

1 The Functional Significance of Bacterial Predators

2 Bruce A. Hungate^{1,2}, Jane C. Marks^{1,2}, Mary E. Power³, Egbert Schwartz^{1,2}, Kees Jan van
3 Groenigen⁴, Steven J. Blazewicz⁵, Peter Chuckran^{1,2}, Paul Dijkstra^{1,2}, Brianna K. Finley^{1,2}, Mary
4 K. Firestone⁶, Megan Foley^{1,2}, Alex Greenlon⁵, Michaela Hayer¹, Kirsten S. Hofmockel^{7,8},
5 Benjamin J. Koch^{1,2}, Michelle C. Mack^{1,2}, Rebecca L. Mau^{1,9}, Samantha N. Miller¹, Ember M.
6 Morrissey¹⁰, Jeff R. Propster^{1,2}, Alicia M. Purcell^{1,2}, Ella Sieradzki⁶, Evan P. Starr¹¹, Bram W.
7 G. Stone¹, César Terrer⁵, Jennifer Pett-Ridge⁵

8
9
10 ¹Center for Ecosystem Science and Society, Northern Arizona University, Flagstaff AZ, USA

11 ²Department of Biological Sciences, Northern Arizona University, Flagstaff AZ, USA

12 ³Department of Integrative Biology, University of California Berkeley, Berkeley, CA, USA

13 ⁴Department of Geography, College of Life and Environmental Sciences, University of Exeter,
14 Exeter, UK

15 ⁵Physical and Life Sciences Directorate, Lawrence Livermore National Laboratory, Livermore,
16 CA, USA

17 ⁶Department of Environmental Science, Policy, and Management, University of California,
18 Berkeley CA, USA

19 ⁷Pacific Northwest National Laboratory, Richland, WA, USA

20 ⁸Department of Agronomy, Iowa State University, Ames Iowa, USA

21 ⁹Pathogen and Microbiome Institute, Northern Arizona University, Flagstaff AZ, USA

22 ¹⁰Division of Plant and Soil Sciences, West Virginia University, Morgantown, WV, USA

23 ¹¹Department of Plant and Microbial Biology, University of California, Berkeley, CA USA

24
25

26 Abstract

27
28 Predation structures food webs, influences energy flow, and alters rates and pathways of
29 nutrient cycling through ecosystems, effects that are well documented for macroscopic predators.
30 In the microbial world, predatory bacteria are common, yet little is known about their rates of
31 growth and roles in energy flows through microbial food webs, in part because these are difficult
32 to quantify. Here, we show that growth and carbon uptake were higher in predatory bacteria
33 compared to non-predatory bacteria, a finding across 15 sites, synthesizing 82 experiments and
34 over 100,000 taxon-specific measurements of element flow into newly synthesized bacterial
35 DNA. Obligate predatory bacteria grew 36% faster and assimilated carbon at rates 211% higher
36 than non-predatory bacteria. These differences were less pronounced for facultative predators
37 (6% higher growth rates, 17% higher carbon assimilation rates), though high growth and carbon
38 assimilation rates were observed for some facultative predators, such as members of the genera
39 *Lysobacter* and *Cytophaga*, both capable of gliding motility and wolfpack hunting behavior.
40 Added carbon substrates disproportionately stimulated growth of obligate predators, with
41 responses 63% higher than non-predators for the Bdellovibrionales and 81% higher for the
42 Vampirovibrionales, whereas responses of facultative predators to substrate addition were no
43 different from non-predators. This finding supports ecological theory that higher productivity
44 increases predator control of lower trophic levels. These findings also indicate that the functional
45 significance of bacterial predators increases with energy flow, and that predatory bacteria
46 influence element flow through microbial food webs.

47 Introduction

48 Bacteria that prey on other bacteria are too small to engulf their victims, yet they
49 consume them no less ferociously. Members of the Bdellovibrionales attach to prey cells,
50 penetrate the cell membrane, and then take up residence in the host cytoplasm, consuming
51 cellular constituents while growing filaments and producing daughter cells that eventually lyse
52 and kill the prey (1). Some bacterial predators have names that tell their mode of predation:
53 *Vampirovibrio* (2, 3) and *Vampirococcus* (4) insert cytoskeletal protrusions, ‘fangs’, which
54 extract the cytoplasm from the attacked cell. Some members of the genus *Cytophaga* are ‘cell
55 eaters’ (5, 6), and *Lysobacter* are ‘lysers of bacteria’ (7). These and members of the
56 Myxococcales are social organisms which hunt in packs (8, 9). Many of these organisms can also
57 subsist as saprotrophs, and thus are facultative predators (10), in contrast to *Vampirovibrio* and
58 *Bdellovibrio*, which are obligate predators (11). Most of what we know about the physiology,
59 growth, and activity of predatory bacteria has been learned from laboratory studies, because of
60 the difficulty of measuring taxon-specific bacterial activity *in situ*.

61 Predators are thought to be functionally significant in microbial food webs, but
62 quantitative estimates *in situ* have been very difficult to obtain. It is possible to use fluorescent
63 markers and plate counts to estimate growth rates of predators in artificial media (12), but
64 applying such approaches in the field is challenging. For example, it is known that phages prey
65 upon cyanobacteria in rice paddy soils, but the rates of predation are unknown (13).
66 Experimental manipulations of soil protozoa in mesocosm studies demonstrate the importance of
67 these eukaryotic predators for nitrogen cycling (14) and for decomposition of plant litter (15),
68 but the quantitative impacts on these ecosystem processes under field conditions are difficult to
69 measure experimentally. Varying environmental conditions also influence predator-prey

70 interactions: changing moisture content alters soil connectivity, stabilizing or destabilizing
71 predator-prey dynamics (16). It is important that predator activity and growth be measured under
72 realistic and varying conditions.

73 Although protists (17), rotifers (18), nematodes (19), and phages (11, 20, 21) are thought
74 to function as the dominant predators in microbiomes, predatory bacteria are common in both
75 soil (8, 22) and aquatic (23) systems. But beyond their common occurrence in these habitats, we
76 know little of their activity in the wild, how rapidly they grow, their functional significance in
77 food webs, and how they respond to enrichment at the base of the food web through substrate
78 additions.

