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2 **Quantifying microbial associations of dissolved organic matter under global change**

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26

27 **Running title:** DOM-microbe associations under global change

28

29 **Abstract**

30 Microbes play a critical role in regulating the size, composition, and turnover of
31 dissolved organic matter (DOM), which is one of the largest pools of carbon in aquatic
32 ecosystems. Global change may alter DOM-microbe associations with implications for
33 biogeochemical cycles, although disentangling these complex interactions remains a
34 major challenge. Here we develop a framework called Energy-Diversity-Trait integrative
35 Analysis (EDTiA) to examine the associations between DOM and bacteria along
36 temperature and nutrient gradients in a manipulative field experiment on mountainsides
37 in contrasting subarctic and subtropical climates. In both study regions, the chemical
38 composition of DOM correlated with bacterial communities, and was primarily controlled
39 by nutrients and to a lesser degree by temperature. At a molecular-level, DOM-bacteria
40 associations depended strongly on the molecular traits of DOM, with negative
41 associations indicative of decomposition as molecules are more biolabile. Using bipartite
42 networks, we further demonstrated that negative associations were more specialized than
43 positive associations indicative of DOM production. Nutrient enrichment promoted
44 specialization of positive associations, but decreased specialization of negative
45 associations particularly at warmer temperatures in subtropical climate. These global
46 change drivers influenced specialization of negative associations most strongly via
47 molecular traits, while both molecular traits and bacterial diversity similarly affected
48 positive associations. Together, our framework provides a quantitative approach to
49 understand DOM-microbe associations and wider carbon cycling across scales under
50 global change.

51

52 **Introduction**

53 Dissolved organic matter (DOM), one of the largest pools of carbon in aquatic
54 ecosystems ¹, is intimately interlinked with the metabolic processes of complex microbial
55 communities ². Microbial consortia generate “chemodiversity” in the DOM pool by
56 degrading larger molecules into smaller molecules and by synthesizing more refractory
57 compounds from labile substrates ³. These basic processes together lead to the emergence
58 of molecular traits of DOM including chemical structure, stoichiometry, oxidation state,
59 and bioavailability ⁴⁻⁶ that directly determine its environmental persistence ^{7, 8}. DOM, as a
60 carbon source for microbial metabolism, also influences the diversity, structure, and
61 functioning of microbial communities via decomposition and biosynthetic processes ⁹⁻¹³.
62 The resulting resource-consumer relationships can now be characterised in both aquatic
63 ¹⁴⁻¹⁶ and terrestrial ¹⁷ ecosystems owing to recent advances in ultrahigh-resolution mass
64 spectrometry and high-throughput sequencing. Despite the availability of these
65 technologies, little is known about how DOM-microbe associations can be quantified in
66 nature, and are interactively and independently affected by global change drivers, such as
67 elevated temperatures and eutrophication.

68 The effects of global change on DOM-microbe associations can be viewed
69 through three proximal controls (Fig. 1). First, energy supply, such as primary
70 productivity, represents the major source of DOM that supports microbial metabolism ¹⁸⁻
71 ²⁰. In particular, elevated temperature and nutrient inputs can stimulate primary
72 productivity in ways that influences the composition and availability of organic matter ^{21,}
73 ²², but this process also indirectly influence DOM-microbe associations by controlling
74 their diversity and traits ²²⁻²⁵. Second, diversity can generally beget diversity. For
75 example, an increase in the diversity of DOM promotes microbial diversity, and vice
76 versa ¹⁵, which should be reflected as signatures in resource-consumer relationships. Such
77 patterns may arise because resource diversity promotes microbial specialization during
78 biochemical transformations by creating more unique resource niches for consumers to
79 partition ^{26, 27}. Likewise, higher microbial diversity provides more metabolic pathways to
80 decompose and produce molecules, which influences the vulnerability of DOM to
81 degradation ³. Third, DOM-microbe associations depend on the molecular traits of DOM,

82 such as its bioavailability, measured with H/C ratios of individual molecules ²⁸, and
83 microbial traits like life history (i.e., *r*- versus *K*-selection) ²⁹ and resource acquisition
84 (i.e., generalists versus specialists) ²⁷.

85 To integrate the three proximal controls to examine how DOM-microbe
86 associations vary under global change, we developed a framework called Energy-
87 Diversity-Trait integrative Analysis (EDTiA) (Fig. 1). EDTiA relies on the construction
88 of bipartite networks ³⁰ to quantify the specialization between organic molecules and
89 microbial taxa. These networks are investigated using measures of entropy such as the H_2'
90 index ³¹, which quantify resource-consumer relationships at an ecosystem-level. For
91 example, elevated H_2' values convey that there is a high degree of specialization between
92 DOM and microbes ³¹, where in the extreme example, one bacterial taxon consumes or
93 produces a single DOM molecule. By contrast, lower H_2' reflects a more generalized
94 bipartite network where different DOM molecules can be used by a large range of
95 bacterial taxa. Furthermore, EDTiA allows for the integration of global change drivers to
96 explore their relative importance of proximal controls on the specialization of DOM-
97 microbe associations (Fig. 1).

98 We therefore used the EDTiA framework to test how associations between DOM
99 and bacteria were jointly influenced by temperature and nutrient loading in a
100 manipulative field experiment on subtropical and subarctic mountainsides in China and
101 Norway ³². This macroecological approach involved creating microcosms with consistent
102 initial DOM composition but different locally colonised microbial communities and
103 newly produced endogenous DOM. Briefly, we selected five locations with different
104 elevations on each mountainside that spanned a mean annual temperature gradient of 4.2-
105 12.9°C in China and -2.9-0.7 °C in Norway. We established 300 sterile aquatic
106 microcosms composed of natural lake sediments and artificial lake water, which included
107 ten nutrient levels at each elevation. The sediments originated from Taihu Lake, a large
108 eutrophic shallow lake in China, and were added to each microcosm after sterilisation to
109 ensure identical initial DOM supply and composition. Microcosms were left in the field
110 for one month allowing airborne bacteria to colonise, and sediment bacteria were
111 examined using high-throughput sequencing of 16S rRNA genes ³². Additionally, we

112 applied ultrahigh-resolution electrospray ionization Fourier transform ion cyclotron
113 resonance mass spectrometry (FT-ICR MS) to examine sediment DOM features, such as
114 chemodiversity and molecular traits.

115 Our study addresses three questions: (1) How do associations between
116 chemodiversity and microbial biodiversity respond to temperature and nutrient
117 enrichment? (2) How does the specialization of molecular-level associations between
118 DOM and microbes vary along temperature and nutrient gradients? (3) How is the
119 specialization interactively and independently influenced by temperature and nutrient
120 enrichment via the three proximal controls? Results from our study will help advance
121 biogeochemical modeling and improve predictions about carbon turnover along with
122 feedbacks based on resource-based constraints on microbial diversity.

123

124 **Results and Discussion**

125 **(1) DOM features and their microbial associations at a compositional-level**

126 The diversity and molecular traits of DOM were strongly controlled by nutrient
127 enrichment but less by temperature in both mountainsides (Figs. S2-4). Nutrient
128 enrichment generally promoted molecular richness in both regions when all molecular
129 components were considered (Figs. 2a, S5). Using piecewise regression³³ and gradient
130 forest analysis³⁴, we identified breakpoints in molecular composition that mostly
131 occurred between 1.80 and 4.05 mg N L⁻¹ along the nutrient gradient for all molecules at
132 each elevation (Figs. 2a, S6). The effects of nutrient enrichment on molecular traits,
133 however, varied between the two ecoregions (Figs. 2a, S5, S7). For instance, the
134 weighted mean of the H/C ratio in each microcosm decreased with nutrient addition to <
135 1.5, especially at high elevations in China, indicating less bioavailable DOM (Figs. 2a,
136 S5c). The ratio remained consistently higher (≥ 1.5) across all nutrient levels in Norway
137 (Figs. 2a, S5c). Given the identical DOM composition in our study initially, this finding
138 suggests that the contrasting responses reflect differences in the temperature-sensitivity of
139 decomposition and/or nutrient-limited production of DOM by colonising microbes. This

140 inability to resolve the mechanisms underlying these patterns highlights the need for a
141 more mechanistic approach offered by the EDTiA framework.

142 DOM composition was strongly associated with bacteria in both regions, and was
143 mediated by temperature and nutrient enrichment. For instance, although environment
144 (temperature and nutrients) and energy supply had dominant effects on DOM
145 composition, their shared effects with biodiversity (1.0 to 26.7% of explained variation)
146 indicated that these variables also indirectly influenced the associations between DOM
147 and bacteria (Figs. S8-10). These DOM-microbe associations were also supported by a
148 Procrustes analysis^{35,36}, which revealed that more similar mixtures of molecules were
149 related to more similar bacterial communities ($M^2 = 0.701$, $P \leq 0.001$; Fig. 2b), and their
150 associations varied with temperature (that is, elevation) and nutrient enrichment. For
151 example, compositional differences, indicated by the residuals of Procrustes analysis,
152 significantly ($P \leq 0.05$) decreased for all compound classes or elemental combinations at
153 colder temperatures in China (Fig. S11). In Norway, the differences were always lower,
154 on average, and did not vary with temperature (Fig. S11). Nutrient enrichment similarly
155 influenced the correlations between DOM molecular and bacterial compositions
156 estimated from both alpha and beta diversity (Fig. 2c), and these correlations also varied
157 with nutrients for individual compound classes or elemental combinations (Figs. S12,
158 S13). Interestingly, the coordinated compositional changes in DOM and bacteria,
159 measured by the correlation between beta diversities, increased more strongly with
160 nutrient enrichment in Norway than in China, especially at low nutrient levels beneath
161 1.80 mg N L^{-1} (Figs. 2c, S13).

