



**HAL**  
open science

## Tradeoff of CO<sub>2</sub> and CH<sub>4</sub> emissions from global peatlands under water-table drawdown

Yuanyuan Huang, Phillipe Ciais, Yiqi Luo, Dan Zhu, Yingping Wang, Chunjing Qiu, Daniel Goll, Bertrand Guenet, David Makowski, Inge de Graaf, et al.

► **To cite this version:**

Yuanyuan Huang, Phillipe Ciais, Yiqi Luo, Dan Zhu, Yingping Wang, et al.. Tradeoff of CO<sub>2</sub> and CH<sub>4</sub> emissions from global peatlands under water-table drawdown. *Nature Climate Change*, 2021, 11, pp.618-622. 10.1038/s41558-021-01059-w . hal-03255991

**HAL Id: hal-03255991**

**<https://hal.inrae.fr/hal-03255991>**

Submitted on 25 Oct 2021

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1 **Tradeoff of CO<sub>2</sub> and CH<sub>4</sub> emissions from global peatlands under water-table drawdown**

2

3 Yuanyuan Huang<sup>1,2\*</sup>, Phillipe Ciais<sup>1</sup>, Yiqi Luo<sup>3</sup>, Dan Zhu<sup>1</sup>, Yingping Wang<sup>2</sup>, Chunjing Qiu<sup>1</sup>,  
4 Daniel S. Goll<sup>1</sup>, Bertrand Guenet<sup>4</sup>, David Makowski<sup>5,6</sup>, Inge De Graaf<sup>7</sup>, Jens Leifeld<sup>8</sup>, Min Jung  
5 Kwon<sup>1</sup>, Jing Hu<sup>9</sup>, Laiye Qu<sup>10,11</sup>

6

7 <sup>1</sup>Laboratoire des Sciences du Climat et de l'Environnement, LSCE/IPSL, CEA-CNRS-UVSQ,  
8 Université Paris-Saclay, 91191 Gif-sur-Yvette, France

9 <sup>2</sup>CSIRO Oceans and Atmosphere, Aspendale 3195, Australia

10 <sup>3</sup>Center for Ecosystem Science and Society, Department of Biological Sciences, Northern  
11 Arizona University, AZ, USA

12 <sup>4</sup> Laboratoire de Géologie, UMR 8538, Ecole Normale Supérieure, PSL Research University,  
13 CNRS, IPSL, Paris, France.

14 <sup>5</sup> INRAE, AgroParisTech, University Paris- Saclay, UMR MIA 518, 75231 Paris, France

15 <sup>6</sup>CIREN, 45bis Avenue de la Belle Gabrielle, 94130 Nogent-sur-Marne, France

16 <sup>7</sup> Chair of Environmental Hydrological Systems, Faculty of Environmental and Natural  
17 Resources, University of Freiburg, Freiburg, Germany

18 <sup>8</sup>Agroscope, Climate and Agriculture Group, Reckenholzstrasse 191, 8046, Zurich, Switzerland.

19 <sup>9</sup>Wetland Biogeochemistry Laboratory, Soil and Water Science Department, University of  
20 Florida, Gainesville, FL

21 <sup>10</sup>State Key Laboratory of Urban and Regional Ecology, Research Center for Eco-environmental  
22 Science, Chinese Academy of Sciences, 100085 Beijing, China

23 <sup>11</sup>University of Chinese Academy of Sciences, 100049 Beijing, China

24

25 **Abstract**

26 Water table drawdown across peatlands increases carbon dioxide (CO<sub>2</sub>) and reduces methane  
27 (CH<sub>4</sub>) emissions. The net climatic effect remains unclear. Based on observations from 130 sites  
28 around the globe, we found a positive (warming) net climate effect of water table drawdown.  
29 Using a machine-learning based upscaling approach, we predict that peatland water table  
30 drawdown driven by climate drying and human activities will increase CO<sub>2</sub> emissions by 1.13  
31 (95% interval: 0.88 – 1.50 ) Gt yr<sup>-1</sup> and reduce CH<sub>4</sub> by 0.26 (0.14 – 0.52) Gt CO<sub>2</sub>-eq yr<sup>-1</sup>,  
32 resulting in a net increase of greenhouse gas (GHG) of 0.86 (0.36 – 1.36) Gt CO<sub>2</sub>-eq yr<sup>-1</sup> by the  
33 end of the 21<sup>st</sup> century under the RCP8.5 climate scenario. This net source drops to 0.73 (0.2 –  
34 1.2) Gt CO<sub>2</sub>-eq yr<sup>-1</sup> under RCP2.6. Our results point to an urgent need to preserve pristine and  
35 rehabilitate drained peatlands to decelerate the positive (more warming) feedback among water  
36 table drawdown, increased GHG emissions and climate warming.

37

38

39           Covering only ~3 percent of the Earth’s land surface, peatlands store one-third of the  
40 global soil carbon<sup>1</sup>. Peat is formed through a slow accumulation of detritus with litter input  
41 exceeding decomposition rates in waterlogged environments. In pristine peatlands, a shallow  
42 water table or permanently waterlogged condition causes oxygen deficiency, allowing the  
43 accumulation of organic matter over millennia. These anaerobic conditions favor  
44 methanogenesis, and peatlands thus act as a global source of methane (CH<sub>4</sub>) of around 0.8 Gt  
45 CO<sub>2</sub>-eq yr<sup>-1</sup> (1 Gt = 10<sup>15</sup> g)<sup>2</sup>. CH<sub>4</sub> is a greenhouse gas (GHG) with a global warming potential  
46 that is 25 times that of carbon dioxide (CO<sub>2</sub>) over a 100-year time horizon<sup>3</sup>. Pristine peatlands  
47 are a sink of CO<sub>2</sub> of around 0.4 Gt CO<sub>2</sub> yr<sup>-1</sup> at the global scale<sup>2</sup>. The balance between CO<sub>2</sub> sinks  
48 and CH<sub>4</sub> emissions determines the net climatic impact of peatlands. This balance is highly  
49 sensitive to changes in hydrology, particularly the water table position that regulates aerobic  
50 versus anaerobic conditions in the soil column and therefore the production and consumption  
51 processes of CO<sub>2</sub> and CH<sub>4</sub> in the soil profile<sup>4</sup>.

52           Human induced drainage, over-extraction of groundwater and climate drying have  
53 substantially altered peatland hydrology and resulted in a widespread downward movement of  
54 water tables. Around 51 Mha of the world’s peatlands have been drained for agriculture or  
55 forestry<sup>5</sup>. Water table drawdown and associated land subsidence were observed in warm and wet  
56 peat regions such as Indonesia, Malaysia, Thailand, Florida (Everglades) and in specific summer  
57 dry regions such as California (Sacramento delta) and Israel (Lake Hula)<sup>6,7</sup>, or in temperate  
58 countries like the Netherlands<sup>8</sup>. Peatlands across Europe were also found to have undergone  
59 substantial and widespread drying in recent centuries<sup>9</sup>. Globally, drainage and subsequent  
60 conversion of natural peatlands to agriculture and forestry are estimated to emit 0.31–3.38 Gt  
61 CO<sub>2</sub>-eq yr<sup>-1</sup> GHGs (see Supplementary Table 1 for a summary of GHG emissions on degraded  
62 peatlands). These estimates rely on peatland area and GHG emission factors. Both the area and  
63 emission factors and their upscaling are highly uncertain<sup>5,10,11</sup>. It is unclear to what extent and  
64 how water table drawdown directly regulate changes of GHG emissions as it is challenging to  
65 separate compounding effects of other variables such as land clearing and carbon input to the soil  
66 from the new land use types.