79 DNA sequencing and other ‘omics techniques can provide detailed information on the
80 composition and functional potential of the microbiome (24), but most measurements of *in situ*
81 bacterial growth rates lack taxonomic resolution and are conducted at the scale of the entire
82 microbial assemblage (25, 26). Such aggregate measurements mask the contributions of
83 genetically and functionally distinct populations. Even in macroscopic assemblages, taxa are
84 known to vary in their influences on ecosystem processes (27). Techniques that combine isotopes
85 and genetic sequencing hold promise for parsing the contributions of individual microbial taxa to
86 interactions within microbial assemblages and to biogeochemical processes (28, 29).

87 Here, we synthesized measurements using quantitative stable isotope probing (qSIP), a
88 technique that quantifies the isotopic composition of DNA after exposure to an isotope tracer
89 (30). qSIP with ¹³C-labeled organic matter tracks the rate of labeled carbon assimilation into
90 DNA, and qSIP using ¹⁸O-water tracks the incorporation of oxygen from water into DNA.
91 Recovery of the isotope tracer in taxon-specific DNA sequences reflects rates of growth and
92 carbon assimilation of individual microbial taxa (28, 31). The survey conducted here included

93 qSIP measurements conducted in natural microbial assemblages from sites in North America,
94 including 14 soils (one arctic, one boreal, 11 temperate, and one tropical), along with one
95 temperate stream (Fig 1, Table 1). We evaluated this dataset to compare rates of growth by
96 predatory and non-predatory bacteria, and their responses to substrate addition.

97 Methods

98 Atom fraction excess (AFE) values for ^{18}O and ^{13}C were extracted from qSIP measurements.
99 AFE values were used to estimate bacterial growth rates based on ^{18}O assimilation from ^{18}O -
100 labeled water, and ^{13}C assimilation rate from ^{13}C -labeled organic substrates, using methods
101 described in (30, 32, 33). All qSIP measurements involved parallel incubations with samples
102 receiving either isotopically labeled (e.g., 97 atom % ^{18}O - H_2O , 99 atom % ^{13}C -glucose) or
103 unlabeled substrates (e.g., water with natural abundance ^{18}O , or glucose with natural abundance
104 ^{13}C). Incubations lasted for 7.1 ± 1.8 days (average \pm SD). After each incubation, DNA was
105 extracted and subject to density separation via isopycnic centrifugation. Density fractions were
106 collected, the 16S rRNA gene was sequenced, and the total abundance of 16S rRNA gene copies
107 in each fraction was quantified using qPCR. Quantitative stable isotope probing calculations
108 were then applied to estimate the atom fraction excess ^{18}O or ^{13}C of each sequenced taxon (30,
109 31). 16S rRNA amplicon sequence data synthesized here have been deposited at NCBI under
110 product IDs PRJNA649787, PRJNA649546, PRJNA649571, PRJNA649802, PRJNA 669516,
111 PRJNA701328, and PRJNA702085.

112 Across the 15 sites, multiple qSIP measurements were conducted, including experiments
113 within each site. Across all sites and experimental treatments, there were a total of 82 qSIP
114 datasets, and each dataset contained estimates of ^{18}O or ^{13}C AFE for hundreds of bacterial taxa
115 from a particular site and under a given experimental treatment. The identities of bacterial taxa
116 were used to assign taxa to bacterial groups known to be capable of predation or to non-
117 predatory taxa. Predators were assigned based on belonging to one of six bacterial taxonomic
118 groups known to exhibit predatory behavior: Bdellovibrionales, Cytophagales, *Lysobacter*,
119 Myxococcales, Streptomycetales, and Vampirovibrionales. We recognize that assuming these

120 taxa are unambiguously predatory based on their taxonomic assignment is uncertain. In
121 particular, the facultative groups are known to vary in substrate utilization; the designation of
122 “facultative” acknowledges the range of feeding behaviors exhibited by large groups such as the
123 Cytophagales (34), Streptomyetales (35), and Myxococcales (34). Not all taxa in these groups
124 have been documented to be predatory; we use such broad groups because finer divisions are not
125 available for the trophic behaviors of these organisms. Also, our approach relies on taxonomic
126 assignments based on 16S rRNA gene sequences, which can be unreliable for delineating species
127 or strain (36). In 98% of cases, we were able to assign taxa to possible predator groups based on
128 name occurrences in Class, Order, or Family, the higher levels of taxonomic resolution where
129 16S rRNA gene assignments have been found to be more robust (37).

130 Growth rates were estimated using ^{18}O qSIP after accounting for potential differences in
131 the sources of ^{18}O among organisms functioning at different trophic levels. qSIP-derived
132 estimates of growth rate using $^{18}\text{O}\text{-H}_2\text{O}$ begin with the observation that some of the oxygen in
133 DNA is derived from the oxygen in water, so the assimilation of ^{18}O from water into DNA
134 reflects its rate of replication, a proxy for cellular growth (38). Ribose sugars, nitrogenous bases,
135 and phosphate (39) all acquire oxygen from water (38). Therefore, the DNA of predators will
136 likely contain oxygen both from water in their growth environment as well as from cellular
137 constituents of prey; these two potential sources of ^{18}O in predator DNA may or may not be
138 additive.

139 To distinguish between these two sources, we compared ^{18}O versus ^{13}C enrichment in
140 predatory taxa—since many of our SIP studies included treatments with both labeled water and
141 labeled organic C substrates (Table 1). It is standard in food web studies using isotope tracers to
142 treat the ^{13}C isotope composition of predator taxa as a conservative indicator of the ^{13}C

