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► To cite this version:

Marie Le Geay, Béatrice Lauga, Romain Walcker, Vincent Jassey. A meta-analysis of peatland microbial diversity and function responses to climate change. Soil Biology and Biochemistry, 2024, 189, pp.109287. 10.1016/j.soilbio.2023.109287. hal-04357503

HAL Id: hal-04357503 https://hal.science/hal-04357503v1

Submitted on 21 Dec 2023 $\,$

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15 Abstract

Climate change threatens the capacity of peatlands to continue storing carbon (C) 16 17 belowground. Microorganisms are crucial in regulating the peatland C sink function, but how climate change affects the richness, biomass and functions of peatland 18 19 microbiomes still remains uncertain. Here, we conducted a global meta-analysis of the 20 response of peatland bacterial, fungal and micro-eukaryote communities to climate 21 change by synthesizing data from 120 climate change experiments. We show that 22 climate drivers such as warming, drought and warming-induced vegetation shift strongly 23 affect microbial diversity, community composition, trophic structure and functions. Using 24 meta-analytic structural equation modelling, we developed a causal understanding 25 among the different strands of microbial properties. We found that climate drivers 26 influenced microbial metabolic rates, such as CO₂ fixation and respiration, methane 27 production and oxidation, directly through physiological effects, and indirectly, through 28 microbial species turnover and shifts in the trophic structure of microbial communities. 29 In particular, we found that the response of microbial CO₂ fixation increased for each 30 degree in air temperature gained, while the response of microbial CO₂ respiration 31 tended to decline. When extrapolated at the global peatland scale using the CMIP6 32 model under the SSP5-8.5 scenario, our findings suggest that the increasingly positive 33 response of microbial CO₂ fixation to temperature anomalies in northern latitudes might 34 compensate to some extent for the possible loss of C from microbial CO₂ respiration, 35 possibly allowing peatlands to remain C sinks on long-term. Our findings have crucial 36 implications for advancing our understanding of carbon-climate feedback from 37 peatlands in a warming world.

- 39 Keywords: Warming, drought, vegetation shift, microbial biomass, community composition, soil
- 40 carbon cycle, carbon fixation

41 **1. Introduction**

42 Northern latitudes are expected to experience climate change greater than the global average (Smith et al., 2019; IPCC, 2023). Such a more intense climate change is likely 43 44 to deteriorate major ecosystem functions and services provided by northern 45 ecosystems, such as peatlands. This includes climate regulation, recreational services, 46 and provision for foods and goods (Solomon et al., 2007; Frank et al., 2015; Gallego-47 Sala et al., 2018; Malinauskaite et al., 2019; Swindles et al., 2019; Harris et al., 2022; 48 IPCC, 2023). Because peatlands' response to climate change may exert positive 49 climatic feedback, further exacerbating human-induced warming (Dise, 2009; Qiu et al., 50 2020, 2021), understanding and predicting the response of biotic parameters that 51 underpin peatlands' functioning is of high priority.

52 Peatlands store massive amounts of C belowground, a stock estimated between 53 500 and 1,000 GtC (Nichols and Peteet, 2019; Yu et al., 2021), and hence, exert a net 54 cooling effect on the global climate by removing CO₂ from the atmosphere. Recent 55 modelling approaches predict that undisturbed peatlands could be persistent C sinks in 56 the future (Qiu et al., 2020). Thus, maintaining peatland functioning can be seen as a 57 simple and inexpensive natural-based contribution to mitigate climate change (Qiu et 58 al., 2020; Strack et al., 2022). However, while modelling approaches are valuable tools 59 to predict the fate of peatland global C pool in the future, they also suffer from major 60 flaws such as the under-representation of microbial processes involved in C cycling even though they represent key functions such as decomposition and respiration (Wang 61 et al., 2017; Qiu et al., 2018). Consolidating existing peat models with additional 62 microbial parameters is, therefore, necessary to improve our estimation of peatland C's 63

response to climate change and reduce the uncertainties in model simulations that are caused by the lack of available data. These models are crucial because they can be used to decide the fate of peatlands (restoration or conservation) and they can help predict the effects of such decisions on the peatland C cycle and therefore on the global C cycle (Bonn et al., 2016; Loisel et al., 2020).

69 Identifying key microbial parameters that underpin the C response of peatlands 70 to climate change is an urgent but challenging need. Peatland microbial communities 71 are highly diverse (Andersen et al., 2013), assembled in complex trophic networks 72 (Jassey et al., 2023), and support many biogeochemical functions related to the C cycle 73 (Laiho, 2006; Bardgett et al., 2008; Andersen et al., 2013; Artz, 2013). For instance, 74 microorganisms mediate critical C fluxes, like CH₄ oxidation into CO₂ (Raghoebarsing et 75 al., 2005; Kip et al., 2010), CH₄ emissions (Juottonen, 2020; Juottonen et al., 2022) and 76 CO₂ emissions (Dorrepaal et al., 2009; Hopple et al., 2020). Recent studies further 77 showed the importance of microbial CO₂ fixation in peatlands, which could approximate 78 c. 10% of peatlands CO₂ uptake (Hamard et al., 2021). In addition to being diverse in 79 their functions, peatland microbial communities also showed contrasting responses to 80 climate change, making predictions difficult. For instance, experimental drought and 81 warming have been shown to decrease microbial diversity (Delarue et al., 2015; Song et 82 al., 2021; Carrell et al., 2022), increase bacterial, archaeal and fungal biomass (Delarue 83 et al., 2015; Mpamah et al., 2017; Cao et al., 2018; Jiang et al., 2020; Song et al., 2021) 84 and reduce the abundance of microbial consumers (Jassey et al., 2013, 2016; 85 Lamentowicz et al., 2013; Basińska et al., 2020). These structural shifts often threaten 86 the peatland C balance by increasing microbial metabolisms such as respiration,

methanogenesis and decomposition (Dorrepaal et al., 2009; McCalley et al., 2014;
Gavazov et al., 2018; Jassey et al., 2018; Reczuga et al., 2018; Hopple et al., 2020).
However, negative or neutral responses of microbial communities to climate drivers
have also been reported in numerous studies (Peltoniemi et al., 2015; Defrenne et al.,
2021; Lamit et al., 2021; Xue et al., 2021), raising uncertainty on the role of microbes in
determining the fate of peat C.