162

163 **(2) Networks between DOM and bacteria at a molecular-level**

164 To quantify the associations between DOM and bacteria further at a molecular-
165 level, we first correlated the relative abundance of DOM molecules and bacterial taxa.
166 According to resource-consumer relationships, negative associations likely indicate the
167 degradation of larger molecules into smaller structures, while positive associations may
168 relate to the production of new molecules via degradation or biosynthetic processes. We
169 found that the distribution of negative and positive correlations between DOM molecules

170 and bacterial operational taxonomic units (OTUs) depended strongly on molecular traits.
171 For example, more labile molecules, such as those with $H/C \geq 1.5$, were more likely to
172 show negative Spearman's correlation coefficients ρ with individual OTUs ($P \leq 0.05$),
173 whereas more recalcitrant molecules ($H/C < 1.5$) generally showed more positive
174 correlations ($P \leq 0.05$), especially in Norway (Fig. S14). These findings were even more
175 clearly supported by the differences between the mean of the positive and negative ρ
176 values for each molecule (Figs. 3a, S15). Correlations with individual OTUs were
177 predominantly negative for molecules within a H/C of 1.5-2.0 and O/C of 0.4-1.0,
178 suggesting they were the outcome of degradation processes, while ρ differences peaked
179 with mainly positive values at a H/C of 1.0-1.5 and O/C of 0-0.5 indicative of *in situ*
180 production (Fig. 3a).

181 Subsequently, we quantified DOM-microbe associations along temperature and
182 nutrient gradients using the EDTiA framework. We built bipartite networks of negative
183 and positive interactions between DOM and bacteria at the genus level using Sparse
184 Correlations for Compositional data (SparCC)³⁷. SparCC relies on algorithms for sparse
185 neighborhood and inverse covariance selection, and can infer correlations with a high
186 degree of accuracy under these conditions³⁷. In total, there were 6,916 and 8,409
187 interactions for negative and positive networks ($|\text{SparCC } \rho| \geq 0.3$), respectively, in China,
188 and 1,313 and 2,888 negative and positive interactions, respectively, in Norway (Fig. 3b).
189 The weighted mean of the percentage of SparCC ρ values that were strongly negative (P
190 ≤ 0.05) increased towards high nutrient levels, with the reverse pattern for positive
191 networks, almost exclusively in China (Fig. S16). Such patterns were consistent with the
192 weighted mean SparCC ρ in China (Fig. S16).

193 The negative and positive interaction networks strongly depended on molecular
194 traits, which was further supported by three observations. First, negative and positive
195 networks were associated with different molecule groups categorised by hierarchical
196 cluster analysis based on the 16 molecular traits (Figs. 3b, S17). In China, negative
197 interactions were dominant between molecule clusters 4 and 5, which were largely
198 comprised of recalcitrant molecules with a H/C of < 1.5 (Fig. S17), and bacteria in the
199 phyla Proteobacteria, Bacteroidetes, or Firmicutes (Fig. 3b). The positive interactions

200 were mostly linked to clusters 1 and 3 (Fig. 3b), which mostly represented labile
201 molecules with a H/C of ≥ 1.5 (Fig. S17). In Norway, molecule cluster 4 was mainly
202 negatively linked to Firmicutes and positively linked to α - and β -Proteobacteria (Fig. 3b).
203 Second, molecules generally covaried more similarly with microbes as they shared more
204 similar traits. For example, we detected statistically significant correlations between the
205 pairwise Gower distances³⁸ of the traits and SparCC ρ values of DOM molecules in each
206 region (Mantel test, $P \leq 0.001$; Fig. 3c). Third, molecular traits were more strongly
207 correlated with SparCC ρ in the negative than positive interaction networks for all
208 molecules (Fig. 3c), which was also true for most of the networks when considering
209 compound classes or elemental combinations (Fig. 3d). These correlations, consistent at
210 the OTU level (Fig. 3c), indicate that molecular traits may be better at predicting the
211 decomposition than production of DOM.

212 Finally, we calculated the degree of specialization between DOM and bacteria in
213 the entire negative and positive interaction networks using the H_2' index³¹. We also
214 calculated specialization d' indices for individual DOM molecules and bacterial genera³¹.
215 Elevated H_2' or d' values indicate a high degree of specialization, while lower values
216 suggest increased generalization. We found that networks that were more specialized in
217 the negative associations between DOM and bacteria (i.e., higher H_2' values)
218 corresponded with more specialized communities of DOM molecules (i.e., higher
219 weighted mean d' ; Figs. S18, S19)³¹. For positive networks, H_2' values mirrored those of
220 d' for both DOM and bacteria (Figs. S18, S19). These results suggest that in addition to
221 the specialization perspective of bacteria or DOM, H_2' can summarise resource-consumer
222 relationships at an ecosystem-level. In both regions, H_2' was higher, on average, in
223 negative than positive interaction networks (t -test, $t = 2.11$, $P = 0.04$ in China and $t =$
224 23.57 , $P \leq 0.001$ in Norway; Figs. 4a, S20), indicating a higher degree of specialization in
225 the decomposition than production processes of microbes. Copiotrophs may have a high
226 substrate specificity for labile resources as compared with oligotrophs³⁹, which have
227 multiple metabolic pathways for resource acquisition of complex organic matter and
228 hence lower specialization⁴⁰. The mean specialization H_2' of negative (t -test, $t = -10.19$,
229 $P \leq 0.001$) and positive (t -test, $t = -6.56$, $P \leq 0.001$) networks were also significantly

230 higher in Norway than in China (Fig. 4a), suggesting more specialized decomposition
231 (i.e., negative networks) and thus potentially more degradable DOM in subarctic regions.

232 Nutrient enrichment showed divergent effects on the H_2' of negative or positive
233 interaction networks between the two study regions. Specifically, nutrient enrichment
234 substantially decreased the H_2' of negative networks for all molecules in China (Fig. 4a),
235 which was particularly true when considering only recalcitrant components, such as
236 lignin and CHNO (Fig. S21). Compared to Norway, nutrient enrichment increased the H_2'
237 of positive interactions relatively more at lower elevations in China (Fig. 4a). Nutrient
238 enrichment at the warmer temperatures in the subtropical region could thus contribute to
239 the greater recalcitrance of DOM by reducing the specialization of decomposition (i.e.,
240 negative networks) and resulting in more specialized production of molecules (i.e.,
241 positive networks).

242

243 **(3) Drivers of DOM-microbe associations**

244 We explored the following distal and proximal controls on negative and positive
245 DOM-microbe networks under the EDTiA framework (Fig. 1). The distal drivers were
246 temperature and nutrient enrichment as proxies of climate change and human impacts,
247 respectively. The three proximal drivers were energy supply, such as primary
248 productivity and sediment total organic carbon, the diversity of bacteria and DOM, that is
249 the richness and composition of bacteria and DOM, and the DOM molecular traits (Table
250 S1). In addition to bacterial diversity and chemodiversity, molecular traits strongly
251 correlated with H_2' and influenced it through hypothesised casual relationships in
252 structural equation models (SEM) ⁴¹ (Fig. S1).

253 The importance of molecular traits was supported by Pearson correlations (Fig.
254 S22), multiple regression models (Fig. S23) and random forest analyses ⁴² (Fig. 4b). For
255 the negative networks, H_2' showed the highest Pearson correlation coefficient of $r = 0.77$
256 with molecular composition ($P \leq 0.001$), followed by molecular richness ($r = -0.76$, $P \leq$
257 0.001) and N/P ratio ($r = 0.76$, $P \leq 0.001$, Fig. S22). In contrast, H_2' was less correlated
258 with molecular traits for the positive networks (Fig. S22). Multiple regression models

259 revealed that, for negative and positive networks in China, there were statistically
260 significant ($P \leq 0.01$) improvements in the explained variances of models by between 6.2%
261 and 9.1% from including either diversity or molecular traits (Fig. S23). These
262 improvements were larger for the negative interaction networks in Norway (Fig. S23).
263 These effects of diversity and molecular traits were further supported by random forest
264 analyses. Diversity and molecular traits improved the predictive power of models of H_2'
265 by 7.9-26.1% and 2.1-14.8%, respectively, and again, most strongly for the negative
266 interactions in both regions (Fig. S23). Furthermore, H_2' was mainly affected by
267 chemodiversity, such as molecular richness or DOM composition, followed by molecular
268 traits, such as N/P or N/C ratios, in the negative networks, whereas chemodiversity,
269 biodiversity, environmental variables and energy supply were all similarly important in
270 the positive networks (Fig. 4b).

271 We also used SEM to test the hypothesised effects of two global change drivers,
272 climate change and human impacts, on the specialization of DOM-bacteria networks. We
273 compared these effects to other drivers like contemporary nutrients, energy supply,
274 biodiversity, chemodiversity and molecular traits (Fig. S1). The SEM results strongly
275 indicated that there were different constraints on DOM-microbe specialization between
276 negative and positive interaction networks. For the negative networks, both global change
277 drivers strongly influenced H_2' through indirect effects on energy supply and molecular
278 traits, especially in China (Figs. 5, S24). In contrast to Norway, both climate change and
279 human impacts had larger total mean effects of -0.23 and -0.49, respectively, on the H_2'
280 of negative networks in China (Fig. 5a). However, molecular traits had the dominant
281 direct effects on H_2' in both China and Norway, with similar mean standardised effect
282 size of 0.57 ($P \leq 0.001$; Figs. 5b, S24). For the positive networks, there were large total
283 mean effects of climate change (0.51 and -0.40 for China and Norway, respectively) and
284 human impacts (0.44 and 0.62, respectively), both of which indirectly influenced H_2'
285 similarly through biodiversity, chemodiversity and molecular traits (Figs. 5, S24).

286

287 **(4) Implications**

288 The factors that control microbial processing of DOM composition, and
289 consequently its degradation, remain challenging to discern ⁴³, yet are critical for
290 predicting carbon cycling under global change scenarios. We found that associations
291 between DOM and microbial decomposers depended on universal drivers of ecosystem
292 functioning, such as energy supply ^{21,22}, both DOM and microbial compositions ^{8,15}, and
293 molecular traits ^{7,28}. The EDTiA framework we developed provides a unified approach to
294 identify when each of these different proximal drivers is more important, and to separate
295 contrasting biological processes associated with DOM degradation and production that
296 may have obscured previous analyses of bulk DOM pools. In addition to energy supply
297 and the diversity of DOM and bacteria, we found that molecular traits generally helped
298 shape DOM-microbe networks across contrasting climatic zones, especially the negative
299 networks indicative of degradation processes. Although molecular traits are well known
300 to be associated with DOM persistence or vulnerability to degradation ^{7,44}, their influence
301 on the underlying biological mechanisms has remained poorly understood. Our results
302 advance this work by demonstrating when the specialization of DOM-microbe
303 associations changes with molecular traits, and by providing predictions of how
304 specialization might vary under global change.

