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3 **Title:** Extreme carbon fluxes may result from autochthonous particulate organic
4 carbon regulated by the interactions between picophytoplankton and heterotrophic
5 bacteria in river-reservoir systems

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20 Abstract

21 Freshwater is a significant natural source of atmospheric methane (CH₄) and
22 carbon dioxide (CO₂) while also receiving significant amounts of particulate organic
23 carbon (POC) from various origins. The variation in carbon (CH₄ and CO₂) fluxes in
24 freshwater systems is heavily influenced by the sources of POC. The trophic
25 interaction between picophytoplankton (PP) and heterotrophic bacteria (HB) plays a
26 vital role in the carbon cycle within the aquatic system. However, the contributions of
27 different sources of POC to the concentrations and fluxes of CH₄ and CO₂ are still
28 unclear. Here, we explored the contribution of POC from different sources to extreme
29 carbon emission and the interaction between PP and HB. The evidence from isotope
30 analysis further proved that the extreme carbon fluxes were strongly influenced by
31 autochthonous POC rather than allochthonous POC. Network analysis showed that
32 the positive interaction strength between phytoplankton and bacterioplankton in
33 extreme carbon groups was higher than in normal carbon groups. The results of the
34 structure equation modeling analysis also highlighted that the PP-HB interaction
35 strongly drove the extreme carbon values. This study first introduced the probability
36 statistics method to identify and classify high or low extreme carbon values. These
37 findings also highlight the importance of PP and HB in carbon extreme emissions, and
38 we hope our study can provide an important implication for integrating PP-HB
39 interaction into predicting extreme carbon emissions in the river-reservoir ecosystem.

40 **Keywords:** Organic carbon; Autochthonous; Allochthonous; Picophytoplankton;
41 Methane emissions



42 **1. Introduction**

43 Freshwaters are considered important sources of greenhouse gases (GHGs) to the
44 atmosphere (Bauduin et al., 2024). According to estimates in the Sixth Assessment
45 Report by the Intergovernmental Panel on Climate Change (IPCC), annual global CH₄
46 and CO₂ emissions from freshwaters are estimated to be approximately 1.5 Pg CO₂
47 and 159 Tg CH₄ (IPCC, 2021), offsetting approximately 25% of the terrestrial carbon
48 sink (Emilsson et al., 2018). However, these estimates have a high degree of
49 uncertainty, mainly due to the apparent spatiotemporal heterogeneity and variability
50 of CH₄ and CO₂ fluxes across the air-water interface. Thus, it is crucial to reduce
51 these uncertainties in emission estimation from a local to a global scale by improving
52 the understanding of fluctuations in CH₄ and CO₂ concentrations and air-water fluxes.

53 There have been extensive studies on the cause of significant fluctuations in
54 freshwater CH₄ and CO₂ fluxes. The hydrological and hydrodynamic conditions, such
55 as river flow, drought, or floods, are significant factors that regulate this variability.
56 Additionally, meteorological factors like short-term heavy precipitation and winds are
57 non-negligible and significant physical factors causing the large variability of
58 freshwater CH₄ and CO₂ fluxes (Wang et al., 2008). The physical disturbances not
59 only affect the intensity of turbulence mixing at the air-water interface, which changes
60 the rate of air-mass transfer, but also trigger significant input of terrigenous organic
61 carbon (OC) and essential nutrients into freshwater, leading to increased CH₄ and CO₂
62 emissions (Liikanen et al., 2002). For example, the decomposition of a significant
63 input of terrigenous OC in the littoral area of freshwater might lead to the ebullition



64 emission of CH₄ in the summer. On the other hand, ecosystem-level events
65 significantly result in extreme values of CH₄ and CO₂ fluxes as well. The air-water
66 CH₄ flux was expected to exhibit extremely high values during algal blooms,
67 concurrently with low levels of surface water CO₂ concentrations, leading to an
68 apparent CO₂ sink during the blooming period (Sun et al., 2021). It appeared plausible
69 that several ecological factors or processes could contribute to the occurrence or
70 outbreaks of these high or low extremes of CH₄ and CO₂ concentrations in surface
71 water and their air-water fluxes. Yet, compared with the physical processes, how
72 ecological factors or processes could trigger extreme C emissions in freshwaters are
73 not frequently addressed. New mechanisms are needed to be elucidated.

74 The minor component of the planktonic communities (Stockner and Antiam,
75 1986), the picoplankton (defined by a cell size of 0.2-2 µm) (Sieburth et al., 1978),
76 mainly includes autotrophic picophytoplankton and heterotrophic bacteria (Stockner,
77 1988). Picophytoplankton are active and critical primary producers in aquatic
78 ecosystems due to their wide distribution, rapid growth rates, and metabolic
79 capabilities (Stockner, 1988). In the ocean, picophytoplankton can contribute 50-90%
80 of primary productivity (Poulton et al., 2006), significantly providing autochthonous
81 organic carbon to the aquatic ecosystem. Especially during an algal bloom,
82 small-sized phytoplankton, such as picophytoplankton, can fix more CO₂ through
83 photosynthesis. This is because picophytoplankton have higher growth rates and are
84 more effective in nutrient and light acquisition than larger phytoplankton (Irion et al.,
85 2021). Research in the past decade has also shed new light on a large proportion of



86 tiny picophytoplankton to carbon export, especially in oligotrophic oceans
87 (Richardson, 2019). On the other hand, heterotrophic bacteria decompose organic
88 carbon, transferring different sources of OC into CH₄ or CO₂ (Guillemette et al.,
89 2013). It was reported that heterotrophic bacteria can consume 20-60% of the total
90 primary production (Williams, 1981). The effects of heterotrophic bacteria on CH₄ or
91 CO₂ emissions are strongly dependent on the decomposition of organic carbon with
92 different bioavailability (Grasset et al., 2018). Therefore, as an important part of the
93 planktonic communities, picophytoplankton and heterotrophic bacteria undoubtedly
94 are essential components for understanding the carbon cycle in the aquatic ecosystem.

95 Interactions between picophytoplankton and heterotrophic bacteria are critical
96 for exploring the possible mechanisms that regulate CH₄ and CO₂ dynamics in aquatic
97 ecosystems. Picophytoplankton and heterotrophic bacteria do not exist in isolation
98 (Faust and Raes, 2012), and there are complex ecological interactions between them,
99 which span mutualism, commensalism, parasitism, and competition (Seymour et al.,
100 2017). In brief, the relationship between picophytoplankton and heterotrophic bacteria
101 is based on resource provision and can be either cooperative (exchange of resources)
102 or competitive (competition for resources) (Amin et al., 2012). Mutualism, a win-win
103 relationship, is found to be the primary relationship between these two
104 microorganisms (Zhang et al., 2021). One example for mutualism is cross-feeding, in
105 which two species exchange metabolic products to facilitate the growth of both
106 (Woyke et al., 2006). For instance, heterotrophic bacteria directly obtain a large
107 proportion of picophytoplankton-derived organic carbon to meet their carbon demand



(Zhou et al., 2022). Autrophic picophytoplankton can utilize vitamins and micronutrients (that is, iron, copper, etc.) released by heterotrophic bacteria (Zhou et al., 2022; Durham et al., 2015). There are two possible mechanisms by which picophytoplankton-heterotrophic bacteria interactions affect CH₄ and CO₂ flux. First, the cooperative relationship between picophytoplankton and heterotrophic bacteria produces strong coupling and positive feedback between these two organisms, increasing microbial metabolic efficiency and full utilization of OC (Coyte et al., 2015). Second, “physical interactions” between picophytoplankton and heterotrophic bacteria in an extracellular microenvironment (that is, “phycosphere”) mediate the level of aggregation of picophytoplankton biomass, which manipulates downward C flux (Seymour et al., 2017). Despite their small size, more than 40% of *Synechococcus* cells were found to be conjoint with heterotrophic bacteria (“physical interaction”) in situ observation (Malfatti and Azam, 2009). Such an increase in picophytoplankton and heterotrophic bacteria cell aggregation mediated by interactions between picophytoplankton and heterotrophic bacteria, especially during the algal blooms, would lead to an increase in the carbon flux exported to the bottom water column (Gärdes et al., 2011), thus offering more substrate for CH₄ production. In recent years, the influence of picophytoplankton and heterotrophic bacteria on the biogeochemical cycle of carbon has been widely discussed in marine ecosystems (Zhou et al., 2022). Little is known about the dynamics of CH₄ and CO₂ production and emissions driven by the interaction of these “specific participants” in freshwaters.