93 The inconsistent responses of peatland microbial communities to climate change 94 components could be tightly linked with climate change magnitude and duration (Jassey 95 et al., 2015, 2018; Hollister et al., 2023), suggesting that sometimes the amplitude of the 96 disturbance ensures that climate-induced changes on biological attributes remain close 97 to a tipping point (Briske et al., 2006). Alternatively, the inconsistency among studies in 98 microbial responses to climate change may also result from the experimental approach 99 used. These inferences often rely on three major approaches, namely field experiments, 100 experiments and space-for-time laboratory manipulative substitutions. These 101 methodological constraints may lead to different results, as data are not generated the 102 same way, and thus limit our ability to properly quantify the impacts of climate change 103 on peatland microbial communities. Overall, studies making a synthesis of information 104 regarding the response of peatland microbial communities and C dynamics sensitivity to 105 climate change remain scarce. Yet, by looking at this response we can make an initial 106 estimate and extrapolate the effects of climate change on microbial attributes at a global 107 scale. This could help to better identify which microbial parameters are key for 108 understanding and predicting peatland responses to climate change.

109 To summarise climate change effects on peatland microbial communities and 110 functions, and hone forecast for particular climate change scenarios, we synthesized 111 microbial responses from 120 experimental studies published in the last decades (1970-112 2023). We screened for changes from a few weeks to several years of experimental 113 climate change (warming, drought, precipitation shift and vegetation shift) conducted in 114 16 different countries (Figure 1, Table S1). In particular, we aimed to quantify the 115 responses and sensitivities of key microbial attributes, including richness, alpha- and 116 beta-diversity, abundance, biomass and functions (respiration, CO₂ and CH₄ oxidation 117 and production, enzyme activities) to climate change drivers and develop causal 118 understanding among these attributes. To achieve this goal, we addressed the following 119 questions: (1) what are the impacts of climate change drivers on peatlands' microbial 120 attributes? (2) do climate drivers affect microbial functions directly through physiological 121 responses or indirectly through changes in microbial diversity and trophic structure? and 122 (3) what can we learn from models built on the data obtained and extrapolation of future 123 changes in peatland C fluxes?

125 **2. Materials and methods**

126 **2.1 Literature survey**

127 We searched for studies that tested the effect of climate change drivers on microbial 128 properties. Data from multifactor experiments which factorially performed both multiple 129 single-factor treatments and their combination were also included and treated either as 130 single-factor or multiple-factor effects, respectively. Peer-reviewed publications were 131 collected by searching databases such as Web of Science (all databases), Google 132 Scholar, PubMed and the professional network ResearchGate for the period 1 January 133 1970 – 31 March 2023. Climate change drivers considered were: temperature increase 134 (TI), winter warming (WW), drought (DR, including precipitation shifts), warming-induced 135 vegetation shift (VS) and their possible combinations (Table 1). TI and WW were not 136 pooled because some studies were a mix of warming during winter, snow removal and 137 snow addition. We used the following keywords for the title and abstract searches: 138 'peatland' AND 'microorganisms' OR 'microbes' OR 'bacteria' OR 'nematodes' OR 139 'fungi' OR 'virus' OR 'protists' AND 'richness' OR 'abundance' OR 'biomass' OR 140 'function' AND 'warming' OR 'drought' OR 'precipitation shift' OR 'water-table shift' OR 141 'vegetation change'. Personal unpublished (or from under-review studies) data were 142 also included in the database. This literature search resulted in 170 peer-reviewed 143 studies published for the period 1970-2023.

Following this literature search, we selected publications by reading each title and abstract and made sure that they reported climate change effects on microbial properties. Publications that reported significant or non-significant effects of climate

change on microbial properties were then carefully screened by reading the methodsand results sections to identify which of them met the following inclusion criteria:

- Experiments or observations were conducted in peatlands, including bogs, fens
 or palsa mires (Table S1). Because of the paucity of studies, tropical peatlands
 were not included in this synthesis. The latitude cutoff was 30°N;
- 152 Studies reported manipulative experiments conducted *in situ* or in the laboratory -153 and had both control and experimental groups. Each treatment group had 154 several replicates. Natural gradients used as space-for-time design were 155 included as well as regression-based experimental designs. Studies conducted in 156 the field included natural gradient, transplantation and all manipulation directly implemented on the field (open top chamber, irradiation, plant removal, 157 158 protection against the rain, snow removal/addition, peat removal/addition, 159 drainage), other studies including incubation in the laboratory, microcosms and 160 mesocosms were classified as laboratory experiments;
- The studies should include data on at least one microbial attribute related to
 either diversity, biomass, community structure or function. Because of a lack of
 data on viruses, they were not included in our analysis;
- The studies should include experimental and control sample size and p-values
 (or correlation coefficients) in the main text, the figures or the supplementary
 information.
- Based on the above criteria, a total of 120 studies (Table S1) were selected from the
 170 initial studies. The global distribution of the peatlands' experimental sites is shown

in Figure 1. Facing the paucity of multiple-factor experiments with similar combinationsand microbial attributes, only single-factor effects were used.

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172 **2.2 Data collection**

173 For each selected publication, basic information including publication year, climate 174 drivers, site location (fieldwork location or sampling location for laboratory experiments). 175 peatland type (fen, bog, mire and other), experimental type (field or laboratory 176 experiment), sample sizes, methods used for quantifying microbial properties, the 177 manipulation magnitudes of climate drivers, the group of microorganisms (bacteria, 178 archaea, fungi, micro-eukaryotes and total) and the duration of the experimentation 179 were extracted from the methods. We also attributed a functional group to each group of 180 microorganisms (photoautotrophs, consumers, decomposers, archaea, bacteria, fungi 181 and total; Table S2). Microbial consumers were further subdivided into testate 182 amoebae, ciliates, rotifers, flagellates, and nematodes. We defined a consumer as a 183 microorganism feeding on any kind of living microorganisms (bacteria, fungi, protists, 184 and/or metazoan). Mixotrophic microalgae were not included in consumers as poorly 185 known in peatlands.

Then, the p-values related to the responses of each microbial attribute were retrieved from the text or figures. This included microbial richness (Chao1, OTUs, ASVs or species counts), alpha-diversity (Shannon and Simpson), beta-diversity (response of community structure following Hellinger transformation, Bray-Curtis dissimilarity, Jaccard, Gower or UniFrac distances and modification of denaturing gradient gel electrophoresis (DGGE) matrices), abundance (qPCR, microscopy, sequencing and terminal restriction fragment length polymorphism (TRFLP)) and the biomass

193 (microscopy-based, phospholipids-derived fatty acids (PFLA)). Finally, the responses of 194 microbially-driven functions were also recorded and included enzyme activities (alpha 195 and beta-glucosidase, chitinase, aminopeptidases, phosphatase, phenol-oxidases, 196 invertase, urease, peroxidase, glycosidase, hydrolase), CO₂ respiration and fixation, 197 CH_4 production and oxidation and N₂ fixation. All details can be found in Supplementary 198 Tables S2 and S3. In total, 1,069 p-values (or correlation coefficient) were extracted 199 from the 120 selected studies; among them, 24.4% were related to richness/alpha-200 diversity/community structure, 37.9% to abundance/biomass and 37.7% to functions.