305 We found that temperature and eutrophication can change DOM-microbe
306 associations by shifting the three proximal drivers, namely energy, diversity, and traits.
307 For positive bipartite networks, nutrient enrichment generally increased the specialization
308 of DOM-microbe associations, and more so than temperature, by changing biodiversity,
309 chemodiversity, and molecular traits. Positive interactions related to the production of
310 new molecules depend on the specific interacting partners, which is partly supported by
311 the positive relationships between H_2' and d' (Fig. S19). By contrast, both temperature
312 and nutrient enrichment reduced specialization in the negative networks, primarily via
313 changing molecular traits and energy supply. Decomposition processes associated with
314 negative networks may depend more on whether molecules contain structures that resist
315 degradation ⁷, especially in the absence of temperature limitation ⁴⁵. At higher
316 temperatures, such as in subtropical China, energy to degrade these molecules may
317 become more limiting ⁴⁵. We also found that the importance of these distal drivers of
318 climate change and human impacts varied between biomes. For instance, both elevated

319 temperature and eutrophication reduced the specialization of negative DOM-microbe
320 networks indicative of decomposition processes in subtropical China, but these two
321 drivers were less important in subarctic Norway. As their indirect effects via microbial
322 composition varied between biomes, these responses may reflect differences in the
323 biological traits of communities. Future studies with metagenomics could offer a
324 powerful complement to test how microbial traits vary with DOM traits.

325 As inland water worldwide continues to undergo changes in climate ⁴⁶ and trophic
326 state ⁴⁷, our approaches could be applied to predict changes in how microbes degrade and
327 produce DOM. For instance, since hyper-eutrophication occurred in Taihu Lake in May
328 2007, total nitrogen has been reduced by a mean (\pm SD) of 1.24 (\pm 1.41) mg L⁻¹ with
329 strong lake management (Figs. S25, S26). Based on the estimated direct and indirect
330 effects of distal controls in the SEM fitted to the Chinese data (Fig. S1), this
331 oligotrophication, combined with a mean decrease in water temperature of 0.20 (\pm
332 0.87) °C between 2007 and 2018, was predicted to change the specialization of DOM-
333 microbe associations. Specifically, H_2' changed by +0.65 (\pm 0.58) and -0.65 (\pm 0.46) for
334 negative and positive networks, respectively, over this period (Fig. 6a). The greatest
335 changes happened in the most eutrophic part of the lake, including the northwestern
336 lakeshore and the northern Zhushan and Meiliang Bays (Figs. 6b, S27). Although our
337 predictions ignored detailed spatiotemporal environmental variations as used to
338 parameterize the SEM models, they do illustrate the potential to upscale our predictions
339 in real-world settings. This understanding, facilitated through our EDTiA framework,
340 could provide the first steps for improving Earth system models of global biogeochemical
341 cycles ⁴⁸. More generally, our work shows how the molecular traits of DOM will control
342 the responses of DOM-microbe networks and their associated biogeochemical cycles in a
343 changing world.

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355

356 **Conflict of Interest**

357 The authors declare no conflict of interest.

358

359 **Author contributions**

360 JW conceived the idea. JW carried out the field trips and provided the
361 physiochemical and biological data. JL, MC and KJ analysed the DOM. AH and JW
362 performed the statistical analyses. AH wrote the first draft of the manuscript. AH and JW
363 finished the manuscript with the comments from AJT, JTL, JS, KJ, YL and XL. All
364 authors contributed to the intellectual development of this study.

365

366 **Data availability**

367 Bacterial sequences and environmental data are available in Wang *et al* (2016)³².
368 Other data are available from the corresponding author upon reasonable request.

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644

645 **Material and methods**

646 **Experimental design**

647 The comparative field microcosm experiments were conducted on Laojun
648 Mountain in China (26.6959 N; 99.7759 E) in September-October 2013, and on
649 Balggesvarri Mountain in Norway (69.3809 N; 20.3483 E) in July 2013, designed to be
650 broadly representative of subtropical and subarctic climatic zones, respectively, as first
651 reported in Wang *et al.* (2016)³². The annual temperatures ranged from 4.2-12.9 °C in
652 China and -2.9-0.7 °C in Norway. The experiments were characterised by an aquatic
653 ecosystem with consistent initial DOM composition but different locally colonised
654 microbial communities and newly produced endogenous DOM. While allowing us to
655 minimise the complexity of natural ecosystems, the experiment provided a means for
656 investigating DOM-microbe associations at large spatial scales by controlling the initial
657 DOM supply. Briefly, we selected locations with five different elevations on each
658 mountainside. The elevations were 3,822, 3,505, 2,915, 2,580 and 2,286 m a.s.l. on
659 Laojun Mountain in China, and 750, 550, 350, 170 and 20 m a.s.l. on Balggesvarri
660 Mountain in Norway. At each elevation, we established 30 aquatic microcosms (1.5 L
661 bottle) composed of 15 g of sterilised lake sediment and 1.2 L of sterilised artificial lake
662 water, which included one of ten nutrient levels of 0, 0.45, 1.80, 4.05, 7.65, 11.25, 15.75,
663 21.60, 28.80 and 36.00 mg N L⁻¹ of KNO₃. Each nutrient level was replicated three times.
664 The lake sediments were obtained from the centre of Taihu Lake, China, and were
665 aseptically canned per bottle after autoclaving as previously described in Wang *et al.*
666 (2016)³². To compensate for nitrate additions shifting stoichiometric ratios, KH₂PO₄ was
667 added to bottles so that the N/P ratio of the initial overlying water was 14.93, which was
668 similar to the annual average ratio in Taihu Lake during 2007 (14.49). Nutrient levels for
669 the experiments were selected based on conditions of the eutrophic Taihu Lake, and the
670 highest nitrate concentration was based on the maximum total nitrogen in 2007 (20.79 mg
671 L⁻¹; Fig. S27). We chose the nutrient level of this year because a massive cyanobacteria
672 bloom in Taihu Lake happened in May 2007 and initiated an odorous drinking water
673 crisis in the nearby city of Wuxi. The microcosms were left in the field for one month
674 allowing airborne bacteria to freely colonise the sediments and water, and the sediment
675 bacteria were examined using high-throughput sequencing of 16S rRNA genes. The

676 sequences were processed in QIIME (v1.9)⁴⁹ and OTUs were defined at 97% sequence
677 similarity. The bacterial sequences were rarefied to 20,000 per sample. Further details on
678 field experiments, sample collection, physicochemical and bacterial community analyses
679 are available in Wang *et al.* (2016).

680

681 **ESI FT-ICR MS analysis of DOM samples**

682 Highly accurate mass measurements of DOM within the sediment samples were
683 conducted using a 15 Tesla solarix XR system, a ultrahigh-resolution Fourier transform
684 ion cyclotron resonance mass spectrometer (FT-ICR MS, Bruker Daltonics, Billerica,
685 MA) coupled with an electrospray ionization (ESI) interface, as demonstrated previously
686⁵⁰ with some modifications. DOM was solid-phase extracted (SPE) with Agilent VacElut
687 resins before FT-ICR MS measurement⁵¹ with minor modifications. Briefly, an aliquot
688 of 0.7 g freeze-dried sediment was sonicated with 30 ml ultrapure water for 2 h, and
689 centrifuged at 5,000 g for 20 min. The extracted water was filtered through the 0.45 µm
690 Millipore filter and further acidified to pH 2 using 1 M HCl. Cartridges were drained,
691 rinsed with ultrapure water and methanol (ULC-MS grade), and conditioned with pH 2
692 ultrapure water. Calculated volumes of extracts were slowly passed through cartridges
693 based on DOC concentration. Cartridges were rinsed with pH 2 ultrapure water and dried
694 with N₂ gas. Samples were finally eluted with methanol into precombusted amber glass
695 vials, dried with N₂ gas and stored at -20 °C until DOM analysis. The extracts were
696 continuously injected into the standard ESI source with a flow rate of 2 µl min⁻¹ and an
697 ESI capillary voltage of 3.5 kV in negative ion mode. One hundred single scans with a
698 transient size of 4 mega words, an ion accumulation time of 0.3 s, and within the mass
699 range of m/z 150-1200, were co-added to a spectrum with absorption mode for phase
700 correction, thereby resulting in a resolving power of 750,000 (FWHM at m/z 400). All
701 FT-ICR mass spectra were internally calibrated using organic matter homologous series
702 separated by 14 Da (-CH₂ groups). The mass measurement accuracy was typically within
703 1 ppm for singly charged ions across a broad m/z range (150-1,200 m/z).

704 Data Analysis software (BrukerDaltonik version 4.2) was used to convert raw
705 spectra to a list of m/z values using FT-MS peak picker with a signal-to-noise ratio (S/N)

706 threshold set to 7 and absolute intensity threshold to the default value of 100. Putative
707 chemical formulae were assigned using the software Formularity⁵² following the
708 Compound Identification Algorithm⁵³. In total, 19,538 molecular formulas were
709 putatively assigned for all samples (n = 300) based on the following criteria: S/N > 7, and
710 mass measurement error < 1 ppm, considering the presences of C, H, O, N, S and P and
711 excluding other elements or an isotopic signature. All formula assignments were further
712 screened to meet the criteria as follows⁵⁴: (1) formulae containing an odd number of
713 nitrogen atoms had an even nominal m/z and those containing an even number of
714 nitrogen atoms had an odd nominal m/z; (2) the number of hydrogen atoms was at least
715 1/3 of carbon and could not exceed 2C+N+2; (3) the number of nitrogen or oxygen atoms
716 could not exceed the number of carbon atoms; (4) the ratio of O/C was set to 0-1, H/C ≥
717 0.3, N/C ≤ 1, double bond equivalents (DBE) ≥ 0.