67           Field manipulation experiments provide the opportunity to quantify the direct impact of  
68 lowering the water table on peatland GHG emissions. We compiled data from 376 pairs of data  
69 points measuring net ecosystem exchange of CO<sub>2</sub> (NEE), 532 pairs for CH<sub>4</sub> emissions, 209 pairs

70 for gross primary production (GPP) and 407 pairs for ecosystem respiration (or soil respiration in  
71 the absence of live plants, RES). The data were extracted from 130 field sites as documented in  
72 96 publications (Supplementary Figure 1). NEE is jointly controlled by soil and vegetation ( $NEE$   
73  $= GPP + RES$ ). Lowering water tables is expected to accelerate peat decomposition and soil  $CO_2$   
74 release by exposing C rich upper soil layers to oxygen. However, some studies measured either a  
75 decrease or no change in decomposition rates<sup>12</sup>. Increased, no significant change and decreased  
76 vegetation  $CO_2$  uptake (GPP) were also observed from individual studies when the water table  
77 was lowered. Correspondingly, the sign of NEE changes in response to water table drawdown  
78 varies among studies (Supplementary Figure 11). On the other hand, studies mostly reported  
79 reductions in  $CH_4$  emissions by lowering the water table (Supplementary Figure 11). With highly  
80 uncertain soil emissions and plant uptake of  $CO_2$  but generally lower  $CH_4$  emissions, the net  
81 GHG balance, therefore the global climatic impact of water table drawdown remains highly  
82 variable<sup>13,14</sup>.

83 In order to deal with the heterogeneity of experimental results, we conducted a meta-  
84 analysis based on random effect models to quantitatively summarize results across multiple  
85 studies. Our sign convention is a positive sign for  $CO_2$  or  $CH_4$  emissions to the atmosphere, and  
86 a positive sign for a water table depth (WTD) becoming deeper.  $\Delta_{CO_2, WTD}$  represents the  
87 difference of NEE resulting from a drawdown of WTD, and  $\Delta_{CH_4, WTD}$  is the same for the  
88 difference of  $CH_4$  emissions.  $\Delta_{CH_4, WTD}$  is expressed as its  $CO_2$  equivalent assuming its global  
89 warming potential is 25 times of  $CO_2$  over the 100-year time span<sup>3</sup>. The net greenhouse gas  
90 (GHG) balance is defined by  $\Delta_{GHG, WTD} = \Delta_{CO_2, WTD} + \Delta_{CH_4, WTD}$ . Note here that  $\Delta_{GHG, WTD}$ ,  $\Delta_{CO_2, WTD}$ ,  
91  $\Delta_{CH_4, WTD}$  vary with the magnitude of water table drawdown.

92 The estimated mean value of  $\Delta_{CO_2, WTD}$  (Figure 1) is  $62 \text{ mg } CO_2 \text{ m}^{-2} \text{ h}^{-1}$  (47 to 77), all  
93 ranges being defined as 95% confidence intervals (CI), meaning an increase of  $CO_2$  emissions  
94 (or a decreased sink) for a water table becoming deeper. This estimated mean value is  
95 significantly positive since the 95% CI does not overlap zero (Methods; Supplementary Figure 3)  
96 despite individual values of  $\Delta_{CO_2, WTD}$  varying from -497 to  $1234 \text{ mg } CO_2 \text{ m}^{-2} \text{ h}^{-1}$  across sites  
97 (Supplementary Figure 11). Complex responses and interactions of biotic and abiotic processes  
98 make it difficult to identify a unifying mechanism for NEE responses. Vegetation coverage,  
99 species composition, photosynthetic capacity, biomass allocation, substrate quality, nutrient  
100 availability, environmental conditions (e.g., soil temperature, water availability, aeration status),

101 peat physicochemical properties, microtopography, extent of changes in water level and  
102 experimental duration (short-term vs. long-term) are possible factors that have dominant  
103 influences on NEE responses from individual experiments. Overall, water table drawdown  
104 induced an increase in CO<sub>2</sub> emissions from respiration exceeding that of GPP uptake (Figure 1b).  
105 In contrast, the estimated mean value of  $\Delta_{\text{CH}_4, \text{WTD}}$  shown in Figure 1 is -26 mg CO<sub>2</sub>-eq m<sup>-2</sup> h<sup>-1</sup>  
106 (95% CI: -35, -20), revealing a significant reduction of CH<sub>4</sub> emissions or an increase in the CH<sub>4</sub>  
107 sink resulting from decreased methanogenesis and/or enhanced methanotrophy (Figure 1;  
108 Supplementary Figure 3).  $\Delta_{\text{CH}_4, \text{WTD}}$  across sites go from -1120 to 484 mg CO<sub>2</sub>-eq m<sup>-2</sup> h<sup>-1</sup>  
109 (Supplementary Figure 11). Using data from experiments that measured both NEE and CH<sub>4</sub>  
110 emissions, we estimated a significantly positive mean value of  $\Delta_{\text{GHG, WTD}}$  equal to 33 mg CO<sub>2</sub>-eq  
111 m<sup>-2</sup> h<sup>-1</sup> (9 to 57), which implies that lowering WTD leads to a net increase of radiative forcing.  
112 The result of an overall positive  $\Delta_{\text{GHG, WTD}}$  is robust and consistent among different estimating  
113 methods (Supplementary Figure 3).

114 We then quantified the sensitivities of GHG fluxes to the magnitude of water table  
115 drawdown ( $\Delta_{\text{WTD}}$ ), and found that the overall average sensitivity to a 1 cm water table drawdown  
116 was 4.1 (95% CI: 3.3 to 5.0) mg CO<sub>2</sub> m<sup>-2</sup> h<sup>-1</sup> for CO<sub>2</sub> (NEE) and -2.9 (95% CI: -3.6 to -2.2) mg  
117 CO<sub>2</sub>-eq m<sup>-2</sup> h<sup>-1</sup> for CH<sub>4</sub> (Methods, Supplementary Figure 4). The average sensitivity of  $\Delta_{\text{GHG, WTD}}$   
118 was 1.6 (95% CI: 0.8 to 2.3) mg CO<sub>2</sub>-eq m<sup>-2</sup> h<sup>-1</sup> cm<sup>-1</sup> based on a subset of experiments that  
119 measured both NEE and CH<sub>4</sub>. No significant pattern in the regional values of  $\Delta_{\text{GHG, WTD}}$  was  
120 found (Supplementary Figures 5-10; Supplementary Discussion), because of the large inter-site  
121 variability of the observed fluxes, small sample sizes in arctic, tropical and coastal regions, and  
122 nonlinear responses to  $\Delta_{\text{WTD}}$ . The average sensitivity of  $\Delta_{\text{CH}_4, \text{WTD}}$  to unit water table drawdown  
123 was smaller (less reduction) in tropical than boreal and temperate peatlands (Supplementary  
124 Figure 6). The difference between these regions was significant (95% CI not overlap) according  
125 to one of the weighting approaches considered. Respiration of coastal regions had a greater  
126 average sensitivity than non-coastal regions, while differences of NEE (or CH<sub>4</sub>) were  
127 inconsistent (Supplementary Figure 8). Undisturbed coastal regions are more likely to experience  
128 frequent flooding and anoxic conditions, leaving more labile peat susceptible to decomposition if  
129 the water table was lowered. Among different peatland types, the mean  $\Delta_{\text{CO}_2, \text{WTD}}$  per unit  $\Delta_{\text{WTD}}$   
130 was higher in swamps than bogs and fens (not significant, Supplementary Figure 10). Fens had  
131 higher mean  $\Delta_{\text{CO}_2, \text{WTD}}$  and mean  $\Delta_{\text{GHG, WTD}}$  per unit  $\Delta_{\text{WTD}}$  than bogs.

132 Responses of GHG emissions to WTD were non-linear and covaried with peatland types,  
133 regions, land use and management histories, hydrology, vegetation characteristics, climate, and  
134 physicochemical properties of peat<sup>4,13,15-17</sup>. Therefore, upscaling above-estimates to the global  
135 scale can be problematic. To further understand how different factors regulated  $\Delta_{\text{CO}_2, \text{WTD}}$  and  
136  $\Delta_{\text{CH}_4, \text{WTD}}$ , we built random forest models<sup>18</sup> for these two quantities (see Methods). The random  
137 forests were built against site data using as predictors  $\Delta_{\text{WTD}}$ , WTD,  $\text{CO}_2$  (NEE) and  $\text{CH}_4$   
138 emissions under the high (shallow) water table treatment ( $\text{WTD}_{\text{initial}}$ ,  $\text{CO}_{2,\text{initial}}$  and  $\text{CH}_{4,\text{initial}}$  in  
139 short), climatic, topographic, edaphic, biotic, management and experimental factors (Methods;  
140 Supplementary Tables 2, 3). We show in Figure 2 that  $\text{CO}_{2,\text{initial}}$ ,  $\Delta_{\text{WTD}}$  and  $\text{WTD}_{\text{initial}}$  are the most  
141 important predictors of  $\Delta_{\text{CO}_2, \text{WTD}}$ , accounting for 53% of the Gini-based relative importance  
142 (Supplementary Table 4; Figure 2; Supplementary Figures 13, 15). Variations in  $\Delta_{\text{CH}_4, \text{WTD}}$  are  
143 mostly explained by  $\text{CH}_{4,\text{initial}}$ ,  $\Delta_{\text{WTD}}$  and  $\text{WTD}_{\text{initial}}$  (relative importance: 88%; Supplementary  
144 Table 5; Figure 2; Supplementary Figures 14, 15). The models predict that peatlands with a  
145 stronger initial capacity of being  $\text{CO}_2$  sink ( $\text{CO}_{2,\text{initial}}$ ), a shallower  $\text{WTD}_{\text{initial}}$ , and experiencing a  
146 larger  $\Delta_{\text{WTD}}$  have a more positive  $\Delta_{\text{CO}_2, \text{WTD}}$  value (Figure 2, red lines), and that peatlands with a  
147 larger  $\text{CH}_{4,\text{initial}}$  flux to the atmosphere and a bigger  $\Delta_{\text{WTD}}$  experience a stronger reduction in their  
148  $\text{CH}_4$  emissions, i.e., a more negative  $\Delta_{\text{CH}_4, \text{WTD}}$  value (Figure 2, red lines).