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2.3 Calculation of the standardized mean differences

203 We used the standardized mean difference (SMD, unbiased estimator Hedges' q) as an 204 effect size metric to estimate the magnitude and sensitivity of responses of each 205 variable (Durlak, 2009). Hedges' g is a unit-free metric modified from Cohen's d 206 estimator (Hedges and Olkin, 1985). Cohen's d estimates the difference between two 207 population means (treatment and control) scaled by the pooled standard deviation of the 208 data (Cohen, 2013). Hedges' g is useful in the ecological meta-analysis because it 209 provides a statistical bias correction to Cohen's d to treat small samples size (Hedges 210 and Olkin, 1985). This metric allows a quantitative assessment of patterns when 211 methodology varies among studies (Elmendorf et al., 2012; Koricheva et al., 2013). 212 Effect sizes were calculated in R (R Core Team, 2022) with the package 'compute.es' 213 (Re ACD, 2013) using p-values (correlation coefficient for regression-based designs), 214 control and treatment sample size. When the responses of variables to climate drivers 215 were negative, SMD was negative, and vice versa for positive responses. For beta-

diversity, we used the absolute value of SMD because it was often difficult to infer the direction of the response to climate drivers. When no specific p-value was associated with non-significant values, we used a value of 0.5 for our SMD calculations. We considered that SMD between -0.20 and 0.20 had a weak effect and that above this range SMD had a medium to high effect (Cohen, 2013).

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2.4 Bias assessment, sensitivity and statistical analyses

223 To test for a potential publication bias we did a funnel plot which consisted of plotting 224 the effect sizes against their standard error (Sterne and Egger, 2001) and we conducted 225 an Egger's regression test (Egger et al., 1997) using the R package 'metafor' v4.4-0 226 (Viechtbauer, 2010; Nair, 2019; Nakagawa et al., 2023). Egger's test is a linear 227 regression of the intervention effect estimates on their standard errors weighted by their 228 inverse variance. In the absence of publication bias the regression slope is supposed to 229 be zero (Rothstein et al., 2006). To test how sensitive our results were to changes in the experimental approach, peatland type or duration of analysis, we also conducted a 230 231 sensitivity analysis. We divided our data into subsets according to the experimental 232 approach used (e.g. laboratory-based or field-based). Then, we divided our data into 233 two other random datasets, calculated the SMDs and associated standard errors for 234 microbial variables, and compared all the results together.

We used linear mixed effect models (LMMs) both to quantify the mean responsiveness of each microbial variable to climate drivers (D), microbial groups (G) and manipulation magnitude (MM) over all studies (fixed effects), and to analyze variation in effect size with peatland type, experimentation type, and method used

(random effects). Linear mixed effects models were run in *R* using the package *'ImerTest'* v3.1-3 (Kuznetsova et al., 2017). In addition, we conducted separate ANOVAs on each microbial variable to test for the potential impact of the random effects alone. Any significant effect of the random effects was further tested using the Tuckey HSD test. The models were checked for the homoscedasticity and normality of the variables and residuals, data were log-transformed when the transformation induced an improvement in the distribution.

All the statistical analyses were performed in R (R Core Team, 2022) using RStudio v12.0 (RStudio Team, 2020) and the graphical representations were done using '*ggplot2*' v3.4.0 (Wickham, 2016).

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2.5 Meta-analytic Structural Equation Modelling

251 We exploited the combined power of microbial diversity, biomass across microbial 252 trophic levels and functions to paint a broad picture of how climate drivers 253 mechanistically affect multiple microbial C processes using MASEM: Meta-Analytic 254 Structural Equation Modelling (Cheung and Chan, 2005; Jak and Cheung, 2020). 255 MASEM technique combines meta-analysis with structural equation modelling, a 256 method that allows for causal inferences and mechanistic understanding while giving a 257 synthetic overview of relationships among variables of interest (Cheung and Chan, 258 2005; Eisenhauer et al., 2015). Generally, MASEM is a two-stage process in which the 259 meta-analysis data are first used to generate a pooled correlation matrix across studies, 260 which is then used to fit a structural equation model (Jak and Cheung, 2020). As almost 261 no match existed between the different strands of microbial data we collected, we used

a different approach, more appropriate to the complex and heterogeneous datasets wegenerated.

264 As a first step, we constructed an a priori MASEM model, which drew from 265 hypotheses based on current theory of soil microbiomes under climate change (Jansson 266 and Hofmockel, 2020; Naylor et al., 2020) and accounted for our expectation that 267 microbial C processes increasingly shift along with climate change intensity because of 268 increasing changes of microbial diversity, biomass and interactions (Figure S1; 269 hypotheses: Table S4). To simplify our MASEM model, we included a composite 270 variable entitled "microbial C-related multifunctionality", which was the combined 271 product of microbial CO₂ fixation and respiration, CH₄ oxidation and production, and C-272 related enzyme activities (hydrolases and phenoloxidases). Modelling with composites 273 in structural equation modelling involved a two-step process (Grace et al., 2016).

274 As a first step, we constructed a SEM model to identify the coefficients of the 275 predictive variables that determine the composite variable 'microbial C-related 276 multifunctionality'. To do so, we constructed a SEM model (hereafter 'latent SEM 277 model') with the unmeasured latent variable 'microbial C-related multifunctionality' 278 (Figure S1). This latent SEM model was run on a pooled matrix using the R package 279 'lavaan' which allows latent variables. The pooled matrix was obtained by iteratively (k =280 50) and randomly selecting twelve effect size values and their respective climate 281 change intensity value for each co-variable across our global database and averaging 282 these matrices. We diagnosed latent SEM model fit based on chi-squared statistics (P >283 0.05), low root-mean-square error of approximation index (RMSEA \leq 0.1), low 284 standardized root-mean-square residual index (SRMR \leq 0.1) and high comparative fit

index (CFI \ge 0.95), and included variables in the latent variable based on these fit indices and Akaike information criterion (AIC) values (low AIC value was preferred for similar model fit). Second, the resulting standardized estimates of the latent variable were used to compute the composite index of 'microbial C-related multifunctionality' in the MASEM model and test its response to shifts in microbial diversity, biomass and interactions (Figure S1). This procedure was performed on temperature increase and drought effects separately.