129 River damming disrupts the natural connectivity of rivers and causes a shift in
130 the aquatic system from lotic to lentic type along the longitudinal gradients towards
131 the dam site (Baxter, 1977). This change significantly affects the river's flow by
132 reducing speed, prolonging the hydraulic retention time, and interrupting sediment
133 movement (Maavara et al., 2020). Reservoirs receive a higher input of terrigenous
134 organic carbon than natural lakes due to their comparably lower ratio of watershed
135 area to surface area and higher shoreline development (Thornton et al., 1990). Over
136 the past two decades, there has been increasing concern about the excessive carbon
137 emissions from reservoirs. This is significant for global carbon biogeochemical cycles
138 and has implications for the hydropower industry. However, organic carbon sources
139 contributing to carbon emission, especially extremes, have yet to be well explored.
140 This lack of understanding hinders the accurate prediction of reservoir carbon
141 emissions in various scenarios.

142 Although extremely high or low CH₄ and CO₂ concentrations in surface water or
143 their air-water fluxes were not frequently detected, it was assumed that the extremes
144 or normal status of C fluxes could represent the distinctive ecosystem-level state and
145 the biogeochemical cycling. Thus, processes and mechanisms of carbon cycling in the
146 river-reservoir system could be further explored through the categorization of extreme
147 or normal status of CH₄ and CO₂ concentrations or air-water fluxes. Therefore, we
148 hypothesized that (1) autochthonous organic carbon (OC) in river-reservoir systems
149 greatly contributes to the occurrences of extreme values of CH₄ and CO₂
150 concentrations; (2) terrigenous OC contributes to the normal values of CH₄ and CO₂



151 concentrations; and (3) The interaction of autotrophic picophytoplankton (PP) and
152 heterotrophic bacteria (HB) could be intensified with an increase in trophic state, thus
153 promoting the production of extreme values of CH₄ and CO₂.

154 To test the hypothesis, we first identified and classified extremely high or low
155 values of CH₄ and CO₂ concentrations and their air-water fluxes across different types
156 of reservoirs in the upper Yangtze River basin in China. Then, we investigated
157 variations and interactions of picophytoplankton and heterotrophic bacteria, together
158 with environmental parameters and stable isotopic evidence. Building on our
159 sampling campaign (Tang et al., 2023), we restructured the information and conducted
160 new analyses. This study enhances prior research through two key contributions:

161 1) We categorized the concentrations and fluxes of CH₄ and CO₂ from the
162 previous datasets into two groups: extreme and normal. This classification is based on
163 the probability of occurrence and offers new insights into the mechanisms that
164 regulate these gases.

165 2) We included new data from pico-phytoplankton and heterotrophic bacteria.
166 This information may provide fresh evidence regarding the interactions between
167 phytoplankton and bacteria that contribute to CH₄ emissions in the extreme group.

168 Hopefully, our study will determine the role of picophytoplankton and
169 heterotrophic bacteria in extreme carbon emissions, which would yield new insights
170 into extreme carbon emissions with the two tiny planktonic communities in
171 river-reservoir systems.

172



173 **2. Materials and methods**

174 *2.1. Study sites and sample collection*

175 Five reservoirs in the upper Yangtze River basin were selected (Fig. 1), including
176 Xiluodu (XLD), Xiangjiaba (XJB), Shizitan Reservoir (SZT), Xiaoba II (XB II) and
177 Three Gorges Reservoir (TGR). Among these five reservoirs, XLD, XJB, and TGR
178 are located on the main stem of the Yangtze River, which are large river-valley
179 dammed cascade reservoirs and mainly serve as hydropower generation and flood
180 control. The SZT (also known as Changshou Lake) is located on the Longxi River, a
181 tributary of the Yangtze River, and functions as tourism now. XB II (with a total
182 capacity of 11300 m³) is a small reservoir only for drinking water supply located on a
183 tertiary tributary named Ganxi Gulley of the Yangtze River. The geographical and
184 project information of these selected reservoirs is described in Table S1.

185 Sampling campaigns were conducted in May, July, and November 2019 to obtain
186 a representative dataset containing different seasons. Twenty-six sampling sites were
187 set in the five selected reservoirs, covering the riverine zone, transitional zone, and
188 lacustrine zone of each reservoir (Fig. 1; Table S2). Water samples for cell
189 enumeration of picophytoplankton and heterotrophic bacteria were filtered through a
190 50-μm nylon sieve. The filtered samples were immediately fixed by glutaraldehyde
191 solution and kept at -80 °C in the laboratory until analysis for flow cytometry analysis.
192 Water samples for bioinformatic analysis of phytoplankton and bacterioplankton were
193 filtered through 0.22 μm Millipore cellulose filters (Milford, USA). The filtered
194 membranes were then kept at -86°C until DNA extraction. The remaining water



195 samples for analysis of environmental parameters were pretreated according to
196 standard methods.

197 2.2. Physicochemical parameters

198 Water temperature (WT), dissolved oxygen (DO), and pH were measured on-site
199 with a multiparameter sonde (YSI®EXO2, USA). The concentrations of chlorophyll a
200 (Chl-a) and different forms of nitrogen and phosphorus in water were measured
201 according to the Monitoring Analysis Method of Water and Wastewater (SEPA, 2002)
202 using a UV-visible spectrophotometer (Shimadzu® UV2700i, Japan).

203 Concentrations of CH₄ and CO₂ in the water phase were measured with the
204 headspace equilibration method (Goldenfum, 2010). In brief, a water sample (200 mL)
205 was gently collected using a polypropylene syringe equipped with a three-way valve.
206 100 mL N₂ (99.999%) gas was added to the syringe to create a headspace. After 3 min
207 of vigorous shaking, the equilibrated headspace gas was injected into a pre-evacuated
208 airbag (Delin® 300 mL, Dalian) for storage until measurement. Gas samples were then
209 analyzed using a stable isotope analyzer (Picarro® G2201-i, USA). The CH₄ and CO₂
210 emission fluxes at the water-air interface were estimated by the thin boundary layer
211 method (Goldenfum, 2010). All measurements were performed in triplicate for quality
212 assurance.

213 The frozen filtered POC membranes were dried at 65 °C for 48 h, fumigated with
214 HCl (12 M) for 12 h to remove particulate inorganic carbon, and wrapped in a tin boat.
215 The wrapped filtered POC membranes were used to analyze the concentrations of
216 POC and PON using a stable isotope mass spectrometer coupled with an elemental



217 analyzer (Thermo Fisher Scientific® Flash HT-Delta V Advantage, USA).

218 *2.3. Analysis of microbial communities*

219 Picophytoplankton and heterotrophic bacteria abundance ($< 2 \mu\text{m}$) in collected
220 samples was determined using a flow cytometer (Beckman Coulter® CytoFLEX,
221 USA). Based on previous methods (Lu et al., 2018; Yang et al., 2019), we pretreated
222 flow cytometry samples and set the discriminator of flow cytometry. Briefly, for
223 picophytoplankton enumeration, 1 mL of unstained sample was taken for analysis.
224 The discriminator was set on two red and one orange fluorescence, respectively. For
225 heterotrophic bacteria enumeration, 20 μL samples were diluted into 1 mL with
226 sterilized water and stained with SYBR Green I (Molecular Probes, USA) for 15 min
227 at room temperature in the dark. The discriminator was set on red and green
228 fluorescence, respectively. Detailed flow cytometry analysis of picophytoplankton and
229 heterotrophic bacteria was described in supplementary method S1.

230 Genomic DNA was extracted and duplicated from the filters with a DNA
231 isolation kit (Mo Bio laboratories® FastDNA SPIN kit, USA) according to the
232 manufacturer's instructions. The duplicate DNA extracts were mixed for the following
233 PCR amplification. The primers used for the phytoplankton 23S rRNA gene were
234 A23SrVF2 and A23SrVR2 (Yoon et al., 2016). The primers used for bacterioplankton
235 16S rRNA gene were 338F and 806R (Ding et al., 2020). Amplicons were purified
236 with an AxyPrep DNA Gel Extraction Kit (Axygen Biosciences, USA). The PCR
237 products of each sample were sequenced on the Illumina MiSeq platform at Majorbio
238 Bio-Pharm Technology, Co., Ltd. (Shanghai, China). DNA extraction, PCR



239 amplification, and high-throughput sequencing were discussed in detail in the
240 supplementary method S2.

241 *2.4. Stable carbon isotopic analysis*

242 $\delta^{13}\text{C}$ of CH_4 and CO_2 in the water phase were analyzed using a stable isotope
243 analyzer (Picarro® G2201-i, USA). Stable isotopes of POC and PON were measured
244 using a stable isotope mass spectrometer coupled with an elemental analyzer (Thermo
245 Fisher Scientific® Flash HT-Delta V Advantage, USA). $\delta^{13}\text{C}$ and $\delta^{15}\text{N}$ of POM were
246 used to determine the contributions of different sources of POC. Stable isotope values
247 of endmembers (C3 plant, C4 plant, coastal soil, and plankton) were summarized in
248 Table S3. DOC concentration and $\delta^{13}\text{-DOC}$ were analyzed by a total organic carbon
249 analyzer-stable isotope mass spectrometer (Elementar® vario cube TOC-isoprime100,
250 Germany).

