Escrig, S., Meibom, A., Ahluwalia, A., Stocker, R., Maritan,
828 A., & Rinaldo, A. (2019). Generalized size scaling of metabolic rates based on single-cell
829 measurements with freshwater phytoplankton. *Proceedings of the National Academy of
830 Sciences of the United States of America*, 116(35), 17323–17329.
831 <https://doi.org/10.1073/pnas.1906762116>

832 Zimmermann, M., Leifeld, J., Conen, F., Bird, M. I., & Meir, P. (2012). Can composition and
833 physical protection of soil organic matter explain soil respiration temperature sensitivity?
834 *Biogeochemistry*, 107(1-3), 423–436. <https://doi.org/10.1007/s10533-010-9562-y>

835

836

837