292 In a second step, MASEM was performed iteratively on k matrices; we used k =293 50 for temperature increase and k = 10 for drought. k was defined according to the 294 minimum size of covariates for temperature increase and drought sub-matrices. Each 295 covariate included in the MASEM model was ranked by intensity magnitude before the 296 random selection. For temperature increase, we ranked data by increasing temperature 297 increase. For drought, we ranked data by increasing effect size as data on drought 298 intensity were not easily available in every study selected from our data compilation. For 299 each iteration, twelve effect size values along with their respective climate change 300 intensity value, peatland type, experiment type and community type information were 301 randomly selected for each co-variate. Then, MASEM was fitted with LMMs ran through 302 piecewise SEM (Lefcheck, 2016). We chose this approach because it allowed us to 303 account for the variation of the standardized estimates according to various random 304 effects (e.g. peatland type, experimentation type, method used, and microbial groups). 305 In addition, compared to covariance-based SEM, this approach allowed us to use the 306 Shipley's test of d-separation to test whether direct or indirect paths are missing from 307 the initial model in predicting microbial C-related multifunctionality. The goodness-of-fit

308 of our MASEM model was evaluated using Fisher's C statistic (P > 0.05) and AIC for 309 each iteration.

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2.6 Projections of microbial responses at global peatland scale and under 312 climate change scenarios

313 We projected at the global northern peatland scale (>30°N) the responses (*i.e.*, SMDs) 314 of main microbial functions defining microbial C-related multifunctionality and its main 315 indirect predictors to forecasted temperature increase. The projected variables were 316 chosen according to the results from MASEM (see section 3.3). No projections were 317 made for drought as we were not able to recover enough data on the drought intensity 318 in every study to build predictive models using IPCC scenarios. Temperature increase 319 predictions were retrieved from the IPCC Interactive Atlas (IPCC, 2021; Iturbide et al., 320 2021) available online at https://interactive-atlas.ipcc.ch/. We extracted the mean annual 321 temperature change in °C projected from the CMIP6 model under the SSP5-8.5 322 scenario for +1.5°C and +3°C warming relative to the 1850-1900 baseline. Maps were 323 downloaded with a ground pixel size of 60 arc minutes. As an envelope for predictions, 324 we used the peatland map from the up-to-date peatland distribution Peat-ML map, a 325 global raster of peatland fractional coverage at 5 arc minute ground pixel resolution 326 (Melton et al., 2022). We extracted temperature change for each scenario (+1°C and 327 +3°C) at each peatland pixel where fractional coverage was upper than 0% in the 328 exclusion of southern and tropical peatlands (<30°N), as these areas were non-covered 329 by our meta-analysis. Each microbial variable has been predicted using generalized 330 effect models with the SMD as a response variable and the temperature change as an

explanatory variable. The models were checked for the homoscedasticity and normality of the variables and residuals, and the quality of predictions was assessed using confidence intervals. Confidence intervals of each prediction were retrieved by making an interval on the scale of the linear predictor, then applying the inverse link function from the model fit to transform the linear level confidence intervals to the response level using 2,000 simulations. The probabilities of the predictions to occur were also calculated and plotted at the global peatland scale.

338

339 3. Results

340 **3.1 Effects of climate change on peatland's microbial richness and diversity**

341 Overall, microbial richness was weakly impacted by climate change drivers. Most of the 342 individual responses had low to medium SMDs (Figure 2a). These responses were 343 dependent on manipulation magnitude (LMMs, P < 0.05; Table 2; Table S5). Bacterial 344 richness was, on average, not affected by temperature increase (-0.01 ± 0.27) and 345 weakly affected by drought (-0.2 \pm 0.3). Temperature increase (-0.59 \pm 0.47) and 346 drought (-0.37 ± 1.12) both decreased micro-eukaryotic richness whereas fungal 347 richness increased with temperature increase (0.96 ± 0.35) and weakly increased with 348 drought (0.16 ± 0.39). Responses of microbial richness facing winter warming and 349 vegetation were all positive and ranged from not significant (bacteria, fungi) to strong 350 effect (archaea, micro-eukaryotes; Figure S2a; Table S6).

The response of microbial alpha-diversity was either positive or negative depending on the microbial group considered (Table S7). Again, the average response of microbial alpha-diversity to climate change drivers was weak (Figure 2b).

354 Temperature increase induced a decrease in bacterial alpha-diversity (-0.56 \pm 0.48) 355 whereas it increased micro-eukaryotic alpha-diversity (0.3 ± 0.69 ; Figure 2b). Drought 356 increased fungal alpha-diversity (1.18 ± 1.62) but had no impact on bacterial and micro-357 eukaryotic alpha-diversity (0.01 \pm 0.47 and 0.003 \pm 0.75 respectively). Winter warming 358 increased micro-eukaryotic alpha-diversity although the effect strongly varied (0.76 \pm 359 1.16; Figure S2b). LMMs did not show any significant impact of the fixed terms 360 (microbial group, climate driver and manipulation magnitude; P > 0.05, Table 2; Table 361 S5) on microbial alpha-diversity.

362 We found that microbial community structure (beta-diversity) systematically 363 responded to climate change drivers (Table S8). At the group level, all microbial groups 364 strongly responded to climate change drivers (Figure 2c). Temperature increase had a 365 stronger effect on micro-eukaryotic (1.16 \pm 0.30) and fungal (1.17 \pm 0.17) community 366 structure than on bacterial community structure (0.67 \pm 0.10). Drought showed a very 367 strong effect on all microbial groups with a mean of SMDs above 1.50. We also 368 observed that winter warming and vegetation shift induced a strong response to 369 microbial beta-diversity (mean of SMDs above 0.8; Figure S2c). LMMs further showed 370 that the microbial group together with climate drivers explained the observed effects (P 371 < 0.05; Table 2; Table S5).

372

373 3.2 Effects of climate change on peatlands microbial biomass and 374 functions

Overall, the response of microbial biomass to climate change strongly depended on the trophic group considered and the manipulation magnitude (P < 0.01 and P < 0.05respectively; Table 2; ; Table S5; Table S9). Most of the effects were medium to strong

378 with a few SMDs within the range of weak effects, notably for drought (Figure 3a; Figure 379 S3; Figure S4a). The biomass of all microbial groups increased with temperature 380 increase (means of SMDs between 0.53 ± 0.27 and 0.85 ± 0.2). The only exception was 381 consumers for whom the biomass showed a very weak response (0.06 ± 0.39). Drought 382 showed a weaker effect than temperature increase on microbial biomasses, except for 383 photoautotrophs (1.01 \pm 0.36) and consumers (-0.67 \pm 0.25). Vegetation shift induced a 384 strong negative response of bacterial and fungal biomasses (SMDs of -1.04 and -2.05, 385 respectively; Figure S4a), and winter warming had negative effects on consumers (-0.73 386 \pm 0.25) and weak negative effect on bacteria (-0.15 \pm 0.52). In contrast, photoautotroph 387 biomass increased with winter warming (0.53 ± 0.11) . Winter warming had a very weak 388 impact on fungal biomass $(0.08 \pm 0.55;$ Figure S4a).