251 In this study, we applied isotopic analysis to specifically explore the impact of
252 organic carbon from autochthonous sources on extreme values of CH_4 and CO_2
253 production. We focused on the two main mechanisms affecting $\delta^{13}\text{C-CH}_4$ and
254 $\delta^{13}\text{C-CO}_2$: (i) physical proces and (ii) biological processes (Han et al., 2018). Our
255 analysis concentrated on the variability of CH_4 and CO_2 in the water column, rather
256 than at the air-water interface, using isotope data. We made the assumption that the
257 fractionation effect induced by CH_4 and CO_2 exchange at the air-water interface, such
258 as dissolution and emission, can be ignored.



259 2.5. *Identification of extreme and normal levels of CH₄ and CO₂ concentrations and*
260 *fluxes*

261 Pearson type III probability distribution curve (Hosking and Wallis, 1997), a
262 widely used probability distribution function in hydrology and meteorological
263 statistics (Sun and Qin, 1989), such as frequency analysis of extreme hydrological
264 events, risk assessment of extreme climate, etc. (Raynal Villaseñor, 2021). Here, we
265 employed Pearson type III probability distribution to determine the extreme and
266 normal values of CH₄ and CO₂ concentrations and fluxes. This method allowed us to
267 calculate the threshold values for extreme values of CH₄ and CO₂ concentrations and
268 fluxes at 10% and 90% probabilities (Ding and Jiang, 2009). Based on these threshold
269 values, we divided the dataset into three groups, i.e. extremely high (Ext_h), normal
270 (nor), and extremely low (Ext_l). The supplementary material method S3 provided
271 threshold values and sample numbers for the above three groups of CH₄ and CO₂
272 concentrations and fluxes, respectively.

273 2.6. *Statistical analysis*

274 Originpro (OriginLab®, USA, education version) was used for graphing. Data
275 analyses were performed by SPSS (IBM, USA). Differences among groups were
276 considered to be statistically significant if $p < 0.05$. Multiple linear regression analysis
277 was conducted to determine whether the main predictor of carbon extreme values was
278 POCauto or POCallo.

279 The trophic state of each sampling site was evaluated based on the trophic level
280 index (TLI) (Tang et al., 2023). Alpha diversity (Shannon-Wiener and Chao1 index)



was calculated by using the *vegan* package. The contributions of different sources to POC were estimated using Bayesian stable isotope mixing models with the *simmr* package (Parnell et al., 2013). The co-occurrence networks of phytoplankton and bacterioplankton were constructed by 16S rRNA and 23S rRNA microbial ASVs using *igraph* package. The main predictors for the abundance of picophytoplankton and heterotrophic bacteria were identified by random forest (RF) analysis with the *randomForest* package. Structure equation modeling (SEM) analysis was implemented by the *lavaan* package to explore the relationships among all variables for both the extreme and normal groups. All these methods mentioned above were described in detail in the supplementary material methods. The setting of the sampling campaign and analysis of water samples were described in our prior research (Tang et al., 2023). All data analyzed in this study are sourced from the same dataset (Tang et al., 2023).

3. Results

3.1. Identification of extreme and normal values of carbon concentrations and fluxes

The extreme and normal values for CH₄ and CO₂ concentrations and fluxes are shown in Table 1. The mean CH₄ concentration (CCH₄) in the normal and extremely high groups were 0.03±0.00 and 0.19±0.02 μmol·L⁻¹, respectively. The mean CH₄ flux (FCH₄) in the extremely low, normal, and extremely high groups were 0.01±0.00, 0.10±0.01, and 0.61±0.14 mmol·m⁻²·d⁻¹, respectively. The mean CCO₂ in the extremely high and normal groups were 6.23 and 3.51 times higher than in the extremely low group, respectively. The mean FCO₂ in the extremely low, normal, and



303 extremely high groups were 0.05 ± 0.83 , 25.72 ± 1.16 and 62.71 ± 8.56 $\text{mmol} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$,
304 respectively. Differences in CH_4 and CO_2 concentrations and fluxes between extreme
305 and normal groups were significant ($p < 0.001$). Since the CH_4 concentration in the
306 whole dataset was higher than the threshold value for the extremely low CH_4
307 concentration ($0.004 \mu\text{mol} \cdot \text{L}^{-1}$), the number of samples corresponding to the
308 extremely low group of CH_4 concentration was 0. Thus, the extremely low group
309 (Ext_1) of CH_4 concentration (CCH₄) was nonexistent.

310 The trophic levels were noticeably different between extreme and normal groups
311 of CH_4 and CO_2 concentrations and fluxes (Table 2). The TLI values in the extremely
312 high group of CCH₄ and FCH₄ were higher than 46.27, which belonged to the
313 eutrophic state. The TLI values fluctuated within 38.91-46.27 in the normal group of
314 CCH₄ and FCH₄, indicating the water in the normal group was mesotrophic. With the
315 increase of trophic state, CCH₄ and FCH₄ exhibited an increasing trend, and CCH₄ and
316 FCH₄ ranged from 0.07 to $0.20 \mu\text{mol} \cdot \text{L}^{-1}$ and 0.06 to $0.18 \text{mmol} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$, respectively
317 (Fig. S3). Both extremely high and extremely low groups of CCO₂ and FCO₂ were
318 eutrophic, but the normal group was mesotrophic (Table 2). CCO₂ and FCO₂
319 decreased from oligotrophic state to eutrophic state, and CCO₂ and FCO₂ ranged from
320 44 to $43 \mu\text{mol} \cdot \text{L}^{-1}$ and 24 to $23 \text{mmol} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$, respectively (Fig. S3).

321 Ternary plots showed that the extremely high values of CCH₄ mainly occurred in
322 July, with a relative percentage up to 56%, than in other months (relative percentage
323 of 44% in May and 0% in November), while most of the normal values of CCH₄
324 appeared in November, accounting for 38% of total normal groups (Fig. 2A). We



325 further observed that the extremely low, normal, and extremely high values of FCH₄
326 mainly occurred in November, May, and July, respectively. On the contrary, the
327 extremely low, normal, and extremely high values of CCO₂ and FCO₂ mainly
328 occurred in July, May, and November, respectively. These results all exhibited that
329 extreme level of carbon concentrations and fluxes (extremely high values for CH₄ and
330 extremely low values for CO₂) mostly appeared in July, which supports the inference
331 that cell aggregation mediated by the PP-HB interaction drives the extreme values of
332 CH₄ and CO₂, especially during the summer blooming period.

333 As Fig. 2B shows, most environmental parameters differed significantly among
334 extremely low, normal, and extremely high groups of CH₄ and CO₂ concentrations and
335 fluxes, with $p < 0.05$. Except for WT and POC, other environmental factors did not
336 show significant differences among the extreme and normal groups of CCH₄ and
337 FCH₄. The mean WT and POC exhibited an increasing trend from the extremely low
338 to extremely high group of CCH₄ and FCH₄ ($p < 0.05$).

339 Results also showed that the mean NO₃⁻-N concentration in the normal group of
340 CCO₂ and FCO₂ was significantly higher than that in the extremely low group of
341 CCO₂ and FCO₂ (Fig. 2B; $p < 0.01$). An increasing trend in mean SRP concentration
342 was observed sequentially from the extremely low to the extremely high group of
343 CCO₂ and FCO₂, and the mean SRP was lowest in the extremely low group (0.02
344 mg·L⁻¹ for CCO₂; 0.02 mg·L⁻¹ for FCO₂) and highest in the extremely high group
345 (0.07 for CCO₂ mg·L⁻¹; 0.07 mg·L⁻¹ for FCO₂); conversely, the mean DO, WT, pH
346 were highest in the extremely low group and lowest in the extremely high group of



347 CCO₂ and FCO₂. Moreover, POC and DOC in the extreme groups (high or low) of
348 CCO₂ were higher than those in the normal group.

349 3.2. Contributions of autochthonous and allochthonous POC

350 The concentrations of autochthonous POC (POC_{auto}) and allochthonous POC
351 (POC_{callo}) were noticeably different among the extreme and normal groups of CH₄
352 (CCH₄) and CO₂ concentrations (CCO₂) (Fig. S4). The POC_{auto} and POC_{callo}
353 concentrations in whole dataset respectively ranged from 0.004 to 0.859 mg·L⁻¹ and
354 0.05 to 1.77 mg·L⁻¹, and were positively correlated with TLI (Figs. S4 and S5). In the
355 extreme and normal groups of CCH₄, mean concentrations of POC_{auto} and POC_{callo}
356 in the extremely high group (0.22±0.08 mg·L⁻¹ for POC_{auto}; 0.46±0.14 mg·L⁻¹ for
357 POC_{callo}) were significantly higher than those in the normal groups (0.07±0.02 mg·L⁻¹
358 for POC_{auto}; 0.30±0.05 mg·L⁻¹ for POC_{callo}) (Fig. S4). In the extreme and normal
359 groups of CCO₂, mean POC_{auto} and POC_{callo} concentrations in the extremely low
360 groups were significantly higher than those in the normal groups (Fig. S4).