718 The assigned molecules were categorised into eight compound classes or 12
719 elemental combinations. The compound classes based on van Krevelen diagrams⁵⁵ were
720 lipids (O/C = 0-0.3, H/C = 1.5-2.0), proteins and amino sugars (O/C = 0.3-0.67, H/C =
721 1.5-2.2), carbohydrates (Carb; O/C = 0.67-1.2, H/C = 1.5-2), unsaturated hydrocarbons
722 (UnsatHC; O/C = 0-0.1, H/C = 0.7-1.5), lignin (O/C = 0.1-0.67, H/C = 0.7-1.5), tannin
723 (O/C = 0.67-1.2, H/C = 0.5-1.5), and condensed aromatics (ConHC; O/C = 0-0.67, H/C =
724 0.2-0.7). The elemental combinations were CH, CHN, CHNO, CHNOP, CHNOS,
725 CHNOSP, CHNS, CHO, CHOP, CHOS, CHOSP and CHS.

726

727 **Estimating DOM features**

728 We considered DOM features from three aspects: alpha diversity, beta diversity
729 and molecular traits. These features were considered for all molecules (19,538 different
730 formulae), but also for subsets of molecules within each category of compound classes or
731 elemental combinations. The dataset based on all molecular formulae was named “All
732 molecules”, while the datasets of subsets of formulae were named by “category name +
733 compounds”. The relative abundance of molecules was calculated by normalizing signal
734 intensities of assigned peaks to the sum of all intensities within each sample. We
735 considered two additional aspects of chemodiversity: chemical alpha diversity and

736 chemical beta diversity. Chemical alpha diversity was calculated using a richness index
737 that counts the total number of peaks in each sample. Chemical beta diversity was
738 calculated with the Bray-Curtis dissimilarity metric, and further represented by the first
739 two axes of a non-metric multidimensional scaling (NMDS) ordination of this
740 dissimilarity. We also considered overall molecular composition, which was visualised
741 across the elevations and nutrient enrichment treatments with detrended correspondence
742 analysis (DCA) ⁵⁶. The analyses of chemical diversity were performed using the R
743 package *vegan* V2.4.6 ⁵⁷.

744 We also calculated 16 molecular traits that could affect microbial associations and
745 were related to molecular weight, stoichiometry, chemical structure, and oxidation state
746 (Table S1). These traits were mass, the number of carbon (C) atoms, the modified
747 aromaticity index (AI_{Mod}) ⁵⁸, DBE ⁵⁸, DBE minus oxygen (DBE_O) ⁵⁸, DBE minus AI
748 (DBE_{AI}) ⁵⁸, standard Gibb's Free Energy of carbon oxidation (GFE) ⁵⁹, Kendrick Defect
749 ($kdefect_{CH_2}$) ⁶⁰, nominal oxidation state of carbon (NOSC), O/C ratio, H/C ratio, N/C
750 ratio, P/C ratio, S/C ratio, and carbon use efficiency (Y_{met}) ⁶¹. All calculations were
751 performed using the R package *ftmsRanalysis* V1.0.0 ⁶² and the scripts at
752 <https://github.com/danczakre/ICRTutorial>. DBE represents the number of unsaturated
753 bonds and rings in a molecule ⁵⁸. Higher values of DBE, AI and NOSC all indicate a
754 higher recalcitrance of DOM. A large Kendrick Defect can indicate a higher degree of
755 oxidation. Lower values of Y_{met} indicate a higher thermodynamic efficiency of metabolic
756 reactions involved in biomass production ⁶¹. Weighted means of formula-based molecular
757 traits (for example the $Mass_{wm}$ for Mass) were calculated as the sum of the product of the
758 trait value for each individual molecule ($Mass_i$) and relative intensity I_i divided by the
759 sum of all intensities ($Mass_{wm} = \sum(Mass_i \times I_i) / \sum(I_i)$) using the R package *FD* V1.0.12 ⁶³.
760 In addition, ten molecular sub-mixtures were grouped based on the 16 molecular traits by
761 hierarchical cluster analysis using Ward's minimum variance method with the R package
762 *stats* V3.6.1.

763

764 **Estimating bacterial communities**

765 The relative abundance of OTUs was calculated by the normalization of read
766 counts of OTUs to the sum of all reads within each sample. Likewise, we considered two
767 aspects of biodiversity: bacterial alpha diversity and beta diversity. Bacterial alpha
768 diversity was calculated using species richness that counts the total number of OTUs in
769 each sample. Bacterial beta diversity was calculated with the Bray-Curtis dissimilarity
770 metric, and further represented by the first two axes of NMDS of this dissimilarity.

771

772 **Estimating associations between DOM and microbes**

773 At the DOM composition level, we examined DOM-microbe associations from
774 the following aspects: Pearson's correlation between alpha diversity of DOM and bacteria,
775 and a Mantel correlation between the beta diversity of DOM and bacteria. We also tested
776 the congruence between DOM and bacterial composition using Procrustes analysis of
777 NMDS coordinates estimated for each community across elevations and nutrient
778 enrichment levels with the Bray-Curtis dissimilarity metric^{35,36}. Procrustes analysis is a
779 technique for comparing the relative positions of points in two multivariate datasets. It
780 attempts to stretch and rotate the points in one matrix, such as points obtained from a
781 NMDS, to be as close as possible to points in another matrix, thus preserving the relative
782 distances between points within each matrix^{35,36}. This procedure yields a measure of fit,
783 M^2 , which is the sum of squared distances between corresponding data points after the
784 transformation. Pointwise residuals indicate the difference between two different
785 community ordinations for each sample. The statistical significance of the Procrustes
786 analysis (i.e., M^2) can then be assessed by randomly permutating the data 1,000 times⁶⁴.
787 This analysis was performed using the R package `vegan` V2.4.6.

788 We further quantified DOM-microbe associations at a molecular level using two
789 different co-occurrence analyses. First, Spearman's rank correlation coefficient ρ was
790 calculated between the relative abundance of each molecule m/z ion and bacterial OTU
791 (or genus). For each molecule, we then calculated the Spearman ρ difference by
792 subtracting the mean absolute ρ value of the negative correlations across all bacterial
793 OTUs from the mean of the positive correlations. Larger positive and negative values
794 indicate that molecules were more strongly positively and negatively correlated with

795 bacterial communities, respectively. The relationships among the Spearman ρ difference,
796 H/C and O/C were summarised using kriging interpolation with the R package automap
797 V1.0.14⁶⁵. Second, SparCC (Sparse Correlations for Compositional data) was applied to
798 build DOM-microbe bipartite networks. SparCC is a correlation method that can infer the
799 interrelationships between DOM and bacteria for compositional data with higher
800 accuracy³⁷ than general correlation approaches, such as Spearman's correlation, because
801 it explicitly assumes that the underlying networks have many missing associations. We
802 used bacterial genera rather than OTUs for bipartite network analysis because there were
803 over 20,000 and 10,000 bacterial OTUs for Norway and China, respectively, and there
804 are computational limits on handling such large bipartite networks for the analyses
805 described in the next paragraph. However, using bacterial genera was reasonable as
806 individual DOM-bacteria associations were similar for both bacterial OTUs and genera
807 ($R^2 > 0.80$, $P \leq 0.001$; Fig. S14). Similar conclusions were also obtained with either
808 OTUs or genera when relating the pairwise distances of molecular traits with SparCC ρ
809 values among DOM molecules in Fig. 3c. To reduce type I errors in the correlation
810 calculations created by low-occurrence genera or molecules, the majority rule was
811 applied, retaining genera or molecules observed in more than half of the total samples (\geq
812 75 samples) in China or Norway. The filtered table, including 1,340 and 1,246 DOM
813 molecules, and 75 and 49 bacterial genera in China and Norway, respectively, was then
814 used for pairwise correlation calculation of DOM and bacteria using SparCC with default
815 parameters³⁷.

816 Finally, bipartite network analysis at a molecule and network level was performed
817 to quantify the specialization of DOM-microbe associations. The threshold correlation for
818 inclusion in bipartite networks was $|\rho| = 0.30$ to exclude weak interactions and we
819 retained the adjacent matrix with only the interactions between DOM and bacteria. We
820 then constructed two types of networks based on negative and positive correlations
821 (SparCC $\rho \leq -0.30$ and $\rho \geq 0.30$, respectively). The SparCC ρ values were multiplied by
822 10,000 and rounded to integers, and the absolute values were taken for negative networks
823 to enable the calculations of specialization indices. A separate negative and positive
824 network was obtained for each microcosm based on its species composition. For the

825 network level analysis, we calculated H_2' , a measure of specialization³⁰, for each
826 network:

$$827 \quad H_2 = -\sum_{i=1}^i \sum_{j=1}^j (p_{ij} \ln p_{ij}),$$

$$828 \quad H_2' = \frac{H_{2\max} - H_2}{H_{2\max} - H_{2\min}},$$

829 where $p_{ij} = a_{ij}/m$, represents the proportion of interactions in a $i \times j$ matrix. a_{ij} is
830 number of interactions between DOM molecule i and bacterial genus j , which is also
831 referred as “link weight”. m is total number of interactions between all DOM molecules
832 and bacterial genera. H_2' is the standardised H_2 against the minimum ($H_{2\min}$) and
833 maximum ($H_{2\max}$) possible for the same distribution of interaction totals.

834 For the molecular level analysis, we calculated the specialization index Kullback-
835 Leibler distance (d') for DOM molecules (d'_i) and bacterial genera (d'_j), which describes
836 the levels of “vulnerability” of DOM molecules and “generality” of bacterial genera,
837 respectively:

$$838 \quad d_i = \sum_{j=1}^j \left(\frac{a_{ij}}{A_i} \ln \frac{a_{ij}m}{A_i A_j} \right),$$

$$839 \quad d'_i = \frac{d_i - d_{\min}}{d_{\max} - d_{\min}},$$

840 where $A_i = \sum_{j=1}^j a_{ij}$ and $A_j = \sum_{i=1}^i a_{ij}$, are the total number of interactions of DOM
841 molecule i and bacterial genus j , respectively. d'_i is the standardised d_i against the
842 minimum (d_{\min}) and maximum (d_{\max}) possible for the same distribution of interaction
843 totals. The equations of d'_j are analogous to d'_i , replacing j by i .