Among microbial consumers, we found that nematodes, ciliates, flagellates and testate amoebae were particularly sensitive to climate change (Figure 3b; Figure S4b). While the biomass of ciliates, nematodes and flagellates increased with temperature increase, testate amoebae showed opposite patterns with a systematic decrease of their biomass in response to climate change (Table S9). LMMs further showed significant effects of microbial group together with climate drivers or with manipulation magnitude on microbial biomass (P < 0.001; Table 2).

At the functional level, we found that climate change overall boosted microbial activities (Figure 3c, Figure S4c, Table S10). However, notable differences were found according to the function considered (P < 0.001; Table 2; Table S5). In terms of carbon emissions, both CO₂ and CH₄ emissions increased with temperature increase (2.28 ± 0.21 and 1.02 ± 0.25 respectively; Figure 3c). Drought also increased CO₂ emissions

401 (1.18 ± 0.32) but decreased CH₄ emissions (-2.01 \pm 0.39). We also found that CH₄ 402 oxidation into CO_2 was less impacted by temperature increase (0.18 ± 0.43) whilst CO_2 403 fixation increased with temperature increase and drought $(1.05 \pm 0.13 \text{ and } 1.36 \pm 1.35)$: 404 Figure 3c). Microbial enzyme activities related to C-cycle (e.g. peroxidase, β -405 glucosidase, chitinase; Table S3) increased with temperature increase (0.38 ± 0.23) and 406 drought (1.34 ± 0.61) . N-related microbial enzyme activities such as nitrogenase, 407 aminopeptidase and urease (Table S3) were weakly impacted by temperature increase 408 (0.2 ± 0.25) but increased with drought (0.48 ± 0.09) . The activity of P-related enzymes (acidic phosphatase activity and P-hydrolase; Table S3) increased with all climate 409 410 change drivers (Figure 3c). Winter warming and vegetation shift also drove important 411 responses of microbial functional activities (Figure S4c). In particular, N-related 412 enzymes were negatively impacted by vegetation shift (-2.54 \pm 3.09). On the opposite, 413 C mineralisation, CO₂ and CH₄ emissions were positively impacted by vegetation shift 414 $(3.38 \pm 1.31; 2.74 \pm 1.06 \text{ and } 0.93 \pm 0.48 \text{ respectively}).$

415

416 **3.3 Publication bias assessment and sensitivity analysis**

We assessed potential bias in publication by conducting an Eggers' regression test and we found no impact for biomass (P = 0.14), richness (P = 0.15), alpha-diversity (P =0.59) and beta-diversity (P = 0.54) data. The only significant bias was found for functions (P = 0.02). When carefully looking at each function, we saw that they responded to climate change drivers toward the same direction which could explain such a bias. Furthermore, when we compared the dataset used in this meta-analysis ('complete') to the four different datasets generated ('field', 'laboratory', 'random1' and 424 'random2'), we saw that all the results pointed toward the same effect (except for a few
425 exceptions, Figure S5-S8).

426

427 3.4 Connections between microbial diversity, biomass and function under 428 climate change

429 Latent SEM models showed that 'microbial C-related multifunctionality' was best defined by microbial CO₂ fixation and CO₂ and CH₄ emissions under temperature increase 430 (Figure 4a). Microbial CO₂ and CH₄ emissions, and hydrolytic and oxidative enzyme 431 432 activities were the best predictors of microbial C-related multifunctionality under drought 433 (Figure 4b). We, therefore, used these variables and their respective standardized 434 estimates to build the composite variable in the MASEMs. MASEMs for temperature 435 and drought showed overall good fits across iterations (Fisher's C statistic, averaged P > 0.05) and high R^2 values (Figure S9a and c). MASEM showed that temperature 436 increase influenced microbial C-related multifunctionality (averaged $R^2 = 0.65$; Figure 437 438 S9a), directly through effects on microbial CO_2 fixation (averaged path = 0.71 ± 0.01) 439 and emission (averaged path = -0.06 ± 0.03) and CH₄ emission (averaged path = $0.26 \pm$ 440 0.03), and indirectly through shifts in microbial beta-diversity (averaged path = $0.22 \pm$ 441 0.08) and the biomass of decomposers (averaged path = 0.09 ± 0.08) and phototrophs 442 (averaged path = 0.13 ± 0.08 ; Figure 4c). Shifts in microbial beta-diversity were further 443 related to shifts in the biomass of decomposers and phototrophs (Figure 4c). Under 444 drought, MASEM evidenced similar mechanisms (Figure 4d). Variation in microbial Crelated multifunctionality (averaged $R^2 = 0.96$; Figure S9b) was driven by shifts in 445 446 microbial beta-diversity (averaged path = 0.13 ± 0.07), decomposer (averaged path =

447 0.69 \pm 0.03) and consumer biomass (averaged path = 0.26 \pm 0.04; Figure 4d), while 448 changes in microbial biomass across trophic levels were also explained by shifts in 449 microbial beta-diversity.

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451

3.5 Potential future changes in microbial C-related functions

452 Based on the MASEM results (Figure 4) we chose to predict potential future changes of 453 microbial C-related functions (including CO₂ emission and fixation, CH₄ emission and oxidation). Our predictive models showed good results both for CO_2 emissions (P = 454 0.023 and $R^2 = 0.36$; Table 3; Figure S10) and CO₂ fixation (P < 0.001, $R^2 = 0.73$; Table 455 456 3; Figure S11). However, the SMDs of CH₄ emission and oxidation did not evidence any 457 significant relationship with temperature increase (P = 0.14 and P = 0.91 respectively; 458 Table 3). Therefore, we only made projections for the future of CO₂ emission and 459 fixation in response to temperature increase.

Projected under the SSP5-8.5 scenario, we found that peatland C-related functions 460 461 will strongly change as a result of climate warming, although in different directions. We 462 notably found a global increase in microbial CO₂ emission and CO₂ fixation rates 463 (Figure 5). Overall, for both projections, SMDs were above the threshold of 0.2 and the 464 highest SMDs were predicted at the most northern latitudes. Our projections of 465 microbial CO₂ emission showed that the response of CO₂ emission is temperature dependent (SMDs between 2 and 4; Figure 5a and b). Indeed, we showed that CO₂ 466 467 emission response to increasing temperature at the highest latitudes will be lower under the 3°C (SMDs around 2.6) than under the 1.5°C scenario (SMDs > 3), although still 468 increasing with increasing temperature. For CO₂ fixation our predictions showed an 469 470 increase of fixation rates along with increasing temperatures at the highest latitudes and

471 across both scenarios (Figure 5c and d). SMDs for CO_2 fixation ranged between 0.5 472 and 5 with most of the SMDs around 2 for the 1.5°C scenario and around 4 for the 3°C 473 scenario.