361 Furthermore, POC_{auto} and POC_{callo} were both positively correlated with the
362 CCH₄, respectively (Fig. 3A). In the extremely high group of CCH₄, we observed a
363 greater slope value between POC_{auto} and CCH₄ than that between POC_{callo} and
364 CCH₄. However, in the normal group of CCH₄, the slope value between POC_{callo} and
365 CCH₄ was higher than that between POC_{auto} and CCH₄. Statistical analysis showed
366 that CCO₂ was significantly positively correlated with POC_{auto}, but the relationships
367 between CCO₂ and POC_{callo} were not significant (Fig. 3B). The slope values between
368 POC_{auto} and CCO₂ were greater than those between POC_{callo} and CCO₂ among the



three groups. The increase in the autochthonous POC contributed to a higher CCH₄ (Fig. 3C) and lower CCO₂ (Fig. 3D), respectively.

3.3. *Picophytoplankton and heterotrophic bacteria abundance across extreme and normal groups*

The abundances of picophytoplankton (PP) and heterotrophic bacteria (HB) varied with extreme and normal groups of CO₂ and CH₄ concentrations (Fig. 4). The abundance of PP and HB respectively ranged from 0.01×10^5 to 5.66×10^5 cells·mL⁻¹ and 0.26×10^5 to 8.90×10^5 cells·mL⁻¹ in the whole dataset (Fig. 4). The difference in PP or HB abundance between extremely high (Ext_h) and normal groups (Nor) of CH₄ concentration was not significant (Fig. 4A). The HB abundance was higher than that of PP in the high (Ext_h) and normal groups (Ext_h) of CH₄ concentration (Fig. 4B). The differences in HB abundance were not significant in three extreme and normal groups of CCO₂ (Fig. 4C). The mean PP abundance in the extremely low group (Ext_l) of CO₂ concentration was significantly higher than those in the normal (Nor) and extremely high groups (Ext_h) of CO₂ concentration. The HB abundance was higher than that of PP in the extremely high (Ext_h) and normal groups (Nor) of CO₂ concentration except in the extremely low group (Ext_l) of CO₂ concentration (Fig. 4D).

We used random forest (RF) modeling (Fig. 5) to identify the main environmental predictors of picophytoplankton and heterotrophic bacteria abundance. The main environmental predictors influencing PP abundance were TP, SRP, DIN, NO₃⁻-N, Chl-a, DO, WT, pH, POC, and DOC ($p < 0.05$) (Fig. 5A). The main



391 environmental predictors also had a certain influence on the HB abundance ($p < 0.05$)
392 (Fig. 5B). The variance explanation of environmental factors for the abundance of PP
393 ($R^2=0.82$) was higher than that of HB ($R^2=0.39$).

394 3.4. Interactions between phytoplankton and bacterioplankton communities

395 The co-occurrence patterns of phytoplankton and bacterioplankton in the
396 extreme and normal groups of CH_4 and CO_2 concentrations were determined using
397 network analysis (Fig. 6; Table 3). Overall, the number of nodes ranged from 101 to
398 184 in all five interaction networks. Most networks consisted of more than 50%
399 positive edges, except in networks for the normal group of CO_2 concentration. In
400 addition, topological properties of the co-occurrence network in normal groups of
401 CH_4 and CO_2 , such as modularity, were higher than those in the extreme groups. In
402 contrast, the average degree showed an exactly opposite trend. The number of
403 phytoplankton-bacterioplankton links decreased from 977 in the extremely high group
404 to 104 in the normal group of CH_4 concentration (Fig. 6A and B). Similarly, the
405 number of phytoplankton-bacterioplankton links in the normal group was also
406 significantly lower than both in the extremely high and extremely low groups of
407 CO_2 concentration (Fig. 6C-E). Compared with communities in normal groups,
408 communities in the extreme groups exhibited a higher interaction strength (that is,
409 links) between phytoplankton and bacterioplankton.

410 3.5. Influential pathways of planktonic communities on CH_4 and CO_2 concentrations

411 We conducted structural equation modeling (SEM) to understand the direct and



indirect relationships between microbial variables and POC with CH₄ and CO₂ concentrations for extreme and normal groups (Fig. 7). Our SEMs explained 96 and 21% of the variance in CH₄ concentrations in the extremely high and normal groups, respectively (Fig. 7A and B). In the extremely high group of CH₄ concentration, CH₄ concentration was directly influenced by picophytoplankton (PP), autochthonous POC (POC_{auto}), and allochthonous POC (POC_{callo}) with path coefficients of 0.77, 0.35 and -0.26, respectively (Fig. 7A). Picophytoplankton could also indirectly affect the extremely high CH₄ concentration by influencing POC_{auto} and POC_{callo}. POC_{auto} and POC_{callo} were positively and negatively correlated with the extremely high CH₄ concentration ($p < 0.01$ and $p < 0.001$, respectively). However, HB didn't show a significant influence on the extremely high CH₄ concentration. In the normal group (Fig. 7B), both POC_{auto} and POC_{callo} were positively correlated with the CH₄ concentration ($p < 0.001$ and $p < 0.01$, respectively), and the path coefficient between POC_{callo} and CH₄ concentration was greater than that between POC_{auto} and CH₄ concentration. However, Chl-a had a negatively direct effect on the normal value of CH₄ concentration with a negative path coefficient of 0.58 ($p < 0.01$).

The selected variables explained 85, 26, and 96% of the variance in CO₂ concentrations in the three groups, respectively (Fig. 7C-E). In the extremely high group of CO₂ concentration, POC_{auto}, POC_{callo}, and HB were not correlated with the CO₂ concentration, while PP significantly affected the extremely high CO₂ concentration ($p < 0.001$) (Fig. 7C). In the normal group of CO₂ concentration, only POC_{callo} had a positively direct impact on the normal value of CO₂ concentration



434 ($p < 0.001$) (Fig. 7D). There was only one indirect path in which PP affected the normal
435 value of CO_2 concentration by influencing POC_{allo}. In the extremely low group of
436 CO_2 concentration, except for POC_{allo}, PP, POC_{auto}, and HB showed a significant
437 direct impact on the extremely low value of CO_2 concentration (Fig. 7E, $p < 0.001$,
438 respectively). PP significantly affected POC_{auto} ($p < 0.01$) and ultimately affected the
439 extremely low value of CO_2 concentration.

440 **4. Discussion**

441 *4.1. Contributions of POC from different sources to CH_4 and CO_2*

442 CH_4 and CO_2 are the dominant gaseous end products of organic carbon (OC)
443 decomposition (Yvon-Durocher et al., 2011), but the potential for CH_4 and CO_2
444 production and emissions differs between different sources of POC (Berberich et al.,
445 2020). In the present study, we hypothesized that (1) the extreme values of CH_4
446 (CCH_4) and CO_2 concentrations (CCO_2) will mainly be fueled by autochthonous POC
447 (POC_{auto}), (2) the normal values of CH_4 and CO_2 concentrations will mainly be
448 stimulated by allochthonous POC (POC_{allo}).