844 Both specialization indices consider interaction abundance and are standardised to
845 account for heterogeneity in the interaction strength and species richness. Weighted
846 means of d' for DOM were calculated for each network as the sum of the product of d'
847 for each individual molecule i (d'_i) and relative intensity I_i divided by the sum of all
848 intensities $d' = \sum(d'_i \times I_i) / \sum(I_i)$. Weighted means of d' for bacteria were calculated as the
849 sum of the d' of each individual bacterial genus j (d'_j) and relative abundance of bacterial
850 genus I_j divided by the sum of all abundance. All calculations were performed using the

851 R package FD V1.0.12. The observed H_2' and d' values ranged from 0 (complete
852 generalization) to 1 (complete specialization)³¹ (Fig. S28). To directly compare the
853 network indices across the elevations or nutrient enrichment levels, we used a null
854 modelling approach. We standardised the three observed specialization indices (S_{observed} ;
855 that is, H_2' , d' of DOM, and d' of bacteria) by calculating their z-scores⁶⁶ using the
856 equation $z_S = (S_{\text{observed}} - \bar{S}_{\text{null}}) / (\sigma_{S_{\text{null}}})$ where \bar{S}_{null} and $\sigma_{S_{\text{null}}}$ were, respectively, the mean
857 and standard deviation of the null distribution of S (S_{null}). One hundred randomised null
858 networks were generated for each bipartite network to derive S_{null} using the *swap.web*
859 algorithm, which keeps species richness and the number of interactions per species
860 constant along with network connectance. The relationships among H_2' , weighted means
861 of d' for DOM molecules and bacterial genera were compared using kriging interpolation
862 with the R package automap V1.0.14. The obtained network was visualised using circlize
863 V0.4.10⁶⁷ and analysed using the R package bipartite V2.15³⁰.

864

865 **Statistical analyses**

866 We used the following explanatory variables related to distal and proximal
867 controls on DOM-microbe associations. Distal environmental drivers included climate
868 change (i.e., water temperature), human impacts (i.e., nutrient enrichment), and
869 contemporary nutrients (i.e., sediment total nitrogen (TN), total phosphorus (TP), NO_x^- ,
870 NO_2^- , NH_4^+ and PO_4^{3-} , and water NO_3^- , NO_2^- , NH_4^+ and PO_4^{3-}). Proximal drivers included
871 energy supply (i.e., sediment total organic carbon, dissolved organic carbon, water pH
872 and sediment Chlorophyll *a* (Chl *a*)), biodiversity (i.e., the species richness and the first
873 two axes of the NMDS of bacterial community composition), DOM chemodiversity (i.e.,
874 the species richness and the first two axes of the NMDS of molecular composition), and
875 DOM molecular traits (i.e., mass, C, Al_{Mod} , DBE, DBE_{O} , DBE_{Al} , GFE, $\text{kdefect}_{\text{CH}_2}$,
876 NOSC, O/C, H/C, N/C, P/C, S/C and Y_{met}). Detailed information about these explanatory
877 variables is listed in Table S1. It should be noted that water pH could be considered to be
878 relevant to primary productivity due to its strong positive correlation with sediment Chl *a*,
879 but their relationships varied across elevations and nutrient levels³². The response
880 variables included DOM features (i.e., alpha diversity, beta diversity and molecular traits)

881 and DOM-microbe network statistics (e.g., H_2'), and were analysed for their patterns and
882 underlying drivers along the two main environmental gradients: elevation and nutrient
883 enrichment.

884 **(1) Patterns of DOM features and DOM-microbe associations along the** 885 **environmental gradients**

886 For DOM features, the relationships between nutrient enrichment and DOM
887 richness or molecular traits were visualised with linear models for all formulae and
888 subsets of formulae within each category of compound classes or elemental combinations
889 across different elevations. We further tested the breakpoints or abrupt changes in DOM
890 composition (i.e., the first axis of DCA) along the gradient of nutrient enrichment using a
891 piecewise linear regression with the R package segmented V1.3.0³³. These breakpoint
892 estimations were supported by gradient forest analysis³⁴, which was used to assess the
893 DOM compositional changes and important breakpoints across multiple molecules along
894 the gradient of nutrient enrichment. This analysis produces the standardised density of
895 splits, that is the kernel density of splits divided by the observation density, which shows
896 where important changes in the abundance of multiple molecules occur along the nutrient
897 gradient and indicates the compositional rate of change. In addition, we estimated the
898 standardised density of splits for subsets of molecules within each category of compound
899 classes or elemental combinations across different elevations. This analysis was
900 performed using the R packages gradientForest V0.1.17³⁴ and extendedForest V1.6.1⁶⁸.

901 For DOM-microbe associations, the relationships between nutrient enrichment
902 and associations at both community and network levels were tested with linear models for
903 all formulae and subsets of formulae within each category of compound classes or
904 elemental combinations across different elevations.

905 **(2) Drivers of DOM features and DOM-microbe associations**

906 To evaluate the key drivers of DOM features and DOM-microbe associations, we
907 used variation partitioning analysis (VPA)⁶⁹, multiple regression, random forest analysis
908⁴² and structural equation modelling (SEM)⁴¹. In particular, the first analysis
909 disentangled the important roles of microbes from other explanatory variables, while the

910 latter three analyses tested the roles of molecular traits and diversity, and their interplay
911 with environments and energy supply.

912 First, VPA was used to quantify the relative contributions of driver categories
913 towards DOM features. We partitioned explanatory variables into the following driver
914 categories: environments (that is, climate change, human impacts and contemporary
915 nutrients), energy supply and biodiversity (Table S1). We selected explanatory variables
916 for regression analyses by forward selection with Akaike information criterion (AIC) ⁷⁰.
917 We also quantified the relative contributions of driver categories for subsets of molecules
918 within each category of compound classes or elemental combinations. VPA was
919 performed with R package *vegan* V2.4.6 ⁷¹.

920 Second, stepwise multiple regression was performed to test the statistical
921 significance and predictive power of the net effects of diversity (i.e., biodiversity and
922 chemodiversity) or molecular traits on the bipartite network specialization H_2' . The net
923 effects of diversity or molecular traits were evaluated by the improvements in the
924 explained variances relative to models without diversity and molecular traits (i.e., in
925 models using only the variables associated with environments and energy supply). The
926 analysis was conducted with forward selection of explanatory variables ⁷². We chose the
927 final model that had the lowest AIC value ⁷³. ANOVA was used to test the statistical
928 significance of two models including or excluding diversity or molecular traits as
929 predictors, and the increase in the model R^2 was determined as the net effects of diversity
930 or molecular traits on H_2' .

931 Third, random forest analysis was conducted to identify the relative importance of
932 environment variables, energy supply, bacterial diversity and DOM molecular drivers on
933 specialization H_2' . The importance of each predictor variable was determined by
934 evaluating the decrease in prediction accuracy (that is, increase in the mean square error
935 between observations and out-of-bag predictions) when the data for that predictor were
936 randomly permuted. The accuracy importance measure was computed for each tree and
937 averaged over the forest (2,000 trees). More details on this method were described in
938 previous literature ⁷⁴. In addition, random forest analysis was also used to test the net

939 effects of diversity or molecular traits on H_2' . This analysis was conducted using the R
940 package randomForestSRC V2.8.0^{75,76}.

941 Finally, SEM was used to explore how specialization H_2' is interactively
942 influenced by global changes (that is, temperature and nutrient enrichment), diversity and
943 molecular traits. The approach begins by hypothesising the underlying structure of causal
944 links as shown in Fig. S1. Then, the model is translated into regression equations, and
945 these equations are evaluated against the data to test the hypothesised links. Through this
946 process, SEM provides an understanding of direct and indirect links of climate change
947 and human impacts on H_2' . Before modelling, all variables in the SEMs were Z-score
948 transformed to allow comparisons among multiple predictors and models. Similar to
949 previous studies⁷⁷, we used composite variables to account for the collective effects of
950 climate change, human impacts, contemporary nutrients, energy supply, biodiversity,
951 chemodiversity and molecular traits, and the candidate observed indicators are given in
952 Table S1. The indicators for each composite were selected based on the multiple
953 regressions for H_2' (Table S2). Based on all the hypothesised links among composite
954 variables (that is, full model; Fig. S1), we examined all alternative models using AIC and
955 overall model fit statistics⁷⁸. We chose the final model to report as that with the lowest
956 AIC value from models with a non-significant χ^2 test ($P > 0.05$), which tests whether the
957 model structure differs from the observed data, high comparative fit index (CFI > 0.95)
958 and low standardised root mean squared residual (SRMR < 0.05) (Table S3). We
959 implemented the SEMs using R package lavaan V.0.5.23⁷⁹.

960

961 **Predictions of DOM-microbe associations in Taihu Lake**

962 Using the parameter estimates obtained from SEM fitted to the bipartite networks
963 in subtropical China, we estimated spatiotemporal variation of DOM-microbe
964 associations in Taihu Lake based on the direct and indirect effects of climate change and
965 eutrophication via the proximal drivers. We first formulated five linear equations to
966 predict the values of contemporary nutrients (P_{nut}), energy supply (P_{energy}), biodiversity
967 (P_{biodiv}), chemodiversity (P_{chemodiv}) and molecular traits (P_{trait}) based on climate and
968 eutrophication drivers:

969 $P_{\text{nut}} = \lambda_{\text{nut,temp}} \times X_T + \lambda_{\text{nut,N}} \times X_N$

970 $P_{\text{energy}} = \lambda_{\text{energy,temp}} \times X_T + \lambda_{\text{energy,N}} \times X_N + \lambda_{\text{energy,nut}} \times P_{\text{nut}}$

971 $P_{\text{biodiv}} = \lambda_{\text{biodiv,temp}} \times X_T + \lambda_{\text{biodiv,N}} \times X_N + \lambda_{\text{biodiv,nut}} \times P_{\text{nut}} + \lambda_{\text{biodiv,energy}} \times P_{\text{energy}}$

972 $P_{\text{chemodiv}} = \lambda_{\text{chemodiv,temp}} \times X_T + \lambda_{\text{chemodiv,N}} \times X_N + \lambda_{\text{chemodiv,nut}} \times P_{\text{nut}} + \lambda_{\text{chemodiv,energy}} \times$
973 P_{energy}

974 $P_{\text{trait}} = \lambda_{\text{trait,temp}} \times X_T + \lambda_{\text{trait,N}} \times X_N + \lambda_{\text{trait,nut}} \times P_{\text{nut}} + \lambda_{\text{trait,energy}} \times P_{\text{energy}} + \lambda_{\text{trait,biodiv}} \times$
975 $P_{\text{biodiv}} + \lambda_{\text{trait,chemodiv}} \times P_{\text{chemodiv}}$

976 where X_T and X_N were water temperature and total nitrogen, respectively, for the
977 32 sites across the whole Taihu Lake (Fig. S27a). The abbreviations of path coefficients
978 (λ) are detailed in Table S4.