474

475 **4 Discussion**

476 Understanding how climate change affects microbial communities and the underlying 477 functions they drive is a critical issue in climate change and microbiology research 478 (Jansson and Hofmockel, 2020). By synthesizing the dynamic changes in peatland 479 microbial communities from 120 studies performed over the past four decades, this 480 meta-analysis provides explicit evidence that climate change consistently impacts 481 peatland microbiomes. This agrees with recent findings in other terrestrial systems 482 (Blankinship et al., 2011; Schindlbacher et al., 2011; Melillo et al., 2017; Romero-483 Olivares et al., 2017; Zhou et al., 2020; Gao et al., 2022; W. Li et al., 2022; Robinson et 484 al., 2023). An interesting outcome of this study demonstrates that climate change 485 drivers systematically promote microbial functions, such as CO₂ fixation and emissions, 486 and CH₄ emissions, suggesting a strong impact of climate change on future peatland 487 biogeochemical cycles. Vegetation shift and winter warming were the least represented 488 climate drivers in our analysis but led to strong responses of microbial communities and 489 functions (Figure S2, S3 and S4), highlighting that these two drivers would merit more 490 attention in future investigations.

491 Our findings show that warming and drought strongly influence microbial 492 attributes in peatlands, which agrees with findings on other terrestrial systems (Lurgi et 493 al., 2012a, 2012b; de Vries and Shade, 2013; Meisner et al., 2013; Zhang et al., 2013;

494 Kaisermann et al., 2017; Zhao et al., 2019; Gao et al., 2022). In particular, both warming 495 and drought reduced bacterial richness and alpha-diversity, while fungal taxonomic 496 attributes increased (Figure 2a and b). Studies from different terrestrial systems pointed 497 toward the same results, supporting that soil fungal communities are usually more 498 resistant than bacteria to drought and warming (Bapiri et al., 2010; de Vries et al., 2012, 499 2018; de Vries and Shade, 2013; Y. Li et al., 2022). The filamentous structure of fungi 500 and their ability to produce osmoregulatory solutes to protect their metabolisms against 501 unfavorable conditions might explain such differences (Maestre et al., 2015: Nielsen et 502 al., 2015). In addition, our results showed that bacterial and fungal community 503 composition and biomass always responded to climate drivers (Figure 2c; Figure 3a; 504 Figure S3), which was further linked to the response of associated ecosystem functions 505 they drive such as CO_2 and CH_4 emissions (Figure 4; Figure 5).

506 Our results also evidenced a positive response of micro-eukaryotes at 507 intermediate trophic levels (Figure 3b), especially for ciliates, flagellates and nematodes 508 which are important bacterial and fungal feeders in microbiomes (Rønn et al., 2012; 509 Geisen et al., 2018; Neilson et al., 2020; Potapov et al., 2022). This suggests that 510 climate drivers may increase the strength of bottom-up effects in the microbial food web 511 and concomitant processes (e.g. activity, growth). In addition, our findings revealed a 512 possible decrease in the relative importance of top-down effects in structuring microbial 513 communities with the loss of top-predators such as testate amoebae. The biomass of 514 testate amoebae systematically and negatively responded to climate change drivers. 515 Trophic downgrading in response to climate change has been observed in many 516 systems (Petchey et al., 1999; Dossena et al., 2012; Ohlberger, 2013), and often results

517 from metabolic constraints of larger organisms (Brose et al., 2012; Lurgi et al., 2012a, 518 2012b). As size ratio is involved in several biological processes, including for instance 519 metabolism, growth rate and density, trophic flow, biomass fluxes and interaction 520 strength, changes in community size structure are likely to exert strong feedback on 521 trophic functioning (Woodward et al., 2005; Brose et al., 2012; Lurgi et al., 2012a; 522 Jassey et al., 2023). This loss of top-predators suggests that climate drivers can 523 restructure microbial food webs in peatlands by causing secondary extinctions along the 524 food web or by altering the diversity and abundance of many taxa from different groups 525 and trophic levels (Petchey et al., 1999; Woodward et al., 2008; Dossena et al., 2012; 526 Heckmann et al., 2012; Jassey et al., 2013; Antiqueira et al., 2018; Reczuga et al., 527 2018; Romero et al., 2018, 2020). These multiple changes along trophic levels may 528 strongly affect ecosystem functions (Allison and Martiny, 2008; Antiqueira et al., 2018). 529 For example, the loss of testate amoebae which feed on a large variety of prey, 530 including bacteria, fungi, microalgae, ciliates, rotifers and nematodes (Yeates and 531 Foissner, 1995; Gilbert et al., 2000, 2003; Wilkinson and Mitchell, 2010; Jassey et al., 532 2013), may strengthen the interactions between basal species (bacteria and fungi) and 533 intermediate consumers, which is known to enhance microbial enzyme activity and 534 metabolic rates (Trap et al., 2015; Sauvadet et al., 2016). Such a hypothesis is 535 supported by our MASEM models. We showed that increasing shifts in decomposer 536 biomass resulting from shifts in consumers were related to shifts in microbial C-related 537 multifunctionality (Figure 4). Hence the restructuring of the microbial food web supports 538 the hypothesis that peatlands could become emitters of CO₂ in response to climate 539 change.

540 Overall, we found that warming and drought strongly impacted multifunctionality 541 related to the C cycle, with a positive response of decomposition (C enzymes) and C 542 emissions (both CO₂ and CH₄) except for CH₄ emissions that decreased with drought. 543 Drought causes aeration of the peat resulting both in unfavourable conditions for 544 methanogens that are very sensitive to oxygen (Zehnder and Stumm, 1988; Dowrick et 545 al., 2006; Wu et al., 2020; Barel et al., 2021) and favourable conditions for CH₄ 546 oxidation (Dowrick et al., 2006; Kang et al., 2018; Perryman et al., 2023). Other meta-547 analyses at the global scale also evidenced that warming significantly increases 548 microbial respiration (Bardgett et al., 2008; Wang et al., 2014; Crowther et al., 2016; 549 Zhou et al., 2016; Xu and Yuan, 2017; Liu et al., 2020), thus corroborating our results 550 and suggesting a loss of C from peatlands in response to climate change (Dorrepaal et 551 al., 2009; Loisel et al., 2020). Now, if we add the response of microbial photoautotrophs 552 to the global microbial picture, the perception of how peatlands may react to climate 553 change differs. Recent work showed that peatland microbes can fix on average 8.8 mg CO₂ hr⁻¹ m⁻², a rate equivalent to about 9% of peatlands' gross CO₂ uptake (Hamard et 554 555 al. 2021). Our synthesis showed that such a CO₂ fixation rate is likely to increase with 556 warming and drought. We suggest that the response of photoautotrophs to climate 557 change may to some extent counterbalance the response of heterotrophic microbes to 558 climate change and partly mitigate the rise in microbial C emissions. Such a hypothesis was further supported by our projections of microbial CO2 emission and fixation at the 559 560 global peatland scale based on future scenarios of the IPCC (CMIP6 model with SSP5-8.5 scenario for +1.5°C and +3°C; Figure 5). Our findings showed a strong and positive 561 562 response of microbial CO_2 fixation rate along with warming at the global peatland scale

and across scenarios, especially in northern latitudes where peatlands are the most abundant. This suggests that peatland microbiomes may take up more C along with temperature increase in the future. This increasingly positive response of microbial CO₂ fixation to temperature anomalies in northern latitudes may be one of the mechanisms possibly allowing peatlands to remain C sinks on the long-term, as predicted by recent model simulations (Gallego-Sala et al., 2018) and experimental studies (Helbig et al., 2022).