143 composition of their prey (40). The qSIP datasets we evaluated included a subset of dual-isotope
144 measurements, where both ^{18}O and ^{13}C were determined in parallel experiments with ^{18}O -labeled
145 H_2O and ^{13}C -labeled carbon substrates. These measurements occurred in separate incubations,
146 with identical conditions and resource availability, but with different isotope labels applied: in
147 one case ^{18}O water was added with a natural abundance carbon substrate, and in the other the
148 carbon substrate was ^{13}C -labeled while the added water was at natural abundance ^{18}O . With these
149 parallel measurements, we were able to estimate both the ^{13}C and ^{18}O for multiple taxa.
150 Across 5 sites and 12 experiments, there were 2197 simultaneous measurements of ^{13}C and ^{18}O ,
151 including 2060 cases of non-predatory taxa and 137 cases of predatory taxa. We evaluated the
152 relationships between ^{18}O and ^{13}C for both predator and non-predator taxa, reasoning that the
153 two sources of ^{18}O to predators (compared to one source for non-predators) would result in
154 predator DNA that was relatively higher in ^{18}O compared to ^{13}C , to the extent these sources were
155 additive. As expected, for a given value of ^{13}C , predator taxa had higher values of ^{18}O than non-
156 predator taxa (Figure S1). We used the difference in the relationships (model II linear
157 regressions) between ^{18}O vs ^{13}C for predators and prey (Figure S1) to predict what the ^{18}O
158 composition of predator taxa would have been based on growth on ^{18}O -labeled H_2O alone. This
159 approach resulted in the following correction, which was applied to all predator taxa in the
160 dataset:

$$161 \quad {}^{18}\text{O}_c = {}^{18}\text{O}_m - ({}^{18}\text{O}_m \times 0.0383 + 0.0065) \quad (\text{Eq 1}),$$

162 where ${}^{18}\text{O}_m$ is the measured predator AFE value and ${}^{18}\text{O}_c$ is the adjusted value.

163 This approach allowed us to avoid overestimating growth rates of predators because of their dual
164 ^{18}O sources and helps ensure values of predator and prey AFE ^{18}O were comparable. For non-
165 predator taxa, we used the measured qSIP ^{18}O AFE value as the estimate of ^{18}O assimilation

166 from ^{18}O - H_2O , the standard approach in ^{18}O -qSIP studies (31, 38). An additional consideration is
167 that oxygen concentration can affect ^{18}O assimilation from labeled water (41). Although oxygen
168 concentrations were not measured in the incubations, for the Mixed Conifer, Ponderosa, Pinyon-
169 Juniper, and Grassland sites included here, median final CO_2 concentrations were 0.31% (0.81%,
170 95th percentile) (42), which translates to a small change in atmospheric O_2 , and suggests that
171 oxygen depletion during the incubations was unlikely to have reached levels shown to affect ^{18}O
172 assimilation from labeled water (41).

173 Experiments with ^{18}O were conducted by adding 97 atom% ^{18}O H_2O to the experimental
174 system and incubating for several days. Because background levels of unlabeled water were
175 present, the ^{18}O composition of water in each incubation was determined as a function of the
176 amount of 97 atom % ^{18}O water added and the amount of background water. Relative growth
177 rate for each taxon was estimated according to equation 7 from ref (31), using AFE $^{18}\text{O}_h$ of
178 individual bacterial taxa, the AFE ^{18}O of water during the incubation, and the duration of the
179 incubation in days.

180 We compared AFE, growth rates, and carbon assimilation rates of predatory and non-
181 predatory bacteria using meta-analysis (metafor package in R (43)), using the log ratios of
182 predator:non-predator as the metric of difference between trophic strategies. This analysis was
183 tested across all sites, treatments, measurement conditions, and tracers. Because some sites
184 included experiments with both ^{18}O and ^{13}C tracers, isotope treatment was nested within site to
185 preserve independence. For all analyses, site was included as a random effect, because sites
186 included multiple effect sizes which were not independent from each other. Computing multiple
187 estimates with the same control group induces dependency on sampling errors, requiring the use

188 of a variance-covariance matrix in the analysis (44). We computed the covariance in log
189 response ratios as

$$190 \quad SD_C^2 / (N_C * C^2) \quad (\text{Eq 2}),$$

191 where SD_C is the standard deviation of the control group, C is the mean, and N_C is the sample
192 size.

193 We tested for the effect of predator identity on AFE, growth rate, and carbon assimilation
194 rate. Predator identity was evaluated by taxonomic assignment and functional group: obligate
195 predators (Bdellovibrionales and Vampirovibrionales) and facultative predators (Cytophagales,
196 *Lysobacter*, Myxococcales, and Streptomycetales). The effect of predator identity was nested
197 within experiment, because multiple predator groups occurred in the same dataset, so their
198 assimilation rates were not independent of each other.

199 We used a similar meta-analysis model to evaluate the influence of added carbon
200 substrates on the relationship between growth rates of predatory and non-predatory bacterial
201 taxa. 24 of the compiled qSIP datasets included experimental substrate additions, in which ^{18}O -
202 H_2O qSIP was conducted in soils amended with various carbon substrates compared to a control.
203 Substrates included glucose (6 experiments), oxalic acid (2), ground plant litter (6), a mixture of
204 glucose and ammonium (4), and a mixture of sugars, organic acids, and amino acids simulating
205 root exudates (6). Across all substrate addition experiments and predator taxonomic groups, there
206 were 113 log ratios comparing predator and non-predator growth rates with substrates added, and
207 187 log ratios comparing predator and non-predator growth rates without substrates added. (The
208 compiled dataset also included experimental manipulations of temperature and of leaf litter
209 species, but the sample sizes were too small to evaluate these as potential drivers.) We evaluated

- 210 the effect of substrate addition on the growth rates of predators using models with both predator
211 identity and substrate as moderators.

212 Results and Discussion

213 Bacterial taxa identified as potentially predatory were detected at all sites and amounted
214 to $7.4 \pm 6.0\%$ of taxa detected at each site (median \pm standard deviation). We refer to these as
215 “predatory bacteria” henceforth, acknowledging the limitations of that designation based on 16S
216 rRNA sequence variation — see methods. Most of the predatory bacteria detected were
217 facultative, with 64.7% from the order Myxococcales, 16% from the class Cytophagia, and 9.2%
218 from the order Streptomycetales. 8% were obligate predatory bacteria, with 7.0% from the order
219 Bdellovibrionales, and 1.0% from the order Vampirovibrionales.