449 Previous studies proved that autochthonous OC will decompose faster than
450 allochthonous OC, thus sustaining higher CO_2 and CH_4 production rates than
451 allochthonous OC (Grasset et al., 2018). This evidence probably supports the view
452 that autochthonous POC supports short-term carbon production and emissions. Our
453 study found steeper slopes between carbon (CH_4 and CO_2) concentrations and
454 autochthonous POC than those between carbon concentrations and allochthonous
455 POC in the extreme groups of CH_4 and CO_2 (Fig. 3A and B). There was more positive



456 correlation between autochthonous POC and the extreme values of CH₄ and CO₂
457 concentrations than those between allochthonous POC and the extreme values of
458 carbon (Table 4), indicating the main contribution of autochthonous POC to the
459 extreme values of CH₄ and CO₂ concentrations. The evidence from isotope analysis
460 further proved and highlighted that the extreme values of CH₄ and CO₂ concentrations
461 were strongly influenced by autochthonous POC (Fig. 8). Photosynthesis and
462 decomposition were the important biological processes controlling concentrations and
463 isotope values of OC and carbon. The input of OC to reservoirs is a complex mixture
464 of autochthonous OC (i.e., OC derived from aquatic primary production) and
465 allochthonous OC (i.e., OC derived from terrigenous input) (Chen et al., 2021). In the
466 extreme group of CH₄ concentration, POC in the surface water was mainly from
467 aquatic plankton, and the average $\delta^{13}\text{C}$ -POC was approximately -26.34‰ (Table S3).
468 Phytoplankton provides a large amount of autochthonous POC through
469 photosynthesis, and picophytoplankton was therefore significantly correlated with
470 POC ($p < 0.01$, Fig. 8A). However, in summer, phytoplankton may assimilate HCO₃⁻
471 as an inorganic C source under CO₂ limitation during intense photosynthesis, which
472 weakens the discrimination of ¹³C and enriches organic matter with ¹³C (Fogel and
473 Cifuentes, 1993). The above reasoning explained why the ¹³C enrichment in the
474 surface water DOC with the increase of the Chl-a ($p < 0.01$, Fig. 8B). A positive
475 correlation between $\delta^{13}\text{C}$ -POC and CH₄ concentration in the extremely high group of
476 CH₄ ($p < 0.05$, Fig. 8C) indicated that the extreme value of CH₄ was influenced by the
477 decomposition of autochthonous POC. This is probably because the decomposition of



478 OC from phytoplankton preferentially releases ^{12}C and leaves the residual OC
479 enriched in ^{13}C (van Breugel et al., 2005). High productivity may also convert lakes
480 or reservoirs from a CO_2 source to a sink (Balmer and Downing, 2011). The
481 $\delta^{13}\text{C}$ -DOC showed a negative correlation with $\delta^{13}\text{C}$ - CO_2 ($p < 0.01$, Fig. 8D), which
482 could be explained by an increase in phytoplankton photosynthesis (Fig. S6). These
483 results supported the first hypothesis above.

484 Nevertheless, because allochthonous POC accounts for large proportions of
485 aquatic ecosystems, allochthonous POC can support long-term CCH_4 accumulation
486 and emissions (Berberich et al., 2020). Correspondingly, we found steeper slopes
487 between CCH_4 and allochthonous POC than between CCH_4 and autochthonous POC
488 in the normal group of CCH_4 (Fig. 3A). The results of SEM also highlighted that the
489 normal values of CCH_4 and CCO_2 were positively influenced by allochthonous POC
490 (Fig. 7B and D). These results supported our second hypothesis above.

491 There are two main reasons why POC from different sources have varying
492 impacts on carbon production and emissions. First, chemical structure. Autochthonous
493 OC, mainly composed of protein and aliphatic compounds, has relatively simple
494 chemical structure (Kendall et al., 2001). Allochthonous POC, mainly composed of
495 cellulose, has relatively complex chemical structure (Sondergaard and Middelboe,
496 1995). Second, biological availability. Complete degradation of allochthonous POC
497 requires many species with different degradation capabilities, and therefore, the
498 degradation of allochthonous POC is relatively slow, and the yield of carbon is stable
499 (Grasset et al., 2018). In contrast, autochthonous POC, such as algal biomass, a labile



500 carbon source, is easily available for microorganisms (Berberich et al., 2020), thus
501 making the decomposition of autochthonous POC relatively rapid and the yield of
502 carbon production variable. In a word, autochthonous POC can stimulate the
503 production of extreme values of CH₄ and CO₂ in the short term (low probability of
504 occurrence), while allochthonous POC can maintain the normal production of CH₄
505 and CO₂ in the long term (high probability of occurrence).

506 *4.2. Response of picophytoplankton and heterotrophic bacteria to trophic state*

507 Compared to oligotrophic and mesotrophic states, the eutrophic state can provide
508 more resources for phytoplankton and bacterioplankton, thus reducing resource
509 competition between different species (Tang et al., 2023). In this study, we found that
510 the abundances of both picophytoplankton and heterotrophic bacteria in the extreme
511 groups of CCH₄_Ext_h and CCO₂_Ext_l (eutrophic state) were slightly higher than
512 those in the normal groups of CH₄ and CO₂ concentrations (mesotrophic state) (Fig. 4;
513 Table 2; Fig. S7). Recent studies reported that the environments with sufficient
514 resources will reduce niche overlap and enhance coexistence (Pastore et al., 2021).
515 Niche overlap reflects the degree to which species share the factor controlling their
516 growth (such as resources) (Pastore et al., 2021), and low niche overlap is mainly
517 considered weaker competition (Clavel et al., 2011). Our results showed a decrease in
518 the niche overlap of phytoplankton and bacterioplankton from oligotrophic state to
519 eutrophic state (Fig. S8), which agrees with Clavel et al. (2011). Furthermore, in
520 freshwater ecosystems, environmental conditions determine community diversity
521 (Meng et al., 2020). Alpha diversity is considered positively dependent on



522 environmental filters (Stefanidou et al., 2020). The increase in the alpha diversity
523 index was mainly considered as a signal of improved trophic state (Arab et al., 2019).
524 In our study, we found a decrease in alpha diversity of both phytoplankton and
525 bacterioplankton from oligotrophic state to eutrophic state (Fig. S9), which agrees
526 with Meng et al. (2020).

527 Bacterial taxa tended to be divided into r-strategists and K-strategists according
528 to the preference of different OC decomposition (Li et al., 2021). Previous studies
529 reported that the fast-growing bacterial taxa (r-strategists) prefer a environment
530 enriched with labile C, while the slow-growing bacterial taxa (K-strategists) favor a
531 nutrient-poor environment (Dai et al., 2022). In this study, an increase in the
532 proportion of r-strategists to K-strategists with trophic states (Fig. S10) suggested that
533 high eutrophic state provided more autochthonous POC (Fig. S5), promoting the
534 growth of r-strategists. In aquatic ecosystems, picophytoplankton and heterotrophic
535 bacteria have tiny sizes and rapid growth rates and can be characterized as typical
536 competitors (r-strategists). Phytoplankton communities have simplex richness
537 predominated by competitors in eutrophic lakes and rivers (Raffoul et al., 2020). In
538 parallel, prior studies reported that picophytoplankton (PP) contributes 50-90% of
539 primary productivity (Poulton et al., 2006), and HB consumes 20-60% of the total
540 primary production (Williams, 1981).

541 Types of interactions between two species include positive relationships (such as
542 mutualism and commensalism) and negative relationships (such as competition and
543 amensalism) (Faust and Raes, 2012). Our results showed that in co-occurrence



544 networks, the eutrophic communities displayed the highest positive interaction
545 strength between phytoplankton and bacterioplankton compared with the oligotrophic
546 and mesotrophic communities (Figs. 6 and S11). Such an increase supported the
547 inference that the eutrophic state increased the interaction strength between PP and
548 HB. Increased cell density of PP in the eutrophic state (Fig. S7) would reduce the
549 distance between PP and HB (Petrou, 2023), and therefore increase the encounter
550 rates and interactions in the extracellular microenvironment (Christie-Oleza et al.,
551 2017).

552 *4.3. Extreme and normal patterns of carbon emissions driven by picophytoplankton* 553 *and heterotrophic bacteria*

554 Although some extreme CO₂ and CH₄ air-water fluxes could be induced by
555 short-term physical processes, the short-term physical processes were not the focus of
556 our study. We found that water temperature showed no difference between normal and
557 extreme groups of CO₂ fluxes (Fig. 2B). Yet, the picophytoplankton abundance in the
558 extremely low group of CO₂ concentration was significantly higher than that in the
559 normal group of CO₂ concentration (Fig. 4C). These results suggested that the
560 extreme and normal values of CH₄ and CO₂ were probably influenced by ecosystem
561 response (such as microbial community composition or abundance variation), rather
562 than physical factors (such as temperature and wind).

563 In aquatic systems, the growth and functions of microorganisms are influenced
564 mainly by the quantity and quality of substrates (Yang et al., 2023) entering the water.
565 Microbial communities, therefore, structure their responses to OC using different life



566 strategies (Delgado-Baquerizo et al., 2016), which impact water C dynamics. Previous
567 studies reported that microbial community composition is correlated with substrate
568 utilization strategy (Schutter and Dick, 2001). The response of microorganisms to OC
569 from different sources is different on a time scale. Based on the growth rate and
570 effectiveness of C utilization, microbial communities can be classified into two
571 ecological functional groups, r- and K-selected species. Picophytoplankton and
572 heterotrophic bacteria, as r-strategists, have a fast growth rate and a rapid response to
573 labile C (Li et al., 2021). In contrast, K-selected species are slow-growing, decompose
574 recalcitrant C more efficiently, and respond slowly to OC inputs. This could explain
575 why the extreme values of CH₄ and CO₂ concentrations were positively influenced by
576 picophytoplankton (Fig. 7). Hence, picophytoplankton and heterotrophic bacteria play
577 essential roles in maintaining short-term extreme carbon emissions.