570 On the opposite, our results showed an important increase in the response of 571 CO₂ emissions, but mostly at +1.5°C scenario (Figure 5a). Indeed, our projection 572 indicated that the response of microbial CO₂ emissions might decreased in magnitude 573 under the +3°C scenario (Figure 5b). These results suggest that above a certain 574 temperature anomaly, the increase in microbial CO₂ emissions may stagnate or even 575 decrease. Recent meta-analyses in soils found a similar trend with CO₂ emissions 576 decreasing with warming magnitude after a certain temperature threshold (~+2°C; Xu 577 and Yuan, 2017; Yang et al., 2023). This suggests that microbial communities might 578 adapt to climate warming (Rinnan et al., 2009; Melillo et al., 2017; Yang et al., 2023), 579 probably as a result of physiological adaptation (Bradford et al., 2008; Tucker et al., 580 2013) and community changes (Crowther and Bradford, 2013). Another hypothesis that 581 could explain such a decrease in CO₂ emissions with warming has been suggested by 582 Walker et al. (2018). First, warming accelerates growth, respiration and C use by 583 microbial communities, leading to an important release of CO₂. Then, because of a lack 584 of C in the system, the first phase is followed by a decrease in microbial biomass, 585 reducing microbial activities and attenuating CO₂ emission in the long term (Walker et

586 al., 2018). Further studies will be needed to test and verify these hypotheses in 587 peatlands. Furthermore, although very promising, we caution that our projections are an 588 extrapolation from a small dataset of SMDs that does not consider the potential effect of 589 seasons and precipitation changes on microbial C emission and fixation rates. For these 590 reasons, these results merit further support and must be consolidated with additional 591 analyses to increase their robustness. Nevertheless, the probability for the values 592 predicted to be accurate and reliable is relatively high (Figure S12), thus providing some 593 confidence in the projections.

594 To conclude, our global synthesis demonstrates that climate change strongly 595 impacts peatland microbial attributes with notably an important effect on microbial 596 biomass and functions. Our findings underline that considering the microbiome in its 597 entity (i.e., bacteria, fungi, protists and micro-metazoa) and multiple microbial attributes 598 (i.e., richness, diversity, biomass and functions) is key to paint a broad picture of how 599 climate drivers change microbial diversity and trophic interactions, and how these 600 changes drive shifts in microbial C-related processes. Our findings show that biomass 601 across trophic levels and changes in community structure are tightly linked, and 602 together strongly impact microbial functions simultaneously. Therefore, considering 603 biomass across trophic levels and community structure is key to predict shifts in 604 microbial C processes. Our results further provide empirical support for the new 605 hypothesis that microbial CO₂ fixation may regulate microbial climatic feedback to the 606 peatland C cycle, and yield evidence that incorporating microbial CO₂ fixation process 607 into global peatland C models, such as ORCHIDEE-PEAT (Qiu et al., 2018) will likely 608 improve both their mechanistic insight and predictive power. Future studies are needed

to build on this foundation, for example, interrogating to what extent microbial CO_2 fixation counterbalances microbial C losses from CO_2 and CH_4 emissions and decomposition will be crucial for advancing our predictions of carbon-climate feedback from peatlands in a warming world.

613 Acknowledgements

This work has been supported by the MIXOPEAT (Grant No. ANR-17-CE01-0007 to VEJJ) and BALANCE (Grant No. ANR-23-ERCC-0001-01) projects funded by the French National Research Agency. We kindly thank Samuel Plaza for his help in constructing the data basis.

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619 Author contributions

VEJJ conceived the study. MLG constructed the database with the help of VEJJ. MLG
and VEJJ performed numerical analyses. RW performed projections maps. MLG and
VEJJ wrote the first draft of the manuscript with the help of BL. All authors reviewed and
contributed to the final form of the manuscript.

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1169 Table 1. Description of the climate drivers retained in this synthesis.

Climate drivers	Complete name	Description			
ті	Temperature increase	Natural gradient, transplantation, experimental warming, in the field			
		or in laboratory			
WW	Winter warming	Natural or experimental warming during the winter season, snow			
	Winter warning	removal or addition			
DR	Drought	Drought, reduced precipitation or reduction of water availability			
VS	Vegetation shift	Climate-change-induced change of vegetation (for instance			
	vegetation shift	removing of some plants)			

1172Table 2. Summary of the response of richness, alpha-diversity, beta-diversity, biomass and function to1173climate drivers (linear mixed effects models, LMMs). Groups, climate drivers and manipulation magnitude were1174retained as fixed effect terms, whilst the peatland type, experimentation type, method used and study type were1175retained as random effect terms. G^a = microbial group for richness, alpha-diversity, beta-diversity and biomass, and1176the type of function for microbial function, D = climate drivers, MM= manipulation magnitude. Peatland type = bog,1177fen, mire, other or several; experimentation = laboratory or field; method = method used to estimate alpha-diversity,1178beta-diversity and biomass and/or measure microbial functions (see Methods). *** P < 0.001, ** P < 0.01, * P < 0.05.</td>1179

	Fixed effects terms								
	Response variable	Gª	D	мм	D x MM	G ^a x D	G ^a x MM	G ^a x D x MM	Random effects terms
	Richness			*					Peatland type, Experimentation, Method
	Alpha- diversity								Peatland type, Experimentation, Method
	Beta- diversity					*			Peatland type, Experimentation, Method
	Biomass	**		*		***	***		Peatland type, Experimentation, Method
	Functions	***				***			Peatland type, Experimentation, Study
1180									
1181									
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0	Table 3. Summa	ry of the predictive	e models used f	for projections at	t global peatlan	d scale
-						

Parameters	CO ₂ emission	CO ₂ fixation	CH₄ emission	CH₄ oxidation
Number of observations	42	15	41	16
<i>P</i> -value	0.023	0.001	0.14	0.91
R ²	0.36	0.73	0.17	0.18

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1198 **Figure captions**

Figure 1. Peatland coverage and data. Estimated area coverage (in percentage) of peatlands based on the Peat-ML distribution map (Melton et al., 2022). Geometric forms show the global distribution of the experimental sites according to different climate change drivers used in this meta-analysis. TI = temperature increase (n = 41), WW = winter warming (n = 3), DR = drought (n = 32), VS = vegetation shift (n = 2), and MIX = combination of several drivers (n = 42). MIX included TI-DR (n = 25), TI-WW (n = 8), TI-VS (n = 4), DR-VS (n = 4), and TI-DR-VS (n = 1). The map shows only latitude above 30°N.