220 Across all sites and experiments, predatory bacteria assimilated isotope tracer into their
221 DNA at rates $23.1 \pm 7.0\%$ higher than non-predatory bacteria (meta-analysis, $P=0.002$, $N=407$,
222 Figure 2). Climate appeared to have little discernable influence on the differential isotope uptake
223 between predatory and non-predatory bacteria, with weak and non-significant relationships
224 across sites for mean annual temperature ($P=0.336$) and for precipitation ($P=0.738$). Soil pH
225 ($P=0.871$) and soil water content ($P=0.165$) also had no statistically discernable influence on the
226 relative isotope assimilation between predators and non-predators. Given the current design (15
227 sites), power may have been limited for detecting such environmental effects.

228 Predator identity significantly influenced isotope assimilation ($P<0.0001$, Figure 2):
229 although both obligate and facultative predators assimilated the isotope tracers at rates higher
230 than non-predatory bacteria, the difference was larger for obligate ($57.7 \pm 8.4\%$, $P<0.001$)
231 compared to facultative ($17.6 \pm 7.1\%$, $P=0.019$) predatory bacteria. Finer resolution revealed
232 taxon-specific patterns, with especially high isotope uptake in the members of the obligate
233 predator order Vampirovibrionales (2, 3), and in the genus *Lysobacter*, which is known to exhibit
234 wolf-pack type predation (7-9). Isotope uptake was also higher in the Bdellovibrionales,

235 Streptomycetaceae, and Cytophagia, whereas rates of isotope uptake for the Myxococcales,
236 many of which are thought to function as saprotrophs (10), were similar to rates of non-
237 predators. The higher values of recovery of ^{13}C and ^{18}O in the DNA of bacterial predators
238 indicates relatively high rates of element flux through bacterial predators in the microbial food
239 webs represented in this 15-site survey.

240 Across the 15 sites, bacterial growth rates were log-normally distributed, with a median
241 growth rate of 0.035 d^{-1} , and 95% confidence from 0.003 to 0.198 d^{-1} , a range consistent with
242 past estimates (31). The difference in growth rates between predators and non-predators was
243 higher for obligate predators than for facultative predators (Figure 3A). The pattern held for rates
244 of C uptake from ^{13}C -labeled substrates: obligate predators had significantly higher C uptake
245 compared to facultative predators and non-predatory bacteria (Figure 3B).

246 Adding a source of energy for heterotrophs, in the form of carbon substrates,
247 disproportionately stimulated growth rates of obligate predatory bacteria, whereas responses
248 were indistinguishable between facultative predatory and non-predatory bacteria (Fig. 4). This
249 indicates that higher productivity increases top down (predator-mediated) control in food webs,
250 that added energy disproportionately flows to the predator trophic level, and that predators
251 exhibit functional responses to shifts in prey resource availability. These findings are consistent
252 with long-standing ecological theory that predicts the functional importance of predators
253 increases with productivity (45-47), theory that also has support in macroscopic food webs (48,
254 49), and is consistent with observations in polar ocean systems where boom-bust cycles suggest
255 viral response to increased algal productivity (50). The similar response of obligate predators
256 from phylogenetically distant clades (i.e., proteobacteria Bdellovibrionales and cyanobacteria
257 Vampirovibrionales) implies that the mode of feeding determines response. As such, similar

258 results may be expected for other obligate predatory clades such as the widely distributed marine
259 clade OM27 (Deltaproteobacteria) and family Halobacteriovoraceae. Across all predator taxa,
260 adding nitrogen and carbon together elicited a larger ($P < 0.001$) growth response ($38.6 \pm 7.5\%$)
261 compared to adding carbon alone ($19.1 \pm 10.4\%$), indicating that carbon-nitrogen stoichiometry
262 of resources affects energy transfer to predatory bacteria (51).

263 Our findings indicate that predatory bacteria are highly active in microbial food webs,
264 synthesizing DNA with elements derived from added isotope tracers at rates higher than non-
265 predatory bacteria, consistent with evidence from experimental microcosms (52). These results
266 suggest that bacteria should be considered alongside eukaryotes and viruses as important
267 predators in microbial food webs. Similarly, a recent metagenomic qSIP analysis using a ^{13}C -
268 CO_2 tracer introduced via plant root exudates found that ^{13}C recovery in metagenomes associated
269 with putative predator bacteria was comparable to the recovery in viruses and substantially
270 higher than predatory eukaryotes (53). Slower growth might be expected if bacterial predators
271 were inactive or dormant, as are many soil microorganisms (54). Results presented here indicate
272 that bacterial predators grow, metabolize, and feed at higher rates than most bacteria in the soil
273 food web, and that predatory bacteria may exert top-down effects in microbial food chains.
274 Though our analysis focused on predation, techniques that combine isotopes and gene
275 sequencing can also quantify evidence of other ecological interactions in microbiomes and how
276 they shape carbon flow and nutrient cycling in microbiomes. Multiple signatures of interactions
277 among bacteria have now been identified (55-57), informing use of qSIP, metagenomics, and
278 traits to evaluate the functional significance of interactions in diverse microbiomes.

279 Element flux through the microbiome is central to its functioning, and results from
280 macroecology show how ecological interactions — competition (58), mutualism (59), and

281 predation (60, 61) — strongly influence those fluxes. Evidence presented here synthesizing
282 isotope-enabled microbiome analysis couples predator identity and activity *in situ* and
283 demonstrates that predatory bacteria are highly active in environmental microbiomes, more
284 active than the average bacterial member. Patterns observed across the sites surveyed indicate
285 that top-down trophic interactions are an active force that may structure the composition of
286 element flow in microbiomes and clearly suggests the functional significance of predatory
287 bacteria in microbial food webs.

288

289 Acknowledgements

290 We appreciate the discussion from participants at the 2020 LLNL ‘Microbes Persist’ Soil
291 Microbiome Scientific Focus Area meeting which inspired this study. This analysis was
292 supported by the U.S. Department of Energy, Office of Biological and Environmental Research,
293 Genomic Science Program (GSP) awards #SCW1632 and DE-SC0020172, and by a Lawrence
294 Fellow award to C.T. through Lawrence Livermore National Laboratory. Studies surveyed in the
295 meta-analysis were funded by DOE GSP awards DE-SC0016207, DE-SC0020172, SCW1024,
296 SCW1590, and by the US National Science Foundation (DEB-1241094, DEB-1645596, DEB-
297 1655357, EAR-1124078). Work at LLNL was performed under the auspices of LLNL under
298 Contract DE-AC52-07NA27344.