578 Our study found a significant positive correlation between network degree
579 (interaction strength) and CH₄ concentrations in the eutrophic state (Fig. S12). Such a
580 positive correlation corresponds to the third hypothesis that increased interaction
581 between picophytoplankton and heterotrophic bacteria promoted the extreme values
582 of carbon. This is mainly because positive interaction (i.e., cooperation) produces
583 strong coupling and positive feedback between PP and HB (Coyte et al., 2015),
584 increasing microbial metabolic efficiency and full utilization of OC.
585 Picophytoplankton and heterotrophic bacteria have numerous enzymes for
586 depolymerizing fresh labile C (such as autochthonous OC) (Li et al., 2021) and
587 typically flourish in environments enriched in unstable C.



Extremely values of CH₄ and CO₂ concentrations and fluxes were found in July (Fig. 2A). During the algal blooming period, increased cell density of PP (Fig. S7) would enhance the possibility of “physical interaction” between phytoplankton and heterotrophic bacteria (Christie-Oleza et al., 2017). The increase in PP-HB interaction facilitates cell aggregation, increasing carbon flux export to the bottom water column, and providing sufficient substrate for CH₄ production in the bottom layer (Gärdes et al., 2011). Meanwhile, increased cell aggregation reduces respiration and CO₂ production in the upper water column (Hopkinson and Vallino, 2005). These could explain why a higher positive interaction strength (number of links) between phytoplankton and bacterioplankton was found in extreme carbon groups compared with normal groups (Fig. 6). Hence, autochthonous OC critically influenced the fate of extreme values of CH₄ and CO₂ through the interaction between PP and HB.

5. Conclusion

In the upper Yangtze’s river-reservoir system, the normal CH₄ and CO₂ concentrations and fluxes were primarily contributed by the large input of allochthonous OC. In contrast, the extreme values of CH₄ and CO₂ concentrations and fluxes were mainly contributed by autochthonous OC. The picophytoplankton and heterotrophic bacteria and their interactions were important ecological factors and processes affecting extreme values of CH₄ and CO₂. Intensified interactions between PP and HB, due to an increase in the trophic state, which strongly controlled the generation and decomposition of autochthonous POC, concomitantly promoting the extreme production and emissions of CH₄ and CO₂. Our findings provide a new



610 mechanism based on the interaction of picophytoplankton and heterotrophic bacteria,
611 which would contribute to a deeper understanding of extreme carbon emissions in the
612 river-reservoir ecosystem.

613 **Supplements**

614 Supplementary material associated with this article can be found on the
615 additional files.

616 **Data availability**

617 The raw sequencing data has been deposited to the National Center for
618 Biotechnology Information (NCBI) Sequence Read Archive (SRA) database under the
619 following BioProject accession numbers: PRJNA1188301 for 23S rRNA sequencing
620 data (<http://www.ncbi.nlm.nih.gov/bioproject/1188301>) and PRJNA1188367 for 16S
621 rRNA sequencing data (<http://www.ncbi.nlm.nih.gov/bioproject/1188367>).

622 **Author contributions**

623 ZL conceived this study and acquired the research funds. LL provided genome
624 sequence data. YX supervised the flow cytometry analysis. ZL and DW
625 conceptualized the study. FL, QT, YX and LL process data. FL and QT conducted
626 formal analysis. CL and XW assisted with the analysis. FL wrote the manuscript. ZL
627 revised the manuscript. All authors approved the manuscript.



628 **Competing interests**

629 The contact author has declared that none of the authors has any competing
630 interests.

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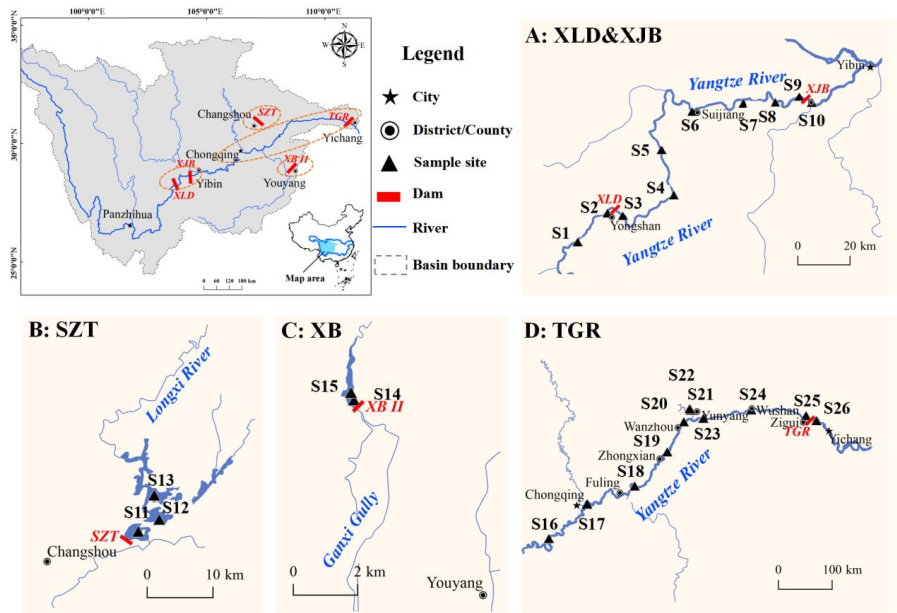
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858 **Figures**



859
860 **Fig. 1.** Location of sampling sites in five reservoirs in the upper Yangtze River. Detailed
861 information on sampling sites in five reservoirs is shown in Table S2.

862

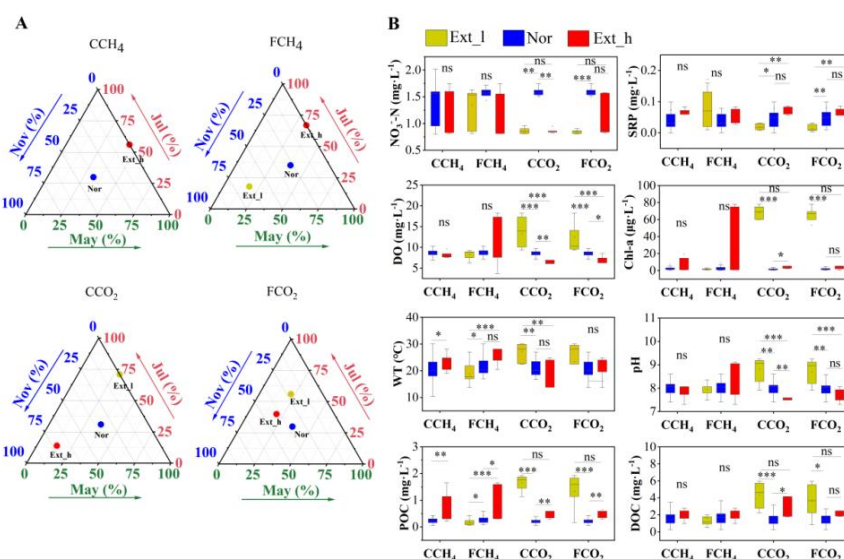
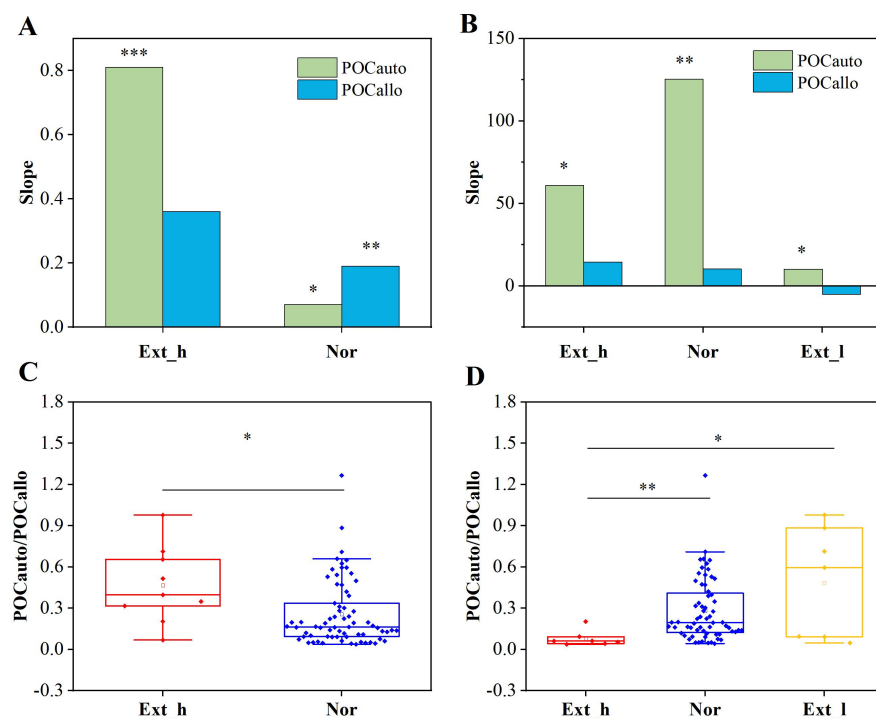
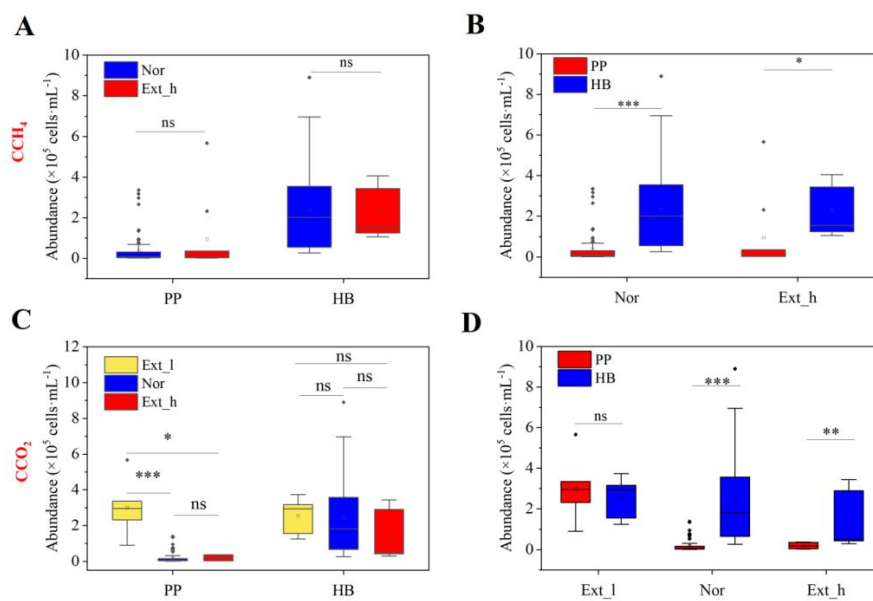