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Figure 2. Standardized mean difference (SMD) showing the response of peatland microbial richness (a), alpha-diversity (b) and beta-diversity (c) to temperature increase (TI) and drought (DR). The black dot shows the mean of SMDs and the bars represent the associated standard error. The filled line shows the null effect size (equal to zero), the grey area with dotted blue lines represents the range [-0.2;0.2] in which SMDs are considered weak. Outside this range SMDs are considered to have medium to high effect. Numbers between brackets indicate the number of observations used to calculate the SMDs.

1214 Figure 3. Standardized mean difference (SMD) showing the response of peatland microbial 1215 biomass grouped by microbial functional groups to temperature increase (TI) and drought (DR) 1216 (a), with a focus on consumers (b). SMD showing the response of peatland microbial functions to 1217 temperature increase (TI) and drought (DR) (c). The black dot shows the mean of SMDs and the bars 1218 represent the standard error associated. The filled line shows the null effect size (equal to zero), the grey 1219 area with dotted blue lines represents the range [-0.2;0.2] in which SMDs are considered weak. Outside 1220 this range SMDs are considered to have medium to high effect. Numbers between brackets indicate the 1221 number of observations used to calculate the SMDs.

1222 Figure 4. Microbial species turnover and biomass across trophic levels are complementary facets 1223 of the response of peatlands' functions to climate change. Latent SEMs showing the best functions 1224 defining microbial C-related multifunctionality under (a) temperature increase ($X^2 = 0.35$, df = 1, P = 0.55; CFI = 1, RMSEA = 0, SRMR = 0.031) and (b) drought ($X^2 = 0.27$, df = 1, P = 0.60; CFI = 1, RMSEA = 0, 1225 1226 SRMR = 0.01). Unmeasured latent variable 'microbial C-related multifunctionality' is represented by a 1227 circle while measured variables are represented by squares. Numbers next to each arrow indicated the 1228 standardized estimates of the model. Standardized estimates derived from the MASEM models under (c) 1229 temperature increase and (d) drought. Circles are the mean of k iterations for each path of the model and 1230 the bars indicate the standard error derived from the k iterations (k = 50 for temperature increase; k = 101231 for drought, more details can be found in Methods). Fit of the MASEM models are given in supplementary 1232 Figure S9. TI = temperature increase, div = alpha-diversity, bdiv = beta-diversity, photot = biomass of 1233 phototrophs, dec = biomass of bacteria and/or fungi, cons = biomass of consumers, C = microbial C-

related multifunctionality. A priori MASEM model and hypotheses behind paths are given in Figure S1 andTable S4.

1236 Figure 5. Predicted standardized mean difference (SMD) for the effect of increasing temperatures

+1.5°C (a) and (c) and +3.0°C (b) and (d) on CO_2 emissions (a) and (b) and CO_2 fixation (c) and (d).

1238 Peatland distribution was retrieved from the peatland distribution Peat-ML map (Melton et al., 2022),

1239 CMIP6 model under the SSP5-8.5 scenario for +1.5 $^{\circ}$ C and +3 $^{\circ}$ C warming related to the 1850-1900

- 1240 baseline was used.
- 1241
- 1242





1266Peatland coverage and data. Estimated area coverage (in percentage) of peatlands based on the Peat-ML1267distribution map (Melton et al., 2022). Geometric forms show the global distribution of the experimental sites1268according to different climate change drivers used in this meta-analysis. TI = temperature increase (n = 41), WW =1269winter warming (n = 3), DR = drought (n = 32), VS = vegetation shift (n = 2), and MIX = combination of several drivers1270(n = 42). MIX included TI-DR (n = 25), TI-WW (n = 8), TI-VS (n = 4), DR-VS (n = 4), and TI-DR-VS (n = 1). The map1271shows only latitude above 30°N.

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Figure 3. Standardized mean difference (SMD) showing the response of peatland microbial biomass grouped by functional type to temperature increase (TI) and drought (DR) (a), with a focus on consumers (b). SMD showing the response of peatland microbial functions to temperature increase (TI) and drought (DR) (c). The black dot shows the mean of SMD and the bars represent the standard error associated. The filled line shows the null effect size (equal to zero), the grey area with dotted blue lines represents the range [-0.2;0.2] in which SMDs are considered weak. Outside this range SMDs are considered to have medium to high effect. Numbers between brackets indicate the number of observations used to calculate SMDs.

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1389 Figure 4. Microbial species turnover and biomass across trophic levels are complementary facets of the 1390 response of peatland's functions to climate change. Latent SEMs showing the best functions defining microbial 1391 C-related multifunctionality under (a) temperature increase ($X^2 = 0.35$, df = 1, P = 0.55; CFI = 1, RMSEA = 0, SRMR = 1392 0.031) and (b) drought ($X^2 = 0.27$, df = 1, P = 0.60; CFI = 1, RMSEA = 0, SRMR = 0.01). Unmeasured latent variable 1393 'microbial C-related multifunctionality' is represented by a circle while measured variables are represented by 1394 squares. Numbers next to each arrow indicated the standardized estimates of the model. Standardized estimates 1395 derived from the MASEM models under (c) temperature increase and (d) drought. Circles are the mean of k iterations 1396 for each path of the model and the bars indicate the standard error derived from the k iterations (k = 50 for 1397 temperature increase; k = 10 for drought, more details can be found in methods). Fit of the MASEM models are given

- 1398 in supplementary Figure S9. TI = temperature increase, div = alpha-diversity, bdiv = beta-diversity, photot = biomass
- 1399 of phototrophs, dec = biomass of bacteria and/or fungi, cons = biomass of consumers, C = microbial C-related
- 1400 multifunctionality. A priori MASEM model and hypotheses behind paths are given in Figure S1 and Table S4.



1424Figure 5. Predicted standardized mean difference (SMD) for the effect of increasing temperatures +1.5°C (a1425and c) and +3.0°C (b and d) on CO2 emissions (a and b) and CO2 fixation (c and d). Peatland distribution was1426retrieved from the peatland distribution Peat-ML map (Melton et al., 2022), CMIP6 model under the SPP8.5 scenario1427for +1.5°C and +3°C warming related to the 1850-1900 baseline was used.