299

300 Figure Legends

301

302

303

304

305

306

307

308 Figure 1. Location of sites included in our meta-analysis of growth rates of predatory and non-
309 predatory bacteria. Additional site information and abbreviations are shown in Table 1. Inset
310 shows a cluster of sites in Arizona (box scale is 1 x 1°).

311

312 Figure 2. Difference in isotope tracer uptake (^{18}O and ^{13}C) between predatory and non-predatory
313 bacteria. From left to right, the first four taxa are facultative predators and the last two are
314 obligate predators. Symbols are means \pm standard errors of the mean. Predator groups (and
315 numbers of experiments in which they occurred) were Bdellovibrionales (n=71), Cytophagia
316 (n=71), Lysobacter (48), Myxococcales (106), Streptomyetaceae (86), and Vampirovibrionales
317 (25). Asterisks indicate cases where means were significantly higher than zero (* P<0.05 and ***
318 P<0.001).

319

320 Figure 3. Relative difference in predator growth rate (A) and ^{13}C uptake rate (B) compared to
321 non-predators. Values are shown separately for facultative (open symbols) and obligate (filled
322 symbols) predators. Symbols are means \pm standard errors of the mean. Statistical results from
323 meta-analysis: *** indicates P<0.001, and + indicates P<0.100.

324

325 Figure 4. Growth response of predatory and non-predatory bacteria to substrates containing
326 organic carbon or carbon plus nitrogen. Values are means \pm SE across 15 sites (Figure 1) where
327 *in situ* growth rates were measured using qSIP with ^{18}O - H_2O . Statistically significant differences
328 from meta-analyses are shown with asterisks, where ** indicates $P < 0.010$ and *** indicates
329 $P < 0.0001$.

330

331 Supplemental Material

332 Figure S1. Relationship between ^{13}C and ^{18}O for predator and non-predator taxa from
333 experiments where both ^{18}O and ^{13}C qSIP were conducted. Lines show major axis model II
334 regression relationships, where models were statistically significant ($P < 0.001$) for both predators:

335 $\text{AFE } ^{18}\text{O}_p = 0.051 + 0.652 \times \text{AFE } ^{13}\text{C}_p$ (Eq. S1),

336 and for non-predators:

337 $\text{AFE } ^{18}\text{O}_n = 0.043 + 0.628 \times \text{AFE } ^{13}\text{C}_n$ (Eq. S2).

338

339

340 Table 1. Site description. The columns “Temperature” and “Substrates” indicate experimental
341 treatments applied during the qSIP assay, with temperatures in degrees C and substrates
342 compared to a control with no added substrate. glucose (glu), glucose with ammonium (glu +
343 NH_4^+), a mixture of compounds simulating root exudates (exu)(62), plant litter, and oxalic acid.
344 Temperature indicates experimental incubation temperatures.

345 Citations

346

347

348

- 349 1. L. Makowski, D. Trojanowski, R. Till, C. Lambert, R. Lowry, R. E. Sockett, J. Zakrzewska-
350 Czerwinska, Dynamics of Chromosome Replication and Its Relationship to Predatory
351 Attack Lifestyles in *Bdellovibrio bacteriovorus*. *Applied and Environmental Microbiology*
352 **85**, 14 (Jul, 2019).
- 353 2. R. M. Soo, B. J. Woodcroft, D. H. Parks, G. W. Tyson, P. Hugenholtz, Back from the dead;
354 the curious tale of the predatory cyanobacterium *Vampirovibrio chlorellavorus*. *PeerJ* **3**,
355 22 (May, 2015).
- 356 3. S. A. Steichen, J. K. Brown, Real-time quantitative detection of *Vampirovibrio*
357 *chlorellavorus*, an obligate bacterial pathogen of *Chlorella sorokiniana*. *Journal of*
358 *Applied Phycology* **31**, 1117-1129 (Apr, 2019).
- 359 4. E. Jurkevitch, Y. Davidov, in *Predatory Prokaryotes. Microbiology Monographs*. .
360 (Springer, Berlin, 2007), vol. 4, pp. 11–56.
- 361 5. R. J. Gumbo, G. Ross, E. T. Cloete, Biological control of *Microcystis* dominated harmful
362 algal blooms. *Afr. J. Biotechnol.* **7**, 4765-4773 (Dec, 2008).
- 363 6. M. Gerphagnon, D. J. Macarthur, D. Latour, C. M. M. Gachon, F. Van Ogtrop, F. H.
364 Gleason, T. Sime-Ngando, Microbial players involved in the decline of filamentous and
365 colonial cyanobacterial blooms with a focus on fungal parasitism. *Environmental*
366 *Microbiology* **17**, 2573-2587 (Aug, 2015).
- 367 7. I. Seccareccia, C. Kost, M. Nett, Quantitative Analysis of *Lysobacter* Predation. *Applied*
368 *and Environmental Microbiology* **81**, 7098-7105 (Oct, 2015).
- 369 8. W. H. Wang, X. Luo, X. F. Ye, Y. Chen, H. Wang, L. Wang, Y. B. Wang, Y. Y. Yang, Z. K. Li,
370 H. Cao, Z. L. Cui, Predatory Myxococcales are widely distributed in and closely correlated
371 with the bacterial community structure of agricultural land. *Applied Soil Ecology* **146**, 10
372 (Feb, 2020).
- 373 9. J. Munoz-Dorado, F. J. Marcos-Torres, E. Garcia-Bravo, A. Moraleda-Munoz, J. Perez,
374 Myxobacteria: Moving, Killing, Feeding, and Surviving Together. *Frontiers in*
375 *Microbiology* **7**, (May, 2016).
- 376 10. E. Jurkevitch, Predatory Behaviors in Bacteria—Diversity and Transitions. *Microbe* **2**, 67-
377 73 (2007).
- 378 11. J. Johnke, Y. Cohen, M. de Leeuw, A. Kushmaro, E. Jurkevitch, A. Chatzinotas, Multiple
379 micro-predators controlling bacterial communities in the environment. *Current Opinion*
380 *in Biotechnology* **27**, 185-190 (Jun, 2014).
- 381 12. R. Sathyamoorthy, A. Maoz, Z. Pasternak, H. Im, A. Huppert, D. Kadouri, E. Jurkevitch,
382 Bacterial predation under changing viscosities. *Environmental Microbiology* **21**, 2997-
383 3010 (Aug, 2019).