Fig. 2. Comparison of months and environmental parameters in extreme and normal groups. Panel A Ternary plots showing the percentage of months (May, July, and November) in which the extremely low (Ext_l), normal (Nor), and extremely high (Ext_h) values of CH₄ and CO₂ concentrations and fluxes occurred. The yellow, blue, and red dots represent the Ext_l, Nor, and Ext_h groups. Panel B Characteristics of NO₃⁻-N, SRP, DO, Chl-a, WT, pH, POC, and DOC in surface water. The yellow, blue, and red boxes represent environmental parameters in the extremely low (Ext_l), normal (Nor), and extremely high (Ext_h) groups of CH₄ and CO₂ concentrations and fluxes, respectively. Asterisks indicate significant difference: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.



873

874 **Fig. 3.** Panels A and B Slope values of POC concentrations (autochthonous POC, allochthonous
875 POC) linear regression analysis with carbon concentrations (CCH₄, CCO₂) in extremely high
876 (Ext_h), normal (Nor) and extremely low (Ext_l) group, respectively. Panels C and D The
877 concentration ratio of autochthonous POC to allochthonous POC (POCauto/POCcallo) in extremely
878 high (Ext_h), normal (Nor) and extremely low (Ext_l) groups of CCH₄ and CCO₂. Asterisks above
879 the bar chart and box plot indicate significant levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.



880

881 **Fig. 4.** Abundance of picophytoplankton and heterotrophic bacteria in the extremely high (Ext_h),

882 normal (Nor) and extremely low (Ext_l) groups of CH₄ (A, B) and CO₂ (C, D) concentrations.

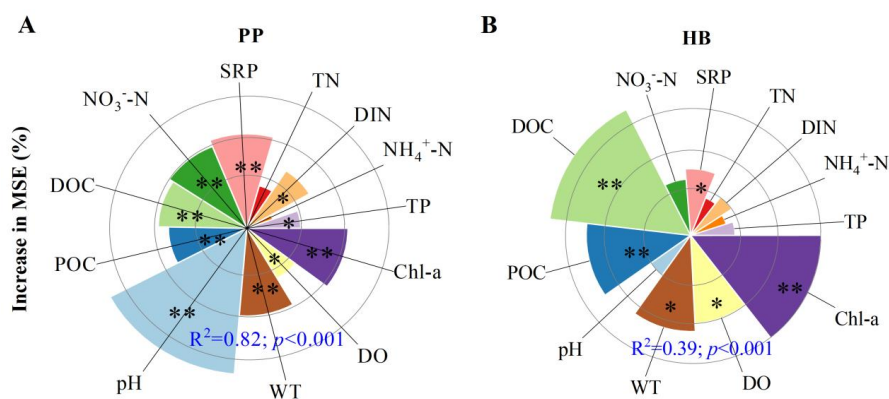
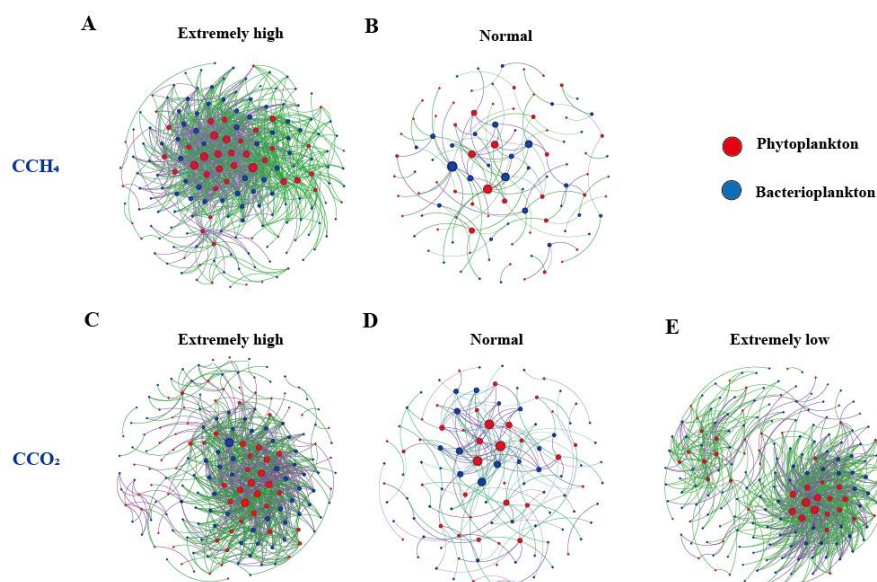


Fig. 5. Environmental predictors of picophytoplankton (A) and heterotrophic bacteria abundance (B). Random forest modelling importance of environmental predictors on picophytoplankton and heterotrophic bacteria abundance were estimated by percentage increases in the mean squared error (%IncMSE). Significance levels of each predictor are as follow: * $p < 0.05$ and ** $p < 0.01$.



888

889 **Fig. 6.** Co-occurrence networks of phytoplankton and bacterioplankton communities based on
 890 correlation analysis. Panels A and B Co-occurrence patterns of phytoplankton-bacterioplankton
 891 interaction network in extremely high and normal groups of CH_4 concentration (CCH_4). Panels C,
 892 D, and E Co-occurrence patterns of phytoplankton-bacterioplankton interaction network in
 893 extremely high, normal, and extremely low groups of CO_2 concentration (CCO_2). Each line
 894 represents a significant correlation between the two taxa, with the green lines representing positive
 895 correlations and the violet lines representing negative correlations. The number of links represents
 896 the strength of interactions between phytoplankton and bacterioplankton. The red and blue nodes
 897 in each network represent phytoplankton and bacterioplankton, respectively. The size of each node
 898 is proportional to the number of connections (that is, degree).