149 By scaling up using the random forest models, we found that arctic peatlands were more  
150 likely to have both positive and negative  $\Delta_{\text{CO}_2, \text{WTD}}$  when conditions varied (Supplementary  
151 Figure 16). The average response curves showed that arctic peatlands were more sensitive to  
152  $\Delta_{\text{WTD}}$  and  $\text{CO}_{2,\text{initial}}$  over the whole predictor space (Supplementary Figure 17).  $\Delta_{\text{CH}_4, \text{WTD}}$  of  
153 tropical peatlands could be less or greater than boreal peatlands when  $\text{CH}_{4,\text{initial}}$  varied  
154 (Supplementary Figures 16, 17). Overall, both  $\Delta_{\text{CO}_2, \text{WTD}}$  and  $\Delta_{\text{CH}_4, \text{WTD}}$  were highly sensitive to  
155  $\Delta_{\text{WTD}}$  when  $\Delta_{\text{WTD}}$  was small (<10 cm), and also became highly sensitive to  $\text{WTD}_{\text{initial}}$  when  
156  $\text{WTD}_{\text{initial}}$  was around the surface.  $\Delta_{\text{CO}_2, \text{WTD}}$  stayed relatively constant when  $\text{WTD}_{\text{initial}}$  was 10 cm  
157 above the surface or 80 cm below the surface.  $\Delta_{\text{CH}_4, \text{WTD}}$  was not responsive to  $\text{WTD}_{\text{initial}}$  for  
158 strong drying or wetting when  $\text{WTD}_{\text{initial}}$  got typically more than 33 cm below the surface or 21  
159 cm above the surface (Figure 2, Supplementary Figures 16, 17). That being said, the above-  
160 mentioned broad patterns emerged from our analyses may not hold under some specific  
161 environmental conditions, due to the strong nonlinearity of response curves. Apart from these  
162 average responses, each individual paired experiment carried a unique response pattern as an

163 outcome of complex interactions involving peatland characteristics, climate and other  
164 environmental factors (Figure 2, grey lines; see Supplementary Figures 13, 14 for the responses  
165 to different factors).

166 Based on future WTD predicted by de Graaf, et al.<sup>19</sup> under their “business as usual”  
167 water demand scenario and the RCP8.5 climate change scenario (Methods), we used the trained  
168 random forest models to compute global gridded CO<sub>2</sub> (NEE) and CH<sub>4</sub> emissions in response to  
169 future water table drawdown. We found both an increase of global peatland NEE, that is, a larger  
170 CO<sub>2</sub> source or a smaller sink by 1.13 (95% probability interval: 0.88 – 1.50 ) Gt CO<sub>2</sub> yr<sup>-1</sup> and a  
171 reduction of peatland CH<sub>4</sub> emissions by 0.26 (0.14 – 0.52) Gt CO<sub>2</sub>-eq yr<sup>-1</sup>, which together  
172 amounts to a net increase of GHG of 0.86 (0.36 – 1.36) Gt CO<sub>2</sub>-eq yr<sup>-1</sup> by 2100 (see Figure 3 and  
173 Supplementary Figures 21, 23, 25, 27). This estimated net GHG budget was 0.73 (0.2 – 1.2) Gt  
174 CO<sub>2</sub>-eq yr<sup>-1</sup> under the RCP2.6 climate scenario by 2100 (see Figure 3 and Supplementary  
175 Figures 22, 24, 26, 28). Under the scenario assuming a 40% less reduction of WTD than the de  
176 Graaf, et al.<sup>19</sup> prediction, the global  $\Delta_{\text{GHG,WTD}}$  reached 0.74 (0.5 – 1.29) Gt CO<sub>2</sub>-eq yr<sup>-1</sup>. A 80%  
177 less reductions of WTD than the de Graaf, et al.<sup>19</sup> prediction yields a global  $\Delta_{\text{GHG,WTD}}$  of 0.53  
178 (0.34 – 0.85) Gt CO<sub>2</sub>-eq yr<sup>-1</sup>. The RCP2.6 climate scenario and a 80% less reduction of water  
179 table drawdown together bring the global  $\Delta_{\text{GHG,WTD}}$  down to 0.42 (0.22 – 0.74) Gt CO<sub>2</sub>-eq yr<sup>-1</sup>.  
180 Note these estimates do not account for anthropogenic impacts other than water table drawdown,  
181 such as land use change or fires.

182 Across different latitudes, regions with high CH<sub>4</sub> reductions generally have high  $\Delta_{\text{CO}_2}$ ,  
183  $\Delta_{\text{WTD}}$  and  $\Delta_{\text{GHG,WTD}}$ . Mid- to high-northern latitudes and tropics dominate the global response of  
184 GHG budgets to water table drawdown due to their large areas (Figure 3; Supplementary Figures  
185 21, 22). Inferred from several drained peat sites in Finland, Laine, et al.<sup>14</sup> suggested a reduced  
186 GHG emission from northern peatlands under future drying because of lower CH<sub>4</sub> emissions and  
187 enhanced vegetation CO<sub>2</sub> uptake offsetting peat CO<sub>2</sub> emissions. We found negative  $\Delta_{\text{GHG,WTD}}$   
188 over Finland (Supplementary Figures 23,24). Across northern peatlands, positive  $\Delta_{\text{GHG,WTD}}$   
189 outweighs negative  $\Delta_{\text{GHG,WTD}}$ , resulting in the positive (warming) feedback on future climate.  
190 We acknowledge large uncertainties in predicting future GHG emissions over northern  
191 peatlands. In particular, permafrost thawing, a critical process that has dramatic impacts on the  
192 climate system<sup>20</sup>, was not included as a predictor in our model. Arctic warming and permafrost  
193 thaw can alter peatland hydrology. Thermokarst peatlands form as a result of permafrost thaw.



194 Thermokarst peatlands are known for their localized patchy landscape with distinguished dry-  
195 wet zones and irregular hummocks and hollows. Considering the big sensitivity of GHG to  $\Delta_{\text{WTD}}$   
196 in arctic peatlands, widespread alterations of hydrology could dramatically change arctic GHG  
197 budgets.

198 Peatlands in Scandinavia, coastal region or along river networks are predicted to  
199 experience high reductions in  $\text{CH}_4$  emissions in response to future water table drawdown  
200 (Supplementary Figures 25,26). Latitudinal average  $\text{CH}_4$  reductions are higher in tropics than  
201 high latitudes. High  $\text{CH}_4$  fluxes, relatively large change of WTD, and its warm environment  
202 make Amazonian peatlands the largest contributor to total  $\text{CH}_4$  reduction in tropics. This  
203 prediction is subject to large uncertainties because of few field observations in Amazonian  
204 peatlands. Few field studies in Amazonian peatlands documented high  $\text{CH}_4$  fluxes<sup>21,22</sup>. The  
205 spatiotemporal variability, hydrologic and biogeochemical controls of  $\text{CH}_4$  emissions across  
206 Amazonian peatlands remain poorly understood. Southeast Asian peatlands show low  $\text{CH}_4$   
207 emissions in comparison to temperate and boreal peatlands<sup>13</sup>, most likely due to poorer substrate  
208 quality (lower carbohydrate and greater aromatic content) of tropical peats<sup>23</sup>. It remains largely  
209 unclear whether the low  $\text{CH}_4$  fluxes are widespread across tropics, or biases from limited sample  
210 size and coverage. Boreal and temperate peatlands had experienced widespread drainage and  
211 peat conversion before the 21<sup>st</sup> century, while tropic peatlands are subject to large scale  
212 disturbance in the future<sup>24</sup>. The recent discovery of the world's largest tropical peatland in Congo  
213 basin<sup>25</sup> highlights the need for additional field observations in tropics to understand hydrological  
214 controls on  $\text{CH}_4$  emissions.