- 384 13. C. G. Lee, T. Watanabe, Y. Fujita, S. Asakawa, M. Kimura, Heterotrophic growth of
385 cyanobacteria and phage-mediated microbial loop in soil: Examination by stable isotope
386 probing (SIP) method. *Soil Science and Plant Nutrition* **58**, 161-168 (2012/04/01, 2012).
- 387 14. M. Clarholm, Interactions of Bacteria, Protozoa and Plants Leading to Mineralization of
388 Soil Nitrogen. *Soil Biology & Biochemistry* **17**, 181-187 (1985).
- 389 15. S. Geisen, S. Hu, T. E. E. dela Cruz, G. F. Veen, Protists as catalyzers of microbial litter
390 breakdown and carbon cycling at different temperature regimes. *The ISME Journal*,
391 (2020/10/01, 2020).
- 392 16. M. Petrenko, S. P. Friedman, R. Fluss, Z. Pasternak, A. Huppert, E. Jurkevitch, Spatial
393 heterogeneity stabilizes predator-prey interactions at the microscale while patch
394 connectivity controls their outcome. *Environmental Microbiology* **22**, 694-704 (Feb,
395 2020).
- 396 17. M. W. Hahn, M. G. Hofle, Grazing of protozoa and its effect on populations of aquatic
397 bacteria. *Fems Microbiology Ecology* **35**, 113-121 (Apr, 2001).
- 398 18. H. Arndt, Rotifers as Predators on Components of the Microbial Web (Bacteria,
399 Heterotrophic Flagellates, Ciliates) — A Review. *Hydrobiologia* **255**, 231-246 (Apr, 1993).
- 400 19. T. Moens, M. Vincx, Observations on the feeding ecology of estuarine nematodes.
401 *Journal of the Marine Biological Association of the United Kingdom* **77**, 211-227 (Feb,
402 1997).
- 403 20. E. P. Starr, S. J. Shi, S. J. Blazewicz, A. J. Probst, D. J. Herman, M. K. Firestone, J. F.
404 Banfield, Stable isotope informed genome-resolved metagenomics reveals that
405 Saccharibacteria utilize microbially-processed plant-derived carbon. *Microbiome* **6**, (Jul,
406 2018).
- 407 21. B. Al-Shayeb, R. S. Basem, L. X. Chen, F. Ward, P. Munk, A. Devoto, C. J. Castelle, M. R.
408 Olm, K. Bouma-Gregson, Y. Amano, C. He, R. I. Méheust, B. Brooks, A. Thomas, A. Lavy,
409 P. M. Carnevali, C. Sun, D. S. A. Goltsman, M. A. Borton, T. C. Nelson, R. Kantor, A. L.
410 Jaffe, R. Keren, I. F. Farag, S. Lei, K. Finstad, R. Amundson, K. Anantharaman, J. Zhou, A.
411 J. Probst, M. E. Power, S. G. Tringe, W. J. Li, K. Wrighton, S. Harrison, M. Morowitz, D. A.
412 Relman, J. A. Doudna, A. C. Lehours, L. Warren, J. H. D. Cate, J. M. Santini, J. F. Banfield,
413 Clades of huge phage from across Earth's ecosystems. *Nature*, (in press).
- 414 22. W. H. Wang, N. Wang, K. K. Dang, W. Dai, L. Guan, B. R. Wang, J. S. Gao, Z. L. Cui, Y. H.
415 Dong, H. Wang, Long-term nitrogen application decreases the abundance and copy
416 number of predatory myxobacteria and alters the myxobacterial community structure in
417 the soil. *Science of the Total Environment* **708**, (Mar, 2020).
- 418 23. B. Paix, J. A. Ezzedine, S. Jacquet, Diversity, Dynamics, and Distribution of Bdellovibrio
419 and Like Organisms in Perialpine Lakes. *Applied and Environmental Microbiology* **85**,
420 (Mar, 2019).
- 421 24. S. Diamond, P. F. Andeer, Z. Li, A. Crits-Christoph, D. Burstein, K. Anantharaman, K. R.
422 Lane, B. C. Thomas, C. L. Pan, T. R. Northen, J. F. Banfield, Mediterranean grassland soil
423 C-N compound turnover is dependent on rainfall and depth, and is mediated by
424 genomically divergent microorganisms. *Nat Microbiol* **4**, 1356-1367 (Aug, 2019).
- 425 25. R. Knight, A. Vrbanac, B. C. Taylor, A. Aksenov, C. Callewaert, J. Debelius, A. Gonzalez, T.
426 Kosciolk, L. I. McCall, D. McDonald, A. V. Melnik, J. T. Morton, J. Navas, R. A. Quinn, J.
427 G. Sanders, A. D. Swafford, L. R. Thompson, A. Tripathi, Z. J. Z. Xu, J. R. Zaneveld, Q. Y.