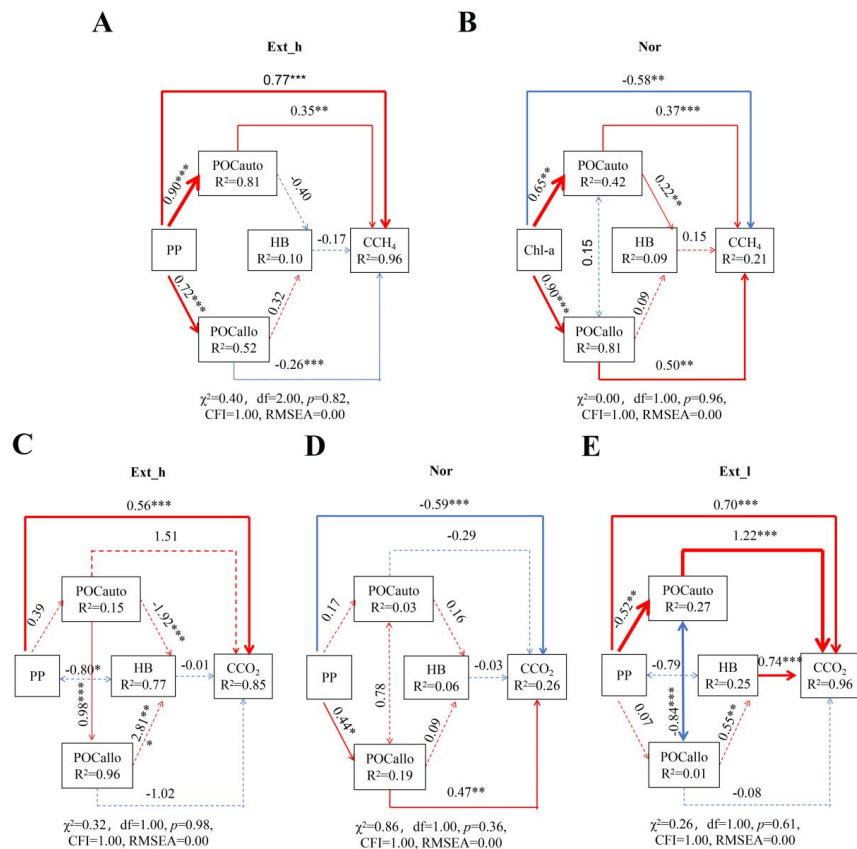
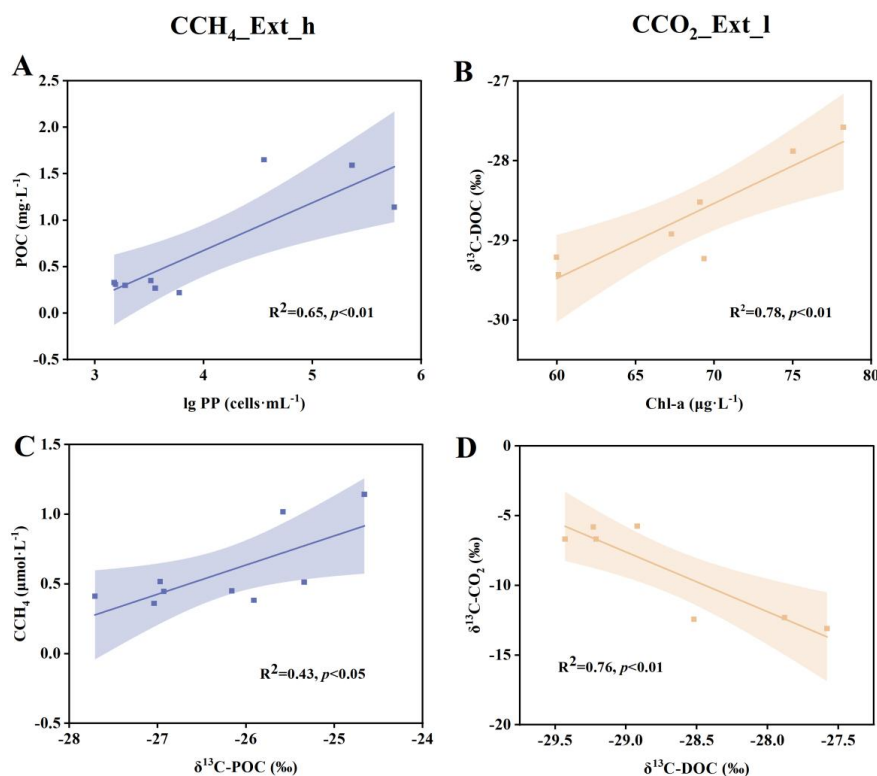


Fig. 7. Structural equation modeling (SEM) describing selected variables' effects on the concentration of CH₄ (A, B) and CO₂ (C, D, E) in the extremely high (Ext_h), normal (Nor) and extremely low (Ext_l) group, respectively. Numbers adjacent to arrows are standardized path coefficients and indicative of the effect size of the relationship. Solid arrows indicate significant paths (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$), and dashed lines represent non-significant paths. The red and blue arrows indicate positive and negative path coefficients, respectively. The width of the arrows represents the strength of relationships. R² denotes the percentage of variance explained by the model. PP, picophytoplankton; HB, heterotrophic bacterial; POCauto, autochthonous POC; POCallo, allochthonous POC; CCH₄ and CCO₂ were the concentrations of CH₄ and CO₂.



910

911 **Fig. 8.** Scatter plots of PP versus POC (A) and $\delta^{13}C-POC$ versus CCH_4 (C) in the extremely high
 912 (Ext_h) group of CCH_4 . Scatter plots of Chl-a versus $\delta^{13}C-DOC$ (B) and $\delta^{13}C-DOC$ versus
 913 $\delta^{13}C-CO_2$ (D) in the extremely low (Ext_l) group of CCO_2 . The violet and yellow areas represent
 914 95% confidence intervals.



915 Tables

916 Table 1

917 Concentrations and fluxes of CO₂ and CH₄ in the extremely low (Ext_l), normal (Nor) and
918 extremely high (Ext_h) groups.

		Mean	SE	Range	N
Ext_l	CCH ₄	-	-	-	-
	FCH ₄	0.01	0.00	0.01-0.02	17
	CCO ₂	12.62	1.49	8.46-18.01	7
	FCO ₂	0.05	0.83	-4.08-3.76	9
Nor	CCH ₄	0.03	0.00	0.00-0.12	69
	FCH ₄	0.10	0.01	0.03-0.29	55
	CCO ₂	44.25	1.33	24.28-64.63	64
	FCO ₂	25.72	1.16	7.24-42.39	64
Ext_h	CCH ₄	0.19	0.02	0.13-0.33	9
	FCH ₄	0.61	0.14	0.36-1.09	6
	CCO ₂	78.66	2.91	71.92-92.74	7
	FCO ₂	62.71	8.56	50.01-93.85	5

919 **Note:** CCH₄ and CCO₂ denote the concentrations of CO₂ and CH₄ in the surface water (μmol·L⁻¹),
920 respectively. FCH₄ and FCO₂ denote the fluxes of CH₄ and CO₂ across the water-air interface
921 (mmol·m⁻²·d⁻¹), respectively. -: not exist; SE: standard error; N: the number of observations.



922 **Table 2**

923 TLI values in extreme and normal groups of CH₄ and CO₂ concentrations and fluxes

Groups	Mean	SE	Range	Trophic state
CCH ₄ _Ext_l	-	-	-	-
CCH ₄ _Nor	44.99	1.07	33.91-70.03	M
CCH ₄ _Ext_h	50.54	4.19	41.13-70.81	E
FCH ₄ _Ext_l	42.04	0.95	36.96-49.14	M
FCH ₄ _Nor	45.79	1.29	33.91-70.03	M
FCH ₄ _Ext_h	54.32	5.79	41.13-70.81	E
TLI				
CCO ₂ _Ext_l	69.11	0.50	67.41-70.80	E
CCO ₂ _Nor	42.39	0.69	33.91-67.87	M
CCO ₂ _Ext_h	51.71	1.80	47.13-58.81	E
FCO ₂ _Ext_l	62.66	4.29	39.49-70.81	E
FCO ₂ _Nor	42.84	0.71	33.91-67.87	M
FCO ₂ _Ext_h	50.65	3.70	38.93-58.81	E

924 **Note:** -: not exist.



Table 3

Topological properties of co-occurrence network of phytoplankton-bacterioplankton interaction in the extremely low (Ext_l), normal (Nor), and extremely high (Ext_h) groups of CH₄ (CCH₄) and CO₂ concentrations (CCO₂).

Network metrics	CCH ₄		CCO ₂		
	Nor	Ext_h	Ext_l	Nor	Ext_h
Number of nodes	101	173	184	108	175
Number of edges	104	977	800	171	841
(Interaction strength)					
Number of positive edges	59	630	543	76	561
	(56.73%)	(64.48%)	(67.87%)	(44.44%)	(66.71%)
Number of negative edges	45	347	257	95	280
	(43.27%)	(35.52%)	(32.12%)	(55.56%)	(33.29%)
Modularity	0.752	0.292	0.404	0.558	0.341
Average degree	2.059	11.295	8.696	3.167	9.611

929



930 **Table 4**

931 Results of multiple linear regression analysis relating GHGs with POC from different sources in
932 the CCH₄_Ext_h and CCO₂_Ext_l group, respectively.

Group	Equations	R ²	p	Significance level	
				T-test	
				t ₁	t ₂
Ext_h	CH ₄ =1.11 (POCauto)-0.10 (POCallo)+0.38	0.74	**	4.34**	-0.61
Ext_l	LgCO ₂ =1.36[Lg(POCauto+1)]+0.29[Lg(POCallo +1)]+0.78	0.70	*	3.02*	0.55

933 **Note:** Asterisks indicate significant levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.