215 A less controversial issue in tropics is the higher  $\text{CO}_2$  emissions following water table  
216 drawdown. Tropical peatlands contain about 5-10% of global soil carbon<sup>26</sup>. Earlier<sup>13</sup> and our  
217 syntheses (Supplementary Figure 6) found an increase in emission of at least  $10 \text{ mg CO}_2 \text{ m}^{-2} \text{ h}^{-1}$   
218 by respiration for each 1cm water table drawdown. Many tropical peatlands are occupied by  
219 swamp forests, and some of them were converted into agricultural land uses with a lowering of  
220 the WTD, which would result in an increase in  $\text{CO}_2$  emissions<sup>27</sup>. In Southeast Asia, 25% of  
221 deforestation occurs in peat swamp forests<sup>27</sup>. Water table management and conservation of  
222 tropical swamp forests are critical for climate mitigation in the tropics, due to the high  $\text{CO}_2$   
223 emissions from swamp forests and the positive feedbacks among water table drawdown, GHG  
224 emissions and climate warming. Under RCP8.5 where  $\text{CO}_2$  emissions continue to rise throughout

225 the 21st century with warmer climate conditions, global  $\Delta_{\text{GHG,WTD}}$  is predicted to increase by  
226 18% more than under the less warm RCP2.6 scenario. These estimates are rather conservative,  
227 because we did not account for the effect of lowering the water table under a warm and drying  
228 climate on  $\Delta_{\text{GHG,WTD}}$ . Positive contributions of water table drawdown to GHGs accelerate future  
229 GHG emissions through climate feedback.

230 This study reveals that despite water table drawdown reduces global peatland  $\text{CH}_4$   
231 emissions, increased  $\text{CO}_2$  flux outweighs the climate benefits of reduced  $\text{CH}_4$  in terms of global  
232 warming potential. Many other adverse environmental and ecological impacts associated with  
233 peatland water table drawdown have already motivated national and international actions to  
234 preserve pristine peatlands and rewet drained peatlands. Controlling the magnitude of future  
235 water table drawdown is an effective measure as future  $\Delta_{\text{CO}_2, \text{WTD}}$  and  $\Delta_{\text{CH}_4, \text{WTD}}$  are largely  
236 regulated by  $\Delta_{\text{WTD}}$  (Supplementary Tables 6-8). Rewetting to ~10 cm above-surface greatly  
237 reduces  $\text{CO}_2$  emission, it may also increase  $\text{CH}_4$  emissions, especially in regions where pristine  
238 peatlands are strong  $\text{CH}_4$  emitters. Instead of rewetting all drained peatlands, care must be taken  
239 in regional implementation, as the tradeoff between  $\text{CO}_2$  decrease and  $\text{CH}_4$  increase is dependent  
240 on many local factors. Climate change mitigation strategies outside peatlands that aim to limit  
241 global warming are also critical for lowering peatland GHG emissions. Finally, despite  
242 significant progresses in peatland studies over recent decades, there are still large uncertainties in  
243 quantifying peatland  $\text{CO}_2$  (NEE)<sup>28,29</sup>,  $\text{CH}_4$  emissions<sup>30</sup> and WTD<sup>19</sup> dynamics over large spatial  
244 scales. Arctic, coastal and tropical regions are highly vulnerable, but largely understudied,  
245 especially in the area of long-term vegetation adaptation. Dominant control on the response of  
246 peatland carbon to water table drawdown may also vary with timescales. As a first step, we  
247 assessed the uncertainty of our prediction through combining different datasets to account for  
248 currently known major uncertainty sources, which is yet to be all inclusive. Additional  
249 observations especially from those under-sampled regions will enable us to reduce the  
250 uncertainty in the estimated response of peatland to climate change and developing appropriate  
251 mitigation strategies in the future.

252

## 253 **References**

254 1 Yu, Z. C., Loisel, J., Brosseau, D. P., Beilman, D. W. & Hunt, S. J. Global peatland  
255 dynamics since the Last Glacial Maximum. *Geophysical Research Letters* **37**,  
256 doi:10.1029/2010gl043584 (2010).

257 2 Frohking, S. *et al.* Peatlands in the Earth's 21st century climate system. *Environmental*  
258 *Reviews* **19**, 371-396, doi:10.1139/a11-014 (2011).

259 3 Myhre, G., D. Shindell, F.-M. Bréon, W. Collins, J. Fuglestedt, J. Huang, D. Koch, J.-F.  
260 Lamarque, D. Lee, B. Mendoza, T. Nakajima, A. Robock, G. Stephens, T. Takemura and  
261 H. Zhang. Anthropogenic and Natural Radiative Forcing. (Cambridge University Press,  
262 Cambridge, United Kingdom and New York, NY, USA, 2013).

263 4 Ise, T., Dunn, A. L., Wofsy, S. C. & Moorcroft, P. R. High sensitivity of peat  
264 decomposition to climate change through water-table feedback. *Nature Geoscience* **1**,  
265 763-766, doi:10.1038/ngeo331 (2008).

266 5 Leifeld, J. & Menichetti, L. The underappreciated potential of peatlands in global climate  
267 change mitigation strategies. *Nature Communications* **9**, doi:10.1038/s41467-018-03406-  
268 6 (2018).

269 6 Hooijer, A. *et al.* Subsidence and carbon loss in drained tropical peatlands.  
270 *Biogeosciences* **9**, 1053-1071, doi:10.5194/bg-9-1053-2012 (2012).

271 7 Nagano, T. *et al.* Subsidence and soil CO<sub>2</sub> efflux in tropical peatland in southern  
272 Thailand under various water table and management conditions. *Mires and Peat* **11**  
273 (2013).

274 8 Erkens, G., van der Meulen, M. J. & Middelkoop, H. Double trouble: subsidence and  
275 CO<sub>2</sub> respiration due to 1,000 years of Dutch coastal peatlands cultivation. *Hydrogeology*  
276 *Journal* **24**, 551-568, doi:10.1007/s10040-016-1380-4 (2016).

277 9 Swindles, G. T. *et al.* Widespread drying of European peatlands in recent centuries.  
278 *Nature Geoscience*, doi:10.1038/s41561-019-0462-z (2019).

279 10 IPCC. in *IPCC, Wetlands, 2014* (2013).

280 11 Wilson, D. *et al.* Greenhouse gas emission factors associated with rewetting of organic  
281 soils. *Mires and Peat* **17**, doi:10.19189/MaP.2016.OMB.222 (2016).

282 12 Laiho, R. Decomposition in peatlands: Reconciling seemingly contrasting results on the  
283 impacts of lowered water levels. *Soil Biology & Biochemistry* **38**, 2011-2024,  
284 doi:10.1016/j.soilbio.2006.02.017 (2006).

285 13 Couwenberg, J., Dommain, R. & Joosten, H. Greenhouse gas fluxes from tropical  
286 peatlands in south-east Asia. *Global Change Biology* **16**, 1715-1732, doi:10.1111/j.1365-  
287 2486.2009.02016.x (2010).

288 14 Laine, J. *et al.* Effect of water-level drawdown on global climatic warming: Northern  
289 peatlands. *Ambio* **25**, 179-184 (1996).

290 15 Prananto, J. A., Minasny, B., Comeau, L. P., Rudiyanto, R. & Grace, P. Drainage  
291 increases CO<sub>2</sub> and N<sub>2</sub>O emissions from tropical peat soils. *Global Change Biology*,  
292 4583-4600, doi:10.1111/gcb.15147 (2020).

293 16 Turetsky, M. R. *et al.* A synthesis of methane emissions from 71 northern, temperate, and  
294 subtropical wetlands. *Global Change Biology* **20**, 2183-2197, doi:10.1111/gcb.12580  
295 (2014).