979 Similarly, we calculated the specialization of DOM-microbe associations (Y_{H2})
980 using a linear equation: $Y_{H2} = \lambda_{H2,temp} \times X_T + \lambda_{H2,N} \times X_N + \lambda_{H2,nut} \times P_{\text{nut}} + \lambda_{H2,energy} \times P_{\text{energy}}$
981 $+ \lambda_{H2,biodiv} \times P_{\text{biodiv}} + \lambda_{H2,chemodiv} \times P_{\text{chemodiv}} + \lambda_{H2,trait} \times P_{\text{trait}}$. We used the predicted values
982 for contemporary nutrients, energy supply, biodiversity, chemodiversity and molecular
983 traits in the overall prediction model to account for the indirect effects of water
984 temperature and total nitrogen on specialization. The models were calculated with a
985 yearly time step based on the annual means of water temperature and total nitrogen for
986 each site during 2007-2018. The temporal changes in specialization were calculated using
987 2007 as a baseline to which all predictions were compared.

988 The above predictions aimed to apply our EDTiA framework to estimate changes
989 in DOM-microbe associations under temperature change and eutrophication in Taihu
990 Lake, and potential uncertainties in the estimated associations should however be noted
991 as follows. First, local environmental variation (e.g., N/P ratio changes) and different
992 microbial species pools between our field microcosms and natural lake sediments would
993 likely influence the accuracy of predictions. Second, spatial and temporal heterogeneity
994 of sediments would influence local environments and the composition of both DOM and
995 microbes and thus the projection of estimates across Taihu Lake. Third, the transferability
996 and extrapolation of SEM models to Taihu Lake would be one of the difficulties in

997 prediction practices. We thus selected the SEM models in China rather than Norway for
998 more similar climatic conditions to the target lake. The annual mean water temperatures
999 in Taihu Lake were covered by the temperature variations across the elevations between
1000 2,286 and 3,822 m a.s.l. in Laojun Mountain, and the annual mean total nitrogen fell into
1001 the gradient of nutrient concentrations between 0 and 36 mg N L⁻¹. Finally, lake
1002 management such as mechanical removal of algae would affect energy supply and
1003 consequently prediction accuracy.

1004

1005

1006 **Figure legends**

1007 **Figure 1. A framework for studying the effects of global change on DOM-**
1008 **microbe associations.** (a) DOM-microbe associations affected by the three proximal
1009 controls, namely energy supply and both the diversity and traits of DOM and microbes.
1010 The relationships among the three controls and their influences on the associations are
1011 shown with single-sided arrows. The DOM-microbe associations, indicated by double-
1012 sided arrows, are measured by bipartite interactions between DOM molecules (circles C_1-
1013 C_i) and microbial species (circles M_1-M_j). The size of circles indicates the abundance of
1014 DOM molecules or microbial species, and the width of arrows is the magnitude of
1015 associations. Commonly used indices summarise the specialization of individual
1016 molecule i and microbial species j , such as d' for DOM and microbes, which describes
1017 the levels of “vulnerability” of DOM molecules and “generality” of microbial species,
1018 respectively. (b) Conceptual framework for understanding DOM-microbe associations
1019 under distal drivers such as global change via the three proximal drivers. For better 3D
1020 visualization, the sizes of triangles decrease towards the top-right, and the color changes
1021 towards different corners of the triangles represent variations in the relative importance of
1022 different proximal drivers under a global change scenario. The background depicts the
1023 primary motivation of this study in examining distal drivers of climate change and
1024 eutrophication in Taihu Lake, China. The left and right waters indicate clean and
1025 cyanobacteria-dominated lake states, respectively, and are separated by a road having the
1026 shapes of western lakeshore and northern Zhushan and Meiliang Bays of Taihu Lake. We
1027 setup field microcosms on mountainsides by adding sediments collected from the lake
1028 centre, and designed nutrient levels and N/P ratio based on nutrient conditions of this lake
1029 ³².

1030

1031 **Figure 2. DOM features and their microbial associations at a compositional**
1032 **level.** (a) The effects of nutrient enrichment on DOM alpha diversity (richness),
1033 composition and molecular traits (e.g., H/C ratio) for all formulae across different
1034 elevations in China (red lines) and Norway (blue lines). Molecular richness and weighted
1035 mean (WM) of H/C ratio were plotted against the nutrient gradient of nitrate, and their

1036 relationships are indicated by solid ($P \leq 0.05$) or dotted ($P > 0.05$) lines estimated using
1037 linear models. For better visualization, we did not include the data points in Fig. 2a but
1038 showed detailed scatter plots in Fig. S5. To visualise the compositional turnover of DOM,
1039 we plotted the standardised density of splits showing where important changes in the
1040 abundance of multiple molecules occurred along the nutrient gradient. The standardised
1041 density of splits was determined by gradient forest analysis³⁴. (b) The congruence
1042 between DOM and bacterial compositions across different elevations in China and
1043 Norway was examined using Procrustes analysis^{35,36}. Each line with circle and triangle
1044 ends connects to a single community of DOM and bacteria, respectively, and is colored
1045 by elevation in either China (red) or Norway (blue). The fit of overall Procrustes
1046 transformation is reported as the M^2 value. (c) The effects of nutrient enrichment on
1047 DOM-microbe associations. The associations were quantified by the Pearson correlation
1048 coefficient r between alpha diversity of DOM and bacteria (upper panel), and by the
1049 Mantel r between the beta diversity of DOM and bacteria (lower panel). We then
1050 visualised these associations with loess regression models along the nutrient gradient.
1051 The colours of the lines indicate the DOM composition for all formulae and categories of
1052 compound classes or elemental combinations.

1053

1054 **Figure 3. Networks between DOM and bacteria.** (a) Strength of the correlations
1055 between DOM molecules and bacterial OTUs in China (upper panel) and Norway (lower
1056 panel). For each molecule, we subtracted the mean absolute Spearman's rank correlation
1057 coefficient ρ of all the negative correlations with individual bacterial OTUs from the
1058 mean of the positive correlations to derive $\Delta\rho$. $\Delta\rho$ was further visualised against the
1059 molecular traits H/C and O/C. (b) The negative and positive bipartite networks between
1060 DOM molecules and bacterial genera in China or Norway estimated using SparCC
1061 (Sparse Correlations for Compositional data)³⁷. Upper nodes represent bacterial genera
1062 coloured by their phylum, while lower nodes represent DOM molecules coloured by the
1063 ten clusters obtained with hierarchical cluster analysis based on 16 molecular traits
1064 described in Fig. S17 and Table S1. A line connecting two nodes indicates an interaction
1065 between a DOM molecule and bacterial genus. (c-d) We examined the relationships

1066 between molecular traits and the negative (left panel) or positive (right panel) DOM-
1067 microbe bipartite networks in China (upper panel) or Norway (lower panel). For all pairs
1068 of DOM molecules, we separately calculated pairwise Gower distances between the
1069 molecular traits and their SparCC ρ values with bacterial OTUs. Statistical significance
1070 between distance matrices was determined with a Mantel test with 999 permutations and
1071 indicated by solid ($P \leq 0.05$) or dotted ($P > 0.05$) lines. We considered all formulae (c)
1072 and also subsets of formulae within the category of compound classes or elemental
1073 combinations (d). For all formulae (c), we calculated SparCC correlation coefficients
1074 based on both bacterial OTUs (grey lines) and genera (black lines).

1075

1076 **Figure 4. Relative importance of diversity and molecular traits in explaining**
1077 **specialization of DOM-microbe networks.** (a) We plotted specialization H_2' against
1078 nutrient enrichment for negative (left panel) and positive (right panel) bipartite networks
1079 for each elevation in China (red lines) and Norway (blue lines). Statistical significance of
1080 linear model fits was indicated by solid ($P \leq 0.05$) or dotted ($P > 0.05$) lines. For better
1081 visualization, we omitted the data points but these are shown in Fig. S20. (b) We
1082 examined the relative importance of all explanatory variables on the H_2' of negative (left
1083 panel) and positive (right panel) bipartite networks in China (red lines) and Norway (blue
1084 lines) using random forest. The relative contribution (%) of each variable towards H_2' is
1085 shown in radar plots. The explanatory variables were grouped by environment, energy,
1086 diversity and traits with consistent colors of ovals or rectangles as in Fig. S1.
1087 Abbreviations of explanatory variables are detailed in Table S1.

1088

1089 **Figure 5. Structural equation models ⁴¹ to explain specialization of DOM-**
1090 **microbe networks.** Stacked bar plots show the standardised effects (Std. effects) of
1091 predictor variables on the H_2' of negative (left panel) and positive (right panel) bipartite
1092 networks in China or Norway estimated from the best supported models. We considered
1093 (a) the total and indirect effects of global change and human impacts via proximal
1094 variables and (b) the total and direct effects of proximal variables. Proximal variables

1095 were energy supply, biodiversity, chemodiversity and molecular traits, and are described
1096 in detail in Table S2. Details of the full structural equation models are shown in Fig. S24.