- 428 Zhu, J. G. Caporaso, P. C. Dorrestein, Best practices for analysing microbiomes. *Nature*
429 *Reviews Microbiology* **16**, 410-422 (Jul, 2018).
- 430 26. J. P. Schimel, J. Gullledge, Microbial community structure and global trace gases. *Global*
431 *Change Biology* **4**, 745-758 (Oct, 1998).
- 432 27. F. S. Chapin III, G. R. Shaver, Individualistic Growth Response of Tundra Plant Species to
433 Environmental Manipulations in the Field. *Ecology* **66**, 564-576 (1985/04/01, 1985).
- 434 28. S. J. Blazewicz, B. A. Hungate, B. J. Koch, E. E. Nuccio, E. Morrissey, E. L. Brodie, E.
435 Schwartz, J. Pett-Ridge, M. K. Firestone, Taxon-specific microbial growth and mortality
436 patterns reveal distinct temporal population responses to rewetting in a California
437 grassland soil. *ISME J* **14**, 1520-1532 (Jun, 2020).
- 438 29. E. M. Morrissey, R. L. Mau, M. Hayer, X. A. Liu, E. Schwartz, P. Dijkstra, B. J. Koch, K.
439 Allen, S. J. Blazewicz, K. Hofmockel, J. Pett-Ridge, B. A. Hungate, Evolutionary history
440 constrains microbial traits across environmental variation. *Nature Ecology and Evolution*
441 **3**, 1064-1069 (2019).
- 442 30. B. A. Hungate, R. L. Mau, E. Schwartz, J. G. Caporaso, P. Dijkstra, N. Van Gestel, B. J.
443 Koch, C. M. Liu, T. A. McHugh, J. C. Marks, E. Morrissey, L. B. Price, Quantitative
444 Microbial Ecology Through Stable Isotope Probing. *Applied and Environmental*
445 *Microbiology*, (2015).
- 446 31. B. J. Koch, T. A. McHugh, E. M. Morrissey, E. Schwartz, N. van Gestel, P. Dijkstra, B. A.
447 Hungate, Estimating taxon-specific bacterial growth rates in intact soil communities.
448 *Ecosphere* **9**, e02090 (2018).
- 449 32. A. M. Purcell, P. Dijkstra, B. Finley, M. Hayer, B. J. Koch, R. L. Mau, E. Morrissey, K. Papp,
450 E. Schwartz, B. W. Stone, B. A. Hungate, Quantitative Stable Isotope Probing with H₂¹⁸O
451 to Measure Taxon-Specific Microbial Growth. *Methods of Soil Analysis* **4**, (2019).
- 452 33. B. K. Finley, M. Hayer, R. L. Mau, A. M. Purcell, B. J. Koch, N. C. van Gestel, E. Schwartz,
453 B. A. Hungate, in *Stable Isotope Probing: Methods and Protocols*, M. G. Dumont, M. H.
454 Garcia, Eds. (Springer, New York, 2019), vol. 2046, pp. 137-149.
- 455 34. I. Imai, Y. Ishida, Y. Hata, Killing of marine phytoplankton by a gliding bacterium
456 Cytophaga sp., isolated from the coastal sea of Japan. *Marine Biology* **116**, 527-532
457 (1993/08/01, 1993).
- 458 35. C. Kumbhar, P. Mudliar, L. Bhatia, A. Kshirsagar, M. Watve, Widespread predatory
459 abilities in the genus *Streptomyces*. *Arch Microbiol* **196**, 235-248 (Apr, 2014).
- 460 36. J. S. Johnson, D. J. Spakowicz, B.-Y. Hong, L. M. Petersen, P. Demkowicz, L. Chen, S. R.
461 Leopold, B. M. Hanson, H. O. Agresta, M. Gerstein, E. Sodergren, G. M. Weinstock,
462 Evaluation of 16S rRNA gene sequencing for species and strain-level microbiome
463 analysis. *Nature Communications* **10**, 5029 (2019/11/06, 2019).
- 464 37. O. Mizrahi-Man, E. R. Davenport, Y. Gilad, Taxonomic classification of bacterial 16S rRNA
465 genes using short sequencing reads: evaluation of effective study designs. *PLoS one* **8**,
466 e53608-e53608 (2013).
- 467 38. E. Schwartz, Characterization of growing microorganisms in soil by stable isotope
468 probing with H₂¹⁸O. *Applied and Environmental Microbiology* **73**, 2541-2546 (Apr,
469 2007).
- 470 39. M. Cohn, A. Hu, Isotopic (¹⁸O) shift in ³¹P nuclear magnetic resonance applied to a
471 study of enzyme-catalyzed phosphate--phosphate exchange and phosphate (oxygen)--

- 472 water exchange reactions. *Proceedings of the National Academy of Sciences of the*
473 *United States of America* **75**, 200-203 (1978).
- 474 40. B. J. Peterson, B. Fry, Stable Isotopes in Ecosystem Studies. *Annual Review of Ecology*
475 *and Systematics* **18**, 293-320 (1987).
- 476 41. O. K. Coskun, V. Ozen, S. D. Wankel, W. D. Orsi, Quantifying population-specific growth
477 in benthic bacterial communities under low oxygen using (H₂O)-O-18. *ISME Journal* **13**,
478 1546-1559 (Jun, 2019).
- 479 42. X. J. A. Liu, B. K. Finley, R. L. Mau, E. Schwartz, P. Dijkstra, M. A. Bowker, B. A. Hungate,
480 The soil priming effect: Consistent across ecosystems, elusive mechanisms. *Soil Biology*
481 *& Biochemistry* **140**, (Jan, 2020).
- 482 43. W. Viechtbauer, Conducting meta-analyses in R with the metafor package. *Journal of*
483 *Statistical Software* **36**, 1-48 (2010).
- 484 44. M. J. Lajeunesse, On the meta-analysis of response ratios for studies with correlated and
485 multi-group designs. *Ecology* **92**, 2049-2055 (2011).
- 486 45. S. D. Fretwell, Regulation of Plant Communities by Food-Chains Exploiting Them.
487 *Perspectives in Biology and Medicine* **20**, 169-185 (1977).
- 488 46. L. Oksanen, S. D. Fretwell, J. Arruda, P. Niemela, Exploitation Ecosystems in Gradients of
489 Primary Productivity *American Naturalist* **118**, 240-261 (1981).
- 490 47. T. Oksanen, M. E. Power, L. Oksanen, Ideal Free Habitat Selection and Consumer-
491 Resource Dynamics. *American Naturalist* **146**, 565-585 (Oct, 1995).
- 492 48. J. T. Wootton, M. E. Power, Productivity, Consumers, and the Structure of a River Food-
493 Chain. *Proceedings of the National Academy of Sciences of the United States of America*
494 **90**, 1384-1387 (Feb, 1993).
- 495 49. J. C. Marks, M. E. Power, M. S. Parker, Flood disturbance, algal productivity, and
496 interannual variation in food chain length. *Oikos* **90**, 20-27 (Jul, 2000).
- 497 50. M. J. Behrenfeld, Y. X. Hu, R. T. O'Malley, E. S. Boss, C. A. Hostetler, D. A. Siegel, J. L.
498 Sarmiento, J. Schullien, J. W. Hair, X. M. Lu, S. Rodier, A. J. Scarino, Annual boom-bust
499 cycles of polar phytoplankton biomass revealed by space-based lidar. *Nature Geoscience*
500 **10**, 118-+ (Feb, 2017).
- 501 51. Z. V. Finkel, J. Beardall, K. J. Flynn, A. Quigg, T. A. V. Rees, J. A. Raven, Phytoplankton in a
502 changing world: cell size and elemental stoichiometry. *Journal of Plankton Research* **32**,
503 119-137 (Jan, 2010).
- 504 52. H. N. Williams, D. S. Lympelopoulou, R. Athar, A. Chauhan, T. L. Dickerson, H. Chen, E.
505 Laws, T.-K. Berhane, A. R. Flowers, N. Bradley, S. Young, D. Blackwood, J. Murray, O.
506 Mustapha, C. Blackwell, Y. Tung, R. T. Noble, Halobacteriovorax, an underestimated
507 predator on bacteria: potential impact relative to viruses on bacterial mortality. *The*
508 *ISME Journal* **10**, 491-499 (2016/02/01, 2016).
- 509 53. E. P. Starr, S. Shi, S. J. Blazewicz, B. J. Koch, A. J. Probst, B. A. Hungate, J. Pett-Ridge, M.
510 K. Firestone, J. F. Banfield, Stable isotope informed genome-resolved metagenomics
511 uncovers potential trophic interactions in rhizosphere soil. *bioRxiv*,
512 2020.2008.2021.262063 (2020).
- 513 54. E. Blagodatskaya, Y. Kuzyakov, Active microorganisms in soil: Critical review of
514 estimation criteria and approaches. *Soil Biology & Biochemistry* **67**, 192-211 (Dec, 2013).