296 17 Jungkunst, H. F. & Fiedler, S. Latitudinal differentiated water table control of carbon  
297 dioxide, methane and nitrous oxide fluxes from hydromorphic soils: feedbacks to climate  
298 change. *Global Change Biology* **13**, 2668-2683, doi:10.1111/j.1365-2486.2007.01459.x  
299 (2007).

300 18 Breiman, L. Random forests. *Machine Learning* **45**, 5-32, doi:10.1023/a:1010933404324  
301 (2001).

- 302 19 de Graaf, I. E. M., Gleeson, T., van Beek, L. P. H., Sutanudjaja, E. H. & Bierkens, M. F.  
303 P. Environmental flow limits to global groundwater pumping. *Nature* **574**, 90-94,  
304 doi:10.1038/s41586-019-1594-4 (2019).
- 305 20 Schuur, E. A. G. *et al.* Climate change and the permafrost carbon feedback. *Nature* **520**,  
306 171-179, doi:10.1038/nature14338 (2015).
- 307 21 Winton, R. S., Flanagan, N. & Richardson, C. J. Neotropical peatland methane emissions  
308 along a vegetation and biogeochemical gradient. *Plos One* **12**,  
309 doi:10.1371/journal.pone.0187019 (2017).
- 310 22 Teh, Y. A., Murphy, W. A., Berrio, J. C., Boom, A. & Page, S. E. Seasonal variability in  
311 methane and nitrous oxide fluxes from tropical peatlands in the western Amazon basin.  
312 *Biogeosciences* **14**, 3669-3683, doi:10.5194/bg-14-3669-2017 (2017).
- 313 23 Hodgkins, S. B. *et al.* Tropical peatland carbon storage linked to global latitudinal trends  
314 in peat recalcitrance. *Nature Communications* **9**, doi:10.1038/s41467-018-06050-2  
315 (2018).
- 316 24 Leifeld, J., Wust-Galley, C. & Page, S. Intact and managed peatland soils as a source and  
317 sink of GHGs from 1850 to 2100. *Nature Climate Change* **9**, 945-+, doi:10.1038/s41558-  
318 019-0615-5 (2019).
- 319 25 Dargie, G. C. *et al.* Age, extent and carbon storage of the central Congo Basin peatland  
320 complex. *Nature* **542**, 86-+, doi:10.1038/nature21048 (2017).
- 321 26 Minasny, B. *et al.* Digital mapping of peatlands - A critical review. *Earth-Science*  
322 *Reviews* **196**, doi:10.1016/j.earscirev.2019.05.014 (2019).
- 323 27 Miettinen, J., Shi, C. H. & Liew, S. C. Deforestation rates in insular Southeast Asia  
324 between 2000 and 2010. *Global Change Biology* **17**, 2261-2270, doi:10.1111/j.1365-  
325 2486.2011.02398.x (2011).
- 326 28 Gallego-Sala, A. V. *et al.* Latitudinal limits to the predicted increase of the peatland  
327 carbon sink with warming. *Nature Climate Change* **8**, 907-+, doi:10.1038/s41558-018-  
328 0271-1 (2018).
- 329 29 Jung, M. *et al.* The FLUXCOM ensemble of global land-atmosphere energy fluxes.  
330 *Scientific Data* **6**, doi:10.1038/s41597-019-0076-8 (2019).
- 331 30 Melton, J. R. *et al.* Present state of global wetland extent and wetland methane modelling:  
332 conclusions from a model inter-comparison project (WETCHIMP). *Biogeosciences* **10**,  
333 753-788, doi:10.5194/bg-10-753-2013 (2013).
- 334

## 335 **Methods**

### 336 **Data collection**

337 We extracted values of GHG fluxes for NEE, ecosystem respiration (or soil respiration in  
338 the absence of live plant), GPP, CH<sub>4</sub> emissions, WTD and ancillary environmental variables  
339 from water table manipulation experiments carried out through mesocosms or/and *in-situ* field  
340 conditions. Mesocosm experiments normally enclose relatively large intact peat monoliths to  
341 manipulate WTD in well-controlled conditions. *in-situ* field experiments alter WTD through  
342 draining, ditching, precipitation exclusion, flooding, building dams or groundwater extraction.  
343 Difference in  $\Delta_{\text{CO}_2, \text{WTD}}$  and  $\Delta_{\text{CH}_4, \text{WTD}}$  between these two types of experiments is not significant

344 (95% CI overlap). We do not separate mesocosm experiments from experiments without peat  
345 enclosure. We treat them as different approaches to manipulate water table depth. We used the  
346 ISI Web of Science database to conduct literature search for the papers published before October  
347 2020 with query terms including “water table”, “carbon”, “methane”, “respiration”, “NEE”,  
348 “primary production”, “drain” and “peatland”. More papers were identified through the Chinese  
349 CNKI platform. Studies included in our database were selected according to several criteria. The  
350 study should measure at least WTD and one flux of CO<sub>2</sub> or CH<sub>4</sub> under both low- and high-water  
351 table treatments over the same time period in the same geographic region and have the same  
352 natural background and land use type. Studies that compare ecosystem responses under altered  
353 water table during different time periods, for example, from Merbold, et al.<sup>31</sup>, were not  
354 incorporated. Studies using laboratory peat columns, with synthetic/repacked soils, artificial  
355 additions (ameliorant, biochar or compost) or through incubations or have a treatment less than 1  
356 month were also excluded. Around 1/3 of studies experienced water table disturbance 10 years  
357 earlier. Some papers reported ecosystem responses to several water table treatments at the same  
358 location. In these cases, we rearranged and paired the datasets to have different combinations of  
359 low vs. high water table treatments. For those papers reporting multiple values across several  
360 years, we compared results from meta-analysis that separates vs. lumps each year’s mean  
361 response. Differences are minor, and we reported results without lumping. In total, we obtained  
362 96 papers that cover 130 locations, mostly in the northern hemisphere (Supplementary Figures 1,  
363 2). A pair of data points reflecting  $\Delta_{\text{WTD}}$  effects on carbon flux includes a target GHG data from  
364 two treatments corresponding to a low and high water table depth in a specific site. In total, we  
365 have 376 pairs on NEE (CO<sub>2</sub>), 532 pairs of CH<sub>4</sub>, 209 pairs of gross primary production (GPP)  
366 and 407 pairs of ecosystem respiration (or soil in the absence of live plants, RES) measurements.

367 For carbon fluxes, we extracted mean values of emission for each treatment, standard  
368 deviations (SD), and sample sizes from each published study. If standard error (SE) rather than  
369 SD was reported, SD was calculated from SE. For experiments that did not document SD or SE  
370 (3-20% of the experiments), we estimated the variance through scaling the mean of each  
371 experiment by the average coefficient of variation within each treatment and each GHG. We also  
372 extracted mean WTD before and after water table manipulation and other ancillary information  
373 (Supplementary Tables 2, 3).

#### 374 **Response quantification**

375 For each pair of data points, we use the difference ( $\Delta_{C, WTD}$ , in unit of mg CO<sub>2</sub>-eq m<sup>-2</sup> h<sup>-1</sup>)  
376 in the mean value (over experimental replicates) of each CO<sub>2</sub> or CH<sub>4</sub> flux under high (shallow)-  
377 ( $\bar{C}_h$ ) and low (deep) -water table ( $\bar{C}_l$ ) (Equation 1) as a metric to quantify the effect of water table  
378 drawdown. We chose the difference instead of the odds ratio (log) to incorporate experiments in  
379 which  $\bar{C}_h$  and  $\bar{C}_l$  vary in sign.