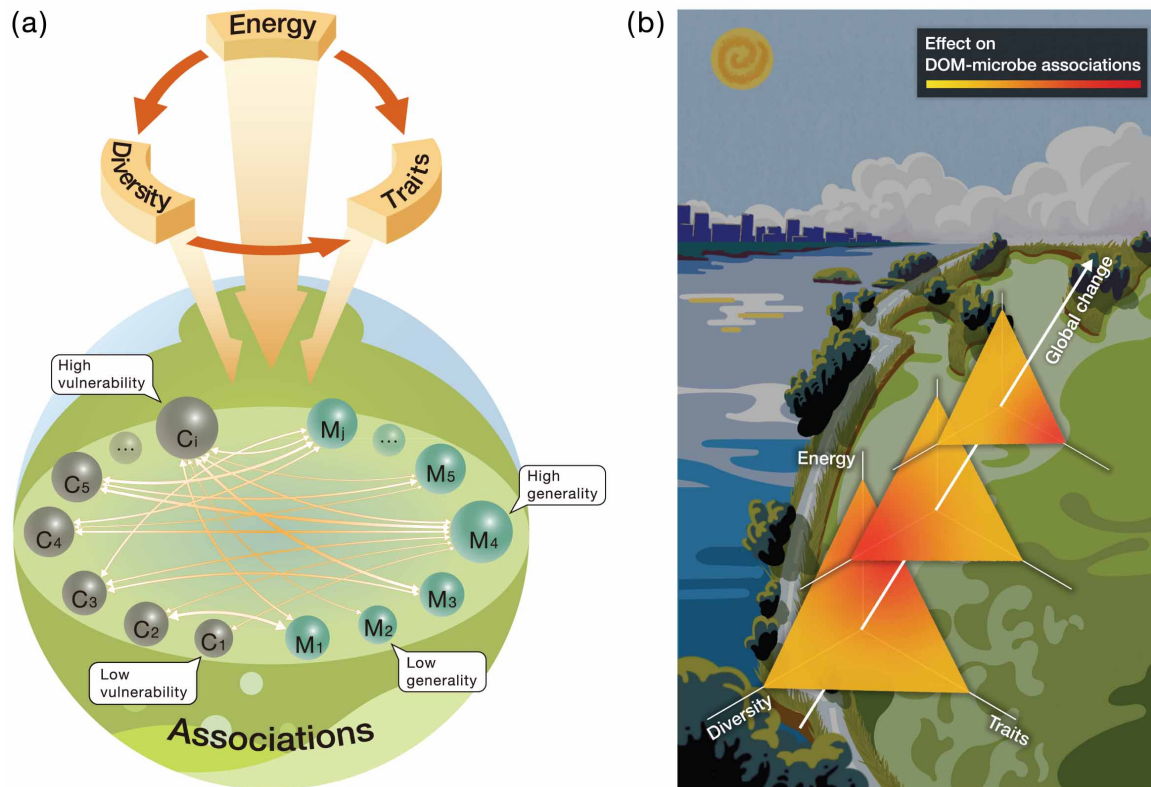
1097

1098 **Figure 6. Decadal change in predicted specialization of DOM-microbe**
1099 **networks in Taihu Lake.** (a) Changes in H_2' of negative (upper panel) and positive
1100 (lower panel) bipartite networks from 2007 to 2018. (b) The spatial distribution of
1101 changes in H_2' of negative (upper panel) and positive (lower panel) networks in 2018
1102 across the Taihu Lake. Estimated changes in H_2' were calculated for the 32 sites across
1103 the whole of Taihu Lake (Fig. S27a) by comparing with the baseline of 2007, and
1104 represent the combined effects of climate change and eutrophication. The colored dots in
1105 (a) indicate H_2' changes for individual sites which are consistent with the figure legend of
1106 (b), and black dots are the mean values for each year. The box in (a) represents the
1107 interquartile (50% of data), the horizontal line in the box represents the median, the
1108 “notch” represents the 95% confidence interval of the median and the “whiskers”
1109 represent the maximum and minimum values.

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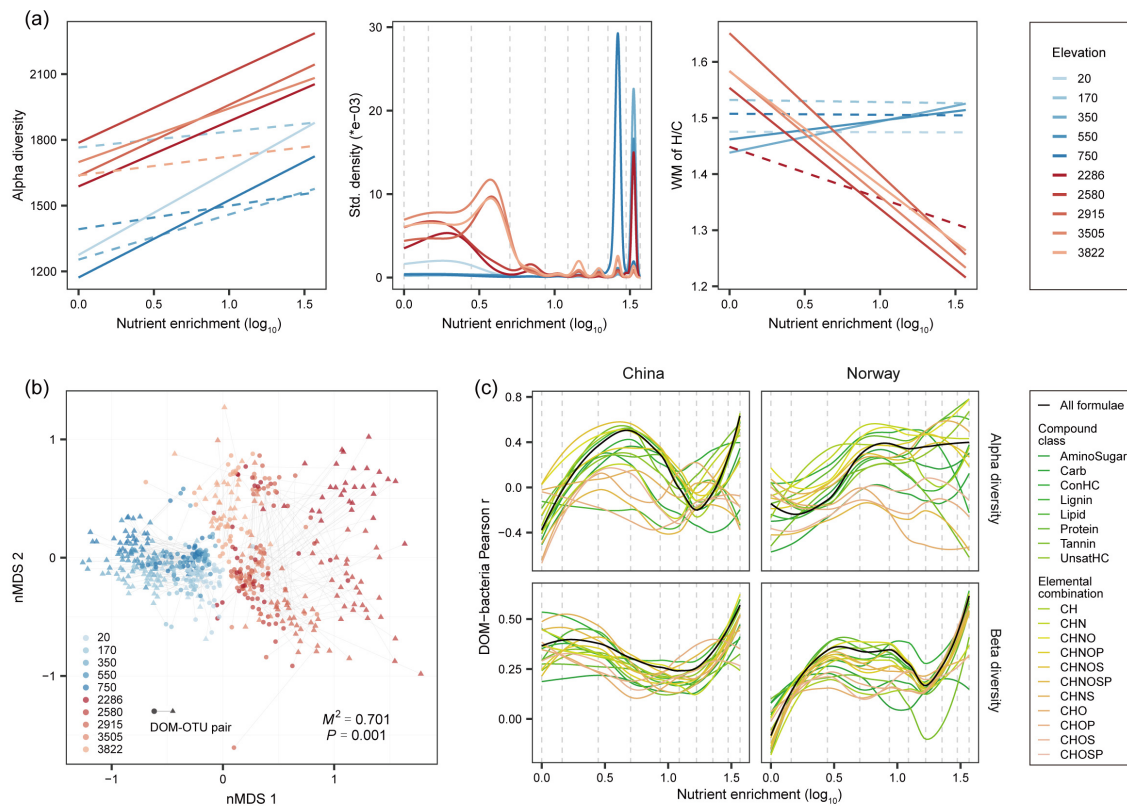
Figure 1



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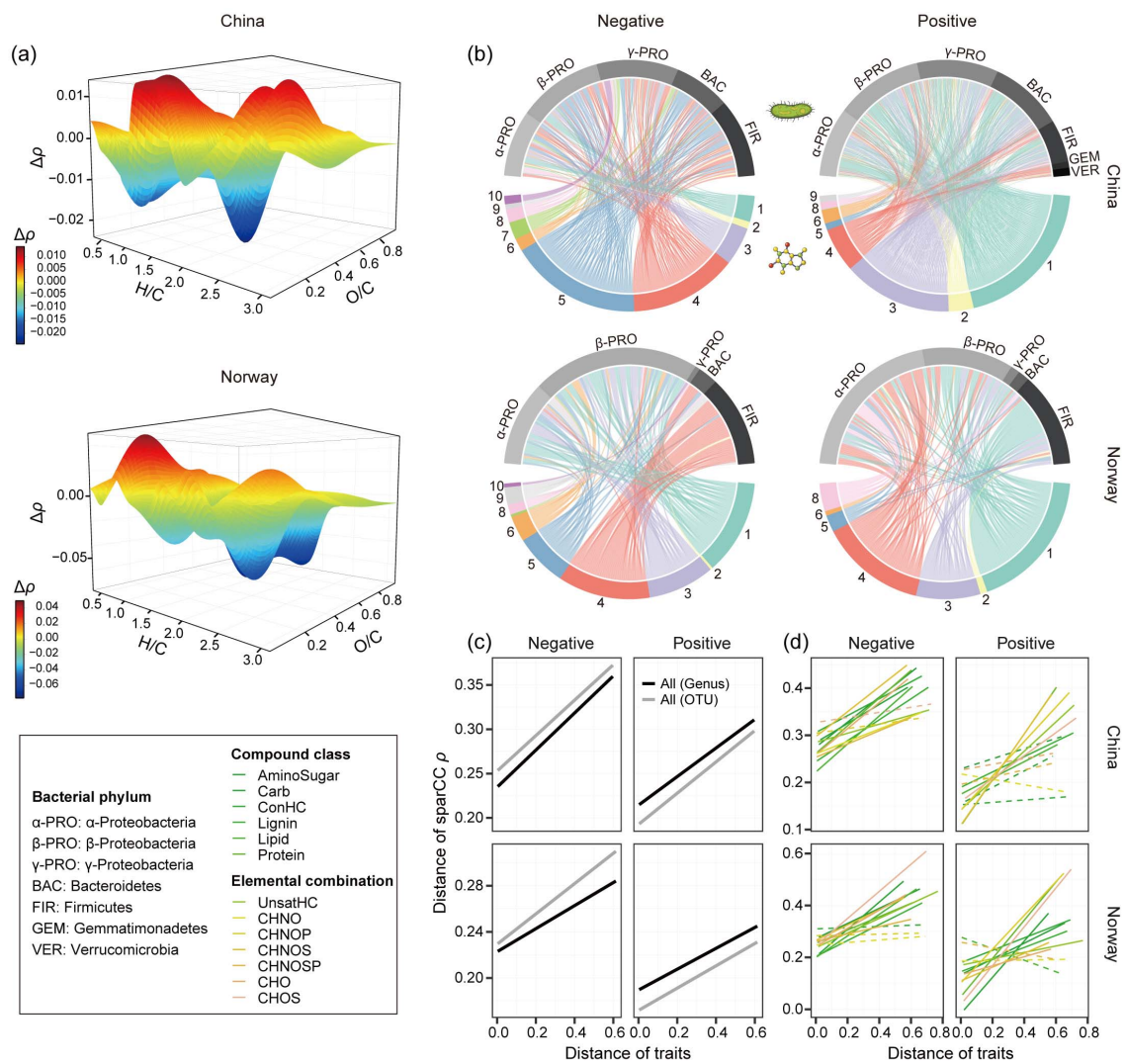
Figure 2