- 515 55. E. R. Green, J. Meccas, Bacterial Secretion Systems: An Overview. *Microbiology*
516 *Spectrum* **4**, (Feb, 2016).
- 517 56. Z. Pasternak, S. Pietrokovski, O. Rotem, U. Gophna, M. N. Lurie-Weinberger, E.
518 Jurkevitch, By their genes ye shall know them: genomic signatures of predatory bacteria.
519 *Isme Journal* **7**, 756-769 (Apr, 2013).
- 520 57. D. Sutton, P. G. Livingstone, E. Furness, M. T. Swain, D. E. Whitworth, Genome-Wide
521 Identification of Myxobacterial Predation Genes and Demonstration of Formaldehyde
522 Secretion as a Potentially Predation-Resistant Trait of *Pseudomonas aeruginosa*.
523 *Frontiers in Microbiology* **10**, (Nov, 2019).
- 524 58. S. Sitch, B. Smith, I. C. Prentice, A. Arneth, A. Bondeau, W. Cramer, J. O. Kaplan, S. Levis,
525 W. Lucht, M. T. Sykes, K. Thonicke, S. Venevsky, Evaluation of ecosystem dynamics, plant
526 geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model.
527 *Global Change Biology* **9**, 161-185 (Feb, 2003).
- 528 59. J. R. Seymour, S. A. Amin, J. B. Raina, R. Stocker, Zooming in on the phycosphere: the
529 ecological interface for phytoplankton-bacteria relationships. *Nat Microbiol* **2**, (Jul,
530 2017).
- 531 60. A. P. Webb, B. D. Eyre, The effect of natural populations of the burrowing and grazing
532 soldier crab (*Mictyris longicarpus*) on sediment irrigation, benthic metabolism and
533 nitrogen fluxes. *Journal of Experimental Marine Biology and Ecology* **309**, 1-19 (Sep,
534 2004).
- 535 61. E. Kristensen, Mangrove crabs as ecosystem engineers; with emphasis on sediment
536 processes. *Journal of Sea Research* **59**, 30-43 (2008).
- 537 62. B. K. Finley, P. Dijkstra, C. Rasmussen, E. Schwartz, R. L. Mau, X. J. A. Liu, N. Van Gestel,
538 B. A. Hungate, Soil mineral assemblage and substrate quality effects on microbial
539 priming. *Geoderma* **322**, 38-47 (Jul, 2018).
- 540

Ecosystem (abbreviation)	Lat	Long	MAT (°C)	MAP (cm)	¹³ C	¹⁸ O	Temperature	Substrates	%Predators
Moist Acidic Tundra (TLK)	68.63	-149.61	-7.0	30	-	+	5, 15, 25, 35	NA	6.8%
Temperate Conifer Forest (AND)	38.63	-120.23	9.1	115	+	+	NA	glu, exu, lit, ox	7.6%
Boreal Forest (SPR)	47.52	-93.46	3.3	77	-	+	5, 15, 25, 35	NA	2.0%
Temperate Grassland (ANG)	39.73	-123.64	13.0	216	-	+	NA	NA	5.7%
Temperate Grassland (HPR)	35.35	-111.73	6.6	66	+	+	5, 15, 25, 35	glu, glu + NH ₄ ⁺	8.4%
Temperate Conifer Forest (BLT)	40.59	-121.38	9.1	115	+	+	NA	glu, exu, lit, ox	7.8%
Temperate Conifer Forest (GRN)	37.16	-119.20	9.1	115	+	+	NA	glu, exu, lit, ox	7.4%
Temperate Grassland (HDG)	35.58	-111.57	13.0	19	+	+	NA	glu, glu + NH ₄ ⁺	4.9%
Temperate Grassland (PJW)	35.50	-111.62	10.5	28	+	+	NA	glu, glu + NH ₄ ⁺	6.0%
Temperate Grassland (PPW)	35.42	-111.67	9.1	52	+	+	NA	glu, glu + NH ₄ ⁺	6.8%
Temperate Broadleaf Forest (HRV)	42.53	-72.19	7.1	110	+	-	NA	gluc, aas, lip, cel	3.2%
Tropical Forest (LUQ)	18.31	-65.74	25.9	176	-	+	5, 15, 25, 35	NA	9.5%
Temperate Grassland (SDG)	34.69	-120.04	16.8	38	-	+	NA	NA	6.7%
Temperate Grassland (HPL)	38.97	-123.12	14.0	96	-	+	NA	NA	6.5%
Temperate Stream (OCR)	34.91	-111.73	8.3	NA	-	+	NA	NA	7.4%