$$380 \quad \Delta_{C, WTD} = \bar{C}_h - \bar{C}_l \quad (1)$$

381 We conducted the meta-analysis with the random-effect model (assuming that between  
382 study variations are randomly distributed) and the inverse variance weighting scheme<sup>32</sup> based on  
383 the extracted values of SD and sample sizes through the Metafor package in R version 3.6.2<sup>33</sup>.  
384 The between study variance (heterogeneity,  $\tau^2$ ) was quantified through the restricted maximum-  
385 likelihood method<sup>33</sup>. 95% confidence interval (CI) was estimated as the Wald-type (i.e., normal)  
386 CI if the standardized residuals of observations are not strongly deviated from theoretical  
387 quantiles of a normal distribution. Otherwise, we applied a bootstrapping CI estimation. We  
388 randomly sampled 90% of the original datasets with replacement and estimated the mean effect  
389 1000 times. 95% CI was calculated as the 2.5% and 97.5% quantiles of the 1000 estimates in R  
390 3.6.2<sup>33</sup>. To test the robustness of our conclusion towards an overall positive or negative  
391 response, we conducted additional meta-analyses under alternative assumptions. First, we  
392 assessed whether the conclusions depended on how individual studies are weighted<sup>34</sup>. We  
393 applied the fixed effect model with weighting based on the number of replicates and with a  
394 uniform weighting. For studies with sample size not published (~20%), we used the average  
395 sample size from our database for corresponding gases. For the fixed effect model, we estimated  
396 the 95% CIs of the mean response through 10000 times bootstrapping using the bootES library<sup>35</sup>.  
397 A significant asymmetry of the funnel plot indicates the bias in compiled studies which tend to  
398 report more results with a significant response compared to studies without. We conducted an  
399 asymmetry test through the regtest function of the Metafor package. We did not detect the  
400 publication bias in the combined effect of CO<sub>2</sub> and CH<sub>4</sub> ( $p=0.31$ ). For CO<sub>2</sub> or CH<sub>4</sub> alone, the  
401 funnel plot ( $p < 0.01$ ) is significantly asymmetry. We corrected the publication bias through the  
402 trimfill function in Metafor. These tests, the fixed effect models and with correction of potential  
403 publication bias, pointed to consistent signs of the overall effects. The average responses are  
404 robust (Supplementary Figure 3).

405 The average sensitivity of  $\Delta_{C,WTD}$  to unit change of  $\Delta_{WTD}$  ( $\frac{\Delta_{C,WTD}}{\Delta_{WTD}}$ , mg CO<sub>2</sub>-eq m<sup>-2</sup> h<sup>-1</sup> cm<sup>-1</sup>)  
406 <sup>1</sup>) was quantified similarly with the random effect model and the inverse variance weighting  
407 scheme. Note that we do not account for variance in WTD, assuming it is relatively well  
408 measured in manipulation experiments. For regional analyses, we grouped samples into arctic  
409 (north of 66.5 °N ), boreal and temperate (30°N – 66.5°N, 66.5°S – 30°S ) and tropical regions  
410 (30°S – 30°N). We also compared coastal vs.non-coastal regions, and among peatland types (bog,  
411 fen, marsh, swamp).

### 412 **Response attribution**

413 Water table manipulation studies differ in peatland types, nutrient status, background  
414 climate and other experimental designs (e.g., initial water table depth, drainage duration and the  
415 magnitude of drainage). Combining driving factors reported from individual studies and the  
416 availability of data across studies, we tested a list of factors to understand what drive  $\Delta_{CO_2, WTD}$   
417 and  $\Delta_{CH_4, WTD}$  through the random forest method. These factors include WTD and carbon fluxes  
418 under high water table treatment ( $WTD_{initial}$ ,  $CO_{2,initial}$  or  $CH_{4,initial}$  ), the magnitude of water table  
419 manipulation ( $\Delta_{WTD}$ ), manipulation duration (short: <1 year; medium: 1-10 years; long: > 10  
420 years), experimental type (mesocosm vs. *in-situ*), land management (managed or not), climatic,  
421 topographic (elevation) and edaphic properties (Supplementary Tables 2, 3). Climatic factors  
422 include mean annual precipitation, mean annual temperature, wind speed, solar radiation, vapor  
423 pressure, aridity (the ratio between potential evapotranspiration and precipitation), potential  
424 evapotranspiration and a range of other bioclimatic variables characterizing the annual trend,  
425 seasonality and extreme climatic conditions. Edaphic properties involve bulk density, pH, soil  
426 carbon content, soil nitrogen, soil phosphorus, soil potassium, cation exchange capacity, base  
427 saturation, clay content, sand content, silt content and volumetric moisture content.

428 Random forest is an ensemble machine learning approach that generates a number of  
429 decision trees<sup>18</sup>, and is capable of capturing non-linear interactions. We sequentially added  
430 explanatory variables one at a time and selected the random forest model that yielded the highest  
431  $R^2$  and the lowest root mean square error (RMSE) through leave-one-out cross-validation  
432 (LOOCV). Climatic, topographic and edaphic factors that are not documented in individual  
433 studies were extracted from high resolution data sources listed in Supplementary Table 3. For  
434  $\Delta_{CO_2, WTD}$ , the selected random forest model (with LOOCV  $R^2=0.52$ ,  $RMSE= 134$  mg CO<sub>2</sub> m<sup>-2</sup> h<sup>-1</sup>  
435 <sup>1</sup>, Supplementary Figure 11) was built through  $CO_{2,initial}$ ,  $\Delta_{WTD}$ ,  $WTD_{initial}$ , soil nitrogen, soil

436 carbon content, potential evapotranspiration, bulk density, volumetric water content at -10 kPa,  
 437 soil pH, wind speed, soil clay content, solar radiation and elevation (Figure 2 and Supplementary  
 438 Figure 13). The first three predictors accounted for 53% of the relative importance  
 439 (Supplementary Table 4).  $\Delta_{\text{CH}_4, \text{WTD}}$  are predictable (LOOCV  $R^2=0.72$ ,  $RMSE = 81 \text{ mg CO}_2\text{-eq}$   
 440  $\text{m}^{-2} \text{h}^{-1}$ , , Supplementary Figure 11) through  $\text{CH}_{4,\text{initial}}$ ,  $\Delta_{\text{WTD}}$ ,  $\text{WTD}_{\text{initial}}$ , wind speed, soil nitrogen  
 441 content, aridity, manipulation duration (Figure 2 and Supplementary Figure 14). The first three  
 442 predictors accounted for 88% of the relative importance (Supplementary Table 5). Tropics  
 443 contribute significantly to  $\text{CO}_2$  and  $\text{CH}_4$  budgets. The small sample size of tropical studies makes  
 444 building regional random forest models infeasible. Despite being built over samples around the  
 445 world, the model performance is comparable between tropical samples ( $\Delta_{\text{CO}_2, \text{WTD}}$ ,  $R^2=0.49$ ,  
 446  $RMSE = 121 \text{ mg CO}_2 \text{ m}^{-2} \text{ h}^{-1}$ ;  $\Delta_{\text{CH}_4, \text{WTD}}$ :  $R^2=0.66$ ,  $RMSE = 48 \text{ mg CO}_2\text{-eq m}^{-2} \text{ h}^{-1}$ ;  
 447 Supplementary Figures 11, 12) and the rest of the world. Earlier synthetic studies revealed that  
 448 relationships between water table and peatland greenhouse emissions were modified by peatland  
 449 types, region and disturbance etc<sup>15,16</sup>. We reconstructed the functional relationship between  
 450  $\Delta_{\text{CO}_2, \text{WTD}}$  ( or  $\Delta_{\text{CH}_4, \text{WTD}}$ ) and different predictors for each individual study, i.e., the Individual  
 451 Conditional Expectation (ICE)<sup>36</sup> (grey lines in Figure 2). Variations among ICE curves capture  
 452 the context-dependent response patterns.