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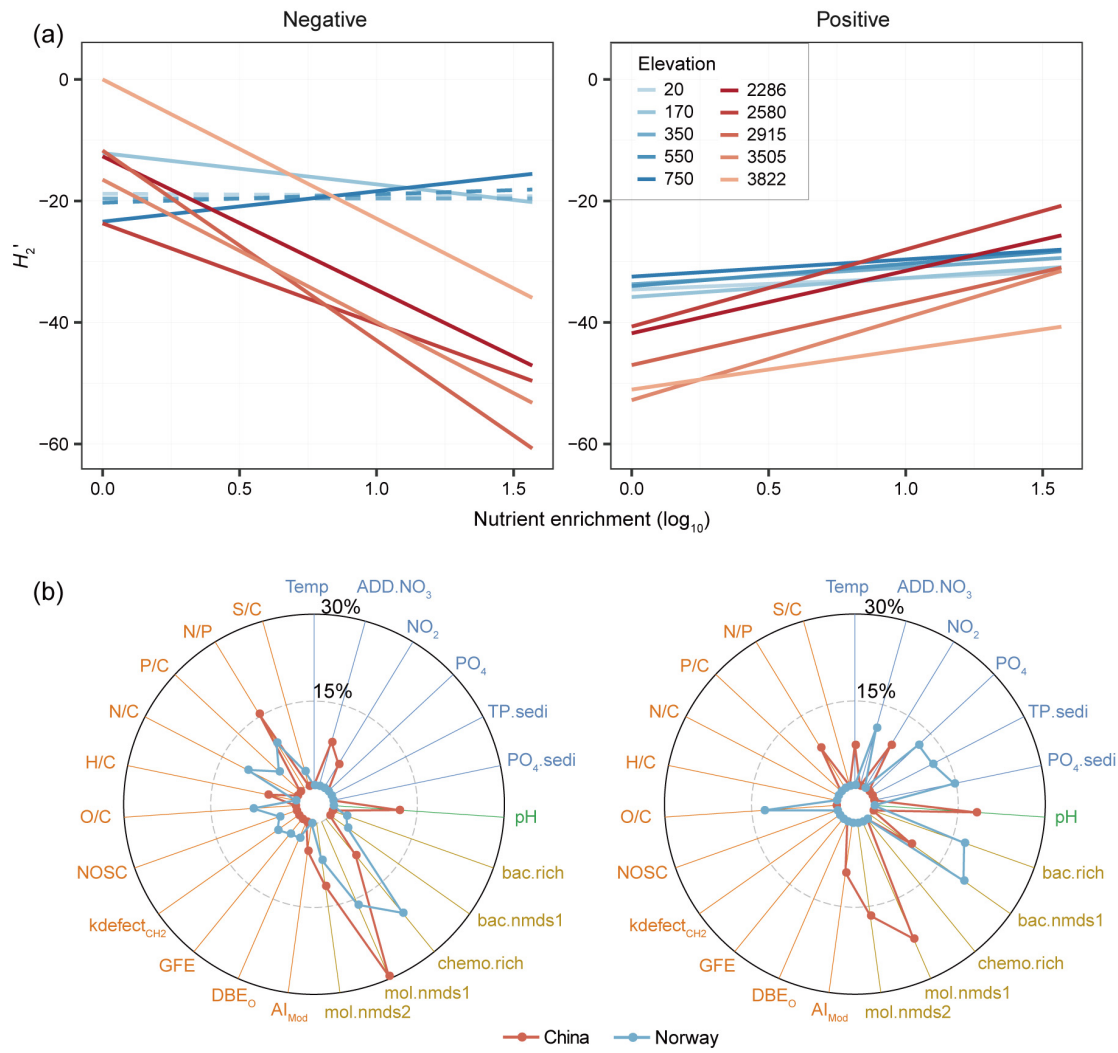
Figure 3



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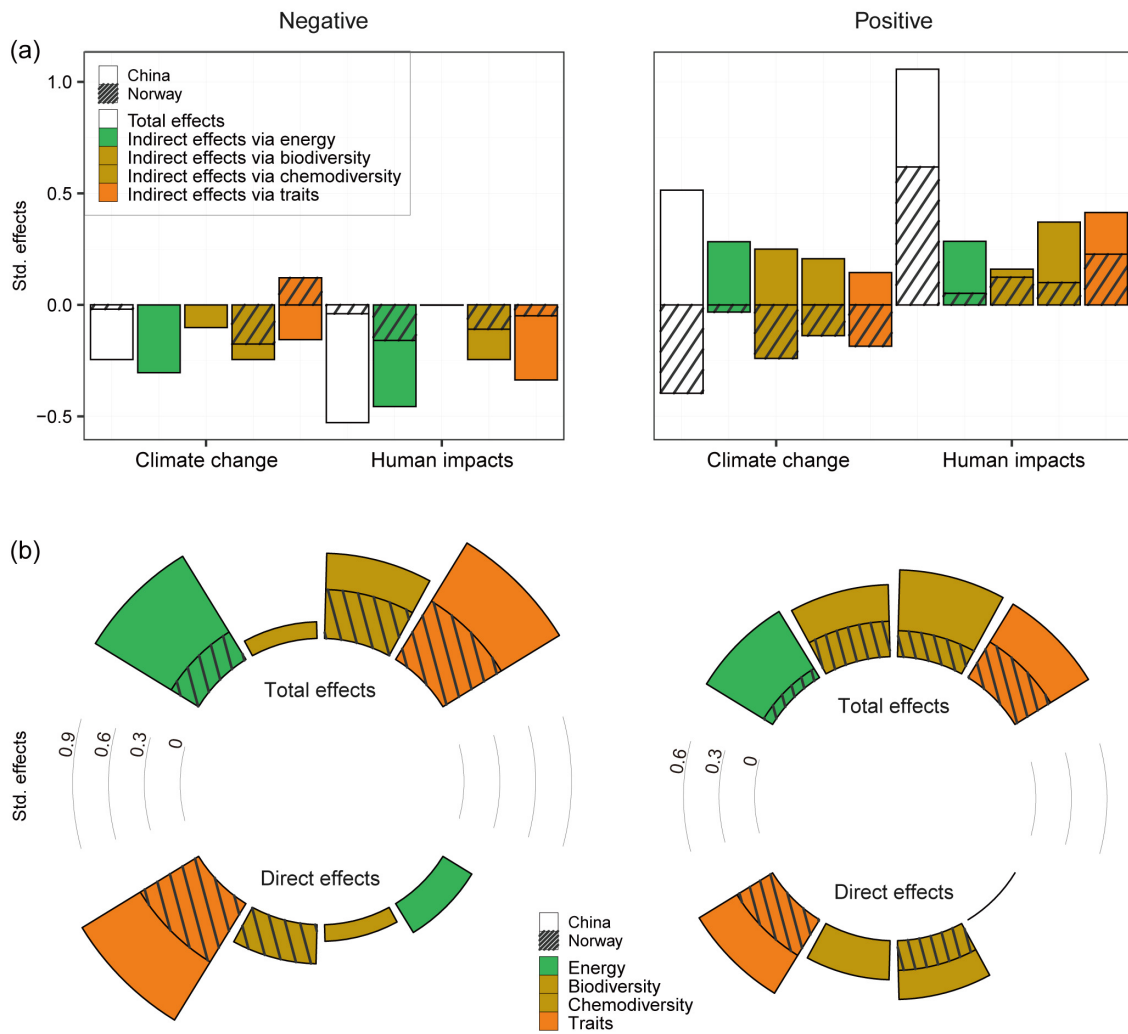
Figure 4



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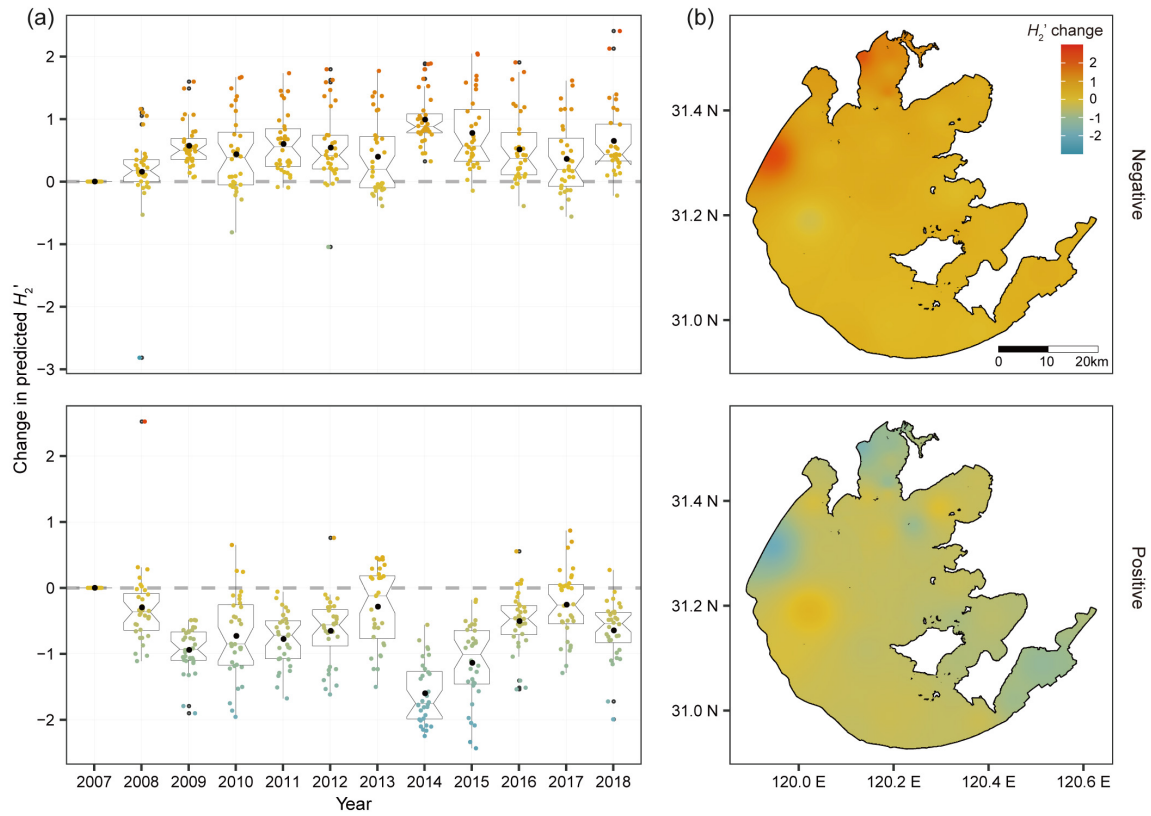
Figure 5



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1121

Figure 6



1122