### 453 **Mapping future impact**

454  $\Delta_{\text{CO}_2, \text{WTD}}$  and  $\Delta_{\text{CH}_4, \text{WTD}}$  at the end of 2100 were predicted using the random forest models  
 455 built above (Methods: Response attribution), with predictors such as  $\Delta_{\text{WTD}}$ ,  $\text{WTD}_{\text{initial}}$ ,  $\text{CO}_{2,\text{initial}}$   
 456 (or  $\text{CH}_{4,\text{initial}}$ ) and future climatic conditions (wind speed, solar radiation, potential  
 457 evapotranspiration, aridity), assuming that edaphic and topographic factors (soil carbon, soil  
 458 nitrogen, bulk density, volumetric water content at -10 kPa, soil pH, soil clay content, and  
 459 elevation) remain equal to their current levels due to their relatively slow change rates. Average  
 460  $\Delta_{\text{CO}_2, \text{WTD}}$  and  $\Delta_{\text{CH}_4, \text{WTD}}$  were estimated through different (if available) predictor datasets (see text  
 461 below and Supplementary Table 3). To verify our main results are not outcomes of overfitting,  
 462 we made predictions with the top three most important predictors, which yielded a global  
 463  $\Delta_{\text{GHG,WTD}}$  of  $1.47 \text{ Gt CO}_2\text{-eq yr}^{-1}$  ( $\Delta_{\text{CO}_2,\text{WTD}}$ : 1.59,  $\Delta_{\text{CH}_4,\text{WTD}}$ : -0.12). This value is larger than the  
 464 prediction from the random forest model built in previous section, and our conclusion of an  
 465 overall positive  $\Delta_{\text{GHG,WTD}}$  is robust.  $\text{CO}_{2,\text{initial}}$  and  $\text{CH}_{4,\text{initial}}$  from predicting datasets are within the  
 466 range spanned by observation datasets used to train the random forest models (Supplementary



467 Figure 20 and Supplementary Table 2). We set the upper limit of  $\Delta_{\text{WTD}}$  to be 300 cm. We varied  
468 this boundary value from 100 to 400cm, and our results stayed the same as  $\Delta_{\text{CO}_2, \text{WTD}}$  and  $\Delta_{\text{CH}_4, \text{WTD}}$   
469  $\Delta_{\text{WTD}}$  are not responsive to further increasing  $\Delta_{\text{WTD}}$  beyond 100cm (Figure 3b, e). Similarly, we set  
470 the upper limit of  $\text{WTD}_{\text{initial}}$  close to the upper limit of the training dataset (around 100cm) to  
471 avoid extrapolating.  $\Delta_{\text{CO}_2, \text{WTD}}$  and  $\Delta_{\text{CH}_4, \text{WTD}}$  are not sensitive to  $\text{WTD}_{\text{initial}}$  when water table depth  
472 is deep (Figure 3c, f). We checked that increasing this boundary value did not change our results.

473 Future WTDs were projected through a physically based global hydrology and water-  
474 resources model PCR-GLOBWB that was coupled to the global groundwater flow model  
475 (MODFLOW) with future climate forcing (HadGEM2-ES) under RCP8.5 GHG emission  
476 scenario and ‘business-as-usual’ water consumptions from de Graaf, et al. <sup>19,37</sup>. By ‘business-as-  
477 usual’, per capita water demand for industry, domestic and livestock uses as well as irrigated  
478 area were assumed to remain constant after 2010. Per unit irrigation demands vary with the  
479 projected climate change. Total future water consumption varies with the projected trends in  
480 population growth and economic development. HadGem2-ES was chosen to capture the average  
481 climatic conditions predicted from GCMs within the Inter-Sectoral Impact Model  
482 Intercomparison Project (ISIMIP, <https://www.isimip.org>). RCP8.5 was used to represent  
483 climatic conditions under the worst-case scenario for future GHG emissions. This coupled  
484 modeling tracks a range of key processes that are critical in global hydrology and water table  
485 dynamics, particularly precipitation, evapotranspiration, runoff, infiltration, surface-groundwater  
486 interactions, capillary rise, groundwater discharge, recharge and lateral flows, water-use by  
487 agriculture irrigation, industries, households and livestock, and return flows of unconsumed  
488 withdrawn water, and showed robust estimates, as compared to observations<sup>37</sup>. This is  
489 considered as the best available dataset on future WTD while we acknowledge potentially large  
490 uncertainties.  $\Delta_{\text{WTD}}$  is the difference between the average WTD during 2050-2100 (future) vs.  
491 1960-2010 (historical). To assess the impact of uncertainties in future  $\Delta_{\text{WTD}}$  quantifications, we  
492 conducted additional predictions with future  $\Delta_{\text{WTD}}$  being 0.2, 0.4, 0.6, 0.8, 1.2, 1.4, 1.6 and 1.8 of  
493 previous quantifications (Supplementary Table 8).

494 We used FLUXCOM NEE to estimate  $\text{CO}_2$  (NEE) before water table drawdown  
495 ( $\text{CO}_{2, \text{initial}}$ ). FLUXCOM NEE merged eddy covariance and remote-sensing observations through  
496 three machine learning techniques (MARS, ANN, RF) <sup>29</sup>. In addition, we incorporated an  
497 ensemble (18 in total) estimation of NEE generated by land models LPJ-GUESS, LPJML,

498 ORCHIDEE-DGVM, ORCHIDEE, VEGAS and VISIT driven by different climate forcing  
499 within the ISIMIP framework (Supplementary Table 3). CH<sub>4</sub> emissions are higher over wetland  
500 compared to upland soils<sup>38</sup>. We used gridded dataset from the Wetland CH<sub>4</sub> Inter-comparison of  
501 Models Project (WETCHIMP) which quantified CH<sub>4</sub> emission rate per wetland area from 7  
502 models (LPJ-Bern, CLM4Me, DLEM ORCHIDEE-ALT, ORCHIDEE, SDGVM and LPJ-WSL)  
503 to cover uncertainties in CH<sub>4,initial</sub><sup>30,39</sup>. Peatland is defined through the PEATMAP<sup>40</sup>, which  
504 combines geospatial information from a variety of peatland-specific databases and histosol  
505 distributions from the Harmonized World Soil Database V1.2 (HWSD) in the regions where  
506 peatland-specific information are not available. The total global peatland area is 4.23 million km<sup>2</sup>  
507 from PEATMAP. We assume no changes in future peatland distribution while acknowledging  
508 uncertainties in peatland area and that future peatland area may expand or shrink with new  
509 discoveries, under future climate change or land use. We tested the duration of water table  
510 manipulation with the manipulation variable going from long (>10 years), medium (1-10 years)  
511 to short-terms (<= 1 year). The impact of manipulation duration is not big, and we reported  
512 results with long-term duration.

513 Future climatic conditions were predicted from GCM runs driven by RCP8.5 (worst) and  
514 RCP2.6 (optimistic) emission scenarios (see ISIMIP). We chose simulations from three GCM  
515 models i.e., the GFDL-ESM2M (wettest), the HadGEM2-ES (average) and the MIROC-ESM-  
516 CHEM (driest) to account for climate uncertainties. Future potential evapotranspiration (PET)  
517 and the aridity index (the ratio between precipitation and PET) were estimated using the Penman  
518 Monteith equation for a hypothetical short grass as the reference surface ( python package,  
519 PyETo, <https://github.com/Evapotranspiration/ETo>).

520 We applied bootstrap resampling and ensemble prediction to estimate prediction  
521 uncertainties. For  $\Delta_{CO_2, WTD}$ , we randomly sampled 80% of our observation samples to build one  
522 random forest model. This random model was then used to make future predictions with  
523 different combinations of predictor datasets. We repeated this bootstrap resampling, random  
524 forest model building and future prediction 200 times. In total, we had 25200 (200 x 21  
525 CO<sub>2,initial</sub> x 2 WTD<sub>initial</sub> x 3 Climate) ensemble members and we calculated the 95% probability  
526 interval as the indicator of prediction uncertainty. Bootstrap resampling provides reasonable  
527 estimation of prediction uncertainty for random forest models<sup>41</sup> and the ensemble approach can  
528 take into account of both uncertainties from random forest algorithms and from predictor

529 variables. Similarly, we conducted 8400 predictions for  $\Delta_{\text{CH}_4, \text{WTD}}$  through 200 times bootstrap  
530 resampling, 7  $\text{CH}_{4, \text{initial}}$  datasets, 2  $\text{WTD}_{\text{initial}}$  datasets and 3 climate datasets (Supplementary  
531 Table 3). To quantify contributions to future  $\Delta_{\text{CO}_2, \text{WTD}}$  and  $\Delta_{\text{CH}_4, \text{WTD}}$ , we conducted a series of  
532 predictions (Supplementary Tables 6, 7) through sequentially replacing climate,  $\Delta_{\text{WTD}}$ ,  $\text{WTD}_{\text{initial}}$   
533 and  $\text{CO}_{2, \text{initial}}$  (or  $\text{CH}_{4, \text{initial}}$ ) by corresponding reference level datasets listed in Supplementary  
534 Table 3.

535

536

537

538 **Code availability**

539 Calculations were conducted through Python 3.7.3, R 3.6.2 and ferret 6.72. Data processing  
540 code and code used to generate figures are provided through  
541 <https://doi.org/10.6084/m9.figshare.13139906.v3><sup>42</sup>.

542 **Data availability**

543 Source datasets and global maps generated in this study are available at  
544 <https://doi.org/10.6084/m9.figshare.13139906.v3><sup>42</sup>.

545

546 **References**

547

- 548 31 Merbold, L. *et al.* Artificial drainage and associated carbon fluxes (CO<sub>2</sub>/CH<sub>4</sub>) in a tundra  
549 ecosystem. *Global Change Biology* **15**, 2599-2614, doi:10.1111/j.1365-  
550 2486.2009.01962.x (2009).
- 551 32 Borenstein, M., Hedges, L. V., Higgins, J. P. T. & Rothstein, H. R. A basic introduction  
552 to fixed-effect and random-effects models for meta-analysis. *Research Synthesis Methods*  
553 **1**, 97-111, doi:10.1002/jrsm.12 (2010).
- 554 33 Viechtbauer, W. Conducting Meta-Analyses in R with the metafor Package. *Journal of*  
555 *Statistical Software* **36**, 1-48 (2010).
- 556 34 van Groenigen, K. J., Osenberg, C. W. & Hungate, B. A. Increased soil emissions of  
557 potent greenhouse gases under increased atmospheric CO<sub>2</sub>. *Nature* **475**, 214-U121,  
558 doi:10.1038/nature10176 (2011).
- 559 35 Kirby, K. N. & Gerlanc, D. BootES: An R package for bootstrap confidence intervals on  
560 effect sizes. *Behavior Research Methods* **45**, 905-927, doi:10.3758/s13428-013-0330-5  
561 (2013).
- 562 36 Goldstein, A., Kapelner, A., Bleich, J. & Pitkin, E. Peeking Inside the Black Box:  
563 Visualizing Statistical Learning With Plots of Individual Conditional Expectation.  
564 *Journal of Computational and Graphical Statistics* **24**, 44-65,  
565 doi:10.1080/10618600.2014.907095 (2015).
- 566 37 de Graaf, I. E. M., Sutanudjaja, E. H., van Beek, L. P. H. & Bierkens, M. F. P. A high-  
567 resolution global-scale groundwater model. *Hydrology and Earth System Sciences* **19**,  
568 823-837, doi:10.5194/hess-19-823-2015 (2015).
- 569 38 Saunio, M. *et al.* The global methane budget 2000-2012. *Earth System Science Data* **8**,  
570 697-751, doi:10.5194/essd-8-697-2016 (2016).
- 571 39 Wania, R. *et al.* Present state of global wetland extent and wetland methane modelling:  
572 methodology of a model inter-comparison project (WETCHIMP). *Geoscientific Model*  
573 *Development* **6**, 617-641, doi:10.5194/gmd-6-617-2013 (2013).
- 574 40 Xu, J. R., Morris, P. J., Liu, J. G. & Holden, J. PEATMAP: Refining estimates of global  
575 peatland distribution based on a meta-analysis. *Catena* **160**, 134-140,  
576 doi:10.1016/j.catena.2017.09.010 (2018).

- 577 41 Coulston, J. W., Blinn, C. E., Thomas, V. A. & Wynne, R. H. Approximating Prediction  
578 Uncertainty for Random Forest Regression Models. *Photogrammetric Engineering and*  
579 *Remote Sensing* **82**, 189-197, doi:10.14358/pers.82.3.189 (2016).  
580 42 Huang, Y. et al. Supporting data for Tradeoff of CO<sub>2</sub> and CH<sub>4</sub> emissions from global  
581 peatlands under water-table drawdown. figshare. Dataset. doi:  
582 10.6084/m9.figshare.13139906 (2020).  
583

#### 584 **Corresponding author**

585 Correspondence to Yuanyuan Huang (yuanyuanhuang2011@gmail.com)

#### 586 **Acknowledgements**

587 Y.H., P.C., D.Z., C. Q. and D.S.G received support from the European Research Council  
588 Synergy project SyG-2013-610028 IMBALANCE-P and Y.H., P.C., D.Z., C.Q., D.S.G., B.G.  
589 and D.M. from the ANR CLAND Convergence Institute (ANR-16-CONV-0003).

#### 590 **Author contributions**

591 Y.H., P.C., L.Q. designed this study. Y. H., L.Q. and I.G.G. contributed the data. Y.H., P.C., Y.  
592 L., D. Z. and L.Q. discussed analyzing methods. Y.H. conducted the analysis and drafted the  
593 manuscript. All authors discussed the results and contributed to writing the manuscript.

#### 594 **Competing interests**

595 The authors declare no competing interests.  
596

#### 597 **Figure legends**

598 Figure 1. Effects of water table drawdown on peatland CO<sub>2</sub> and CH<sub>4</sub> fluxes. a, the net exchange  
599 of CO<sub>2</sub> (NEE), CH<sub>4</sub> and their combined response (GHG). b, ecosystem respiration (or soil  
600 respiration in the absence of live plants, RES) and photosynthetic CO<sub>2</sub> uptake (GPP). *n* is the  
601 number of experiments. Mean effect sizes were obtained through the meta-analysis. Error bars  
602 correspond to 95% confidence intervals. The unit of CH<sub>4</sub> is expressed as its CO<sub>2</sub> equivalent  
603 assuming its global warming potential is 25 times of CO<sub>2</sub>. We define a positive sign for  
604 emissions to the atmosphere and *vice versa*.  
605

606 Figure 2.  $\Delta_{\text{CO}_2, \text{WTD}}$  and  $\Delta_{\text{CH}_4, \text{WTD}}$  in response to predictors. One grey line captures responses per  
607 one pair of field studies to a gradual increase of the corresponding predictor while holding other  
608 predictors constant. Red lines are the averages across individual studies. We show the top three  
609 most important predictors ordered in declining importance from left to right (See Supplementary

610 Figures 13, 14 for other predictors).  $WTD_{initial}$ ,  $CO_{2,initial}$  and  $CH_{4,initial}$  are water table depth, net  
611 ecosystem exchange of  $CO_2$  and  $CH_4$  under high water table.  $\Delta_{WTD}$  is the magnitude of water  
612 table drawdown. Rugs at the bottom indicate the distributions of predictors.

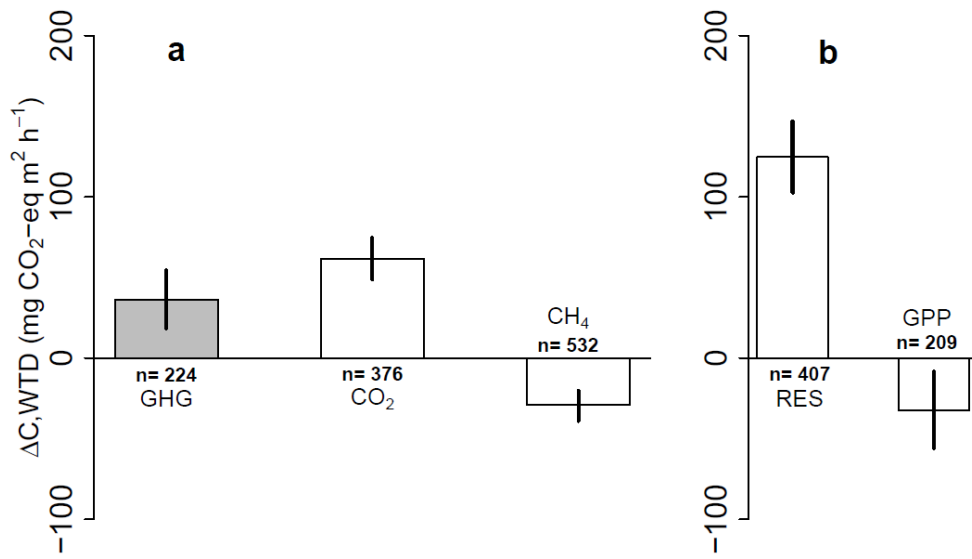
613

614 Figure 3. GHG changes ( $\Delta_{GHG,WTD} = \Delta_{CO_2,WTD} + \Delta_{CH_4,WTD}$ ) in response to water table drawdown by  
615 2100. Panels a, b show results with RCP8.5 climatic variables, and c, d under RCP2.6.  
616 Latitudinal totals (b, d) were estimated through the average values per area across 0.1 degree  
617 latitude band and peatland areas (Supplementary Figures 21, 22), and were smoothed with a  
618 window size of 5 degrees. Shading areas are 95% intervals. White region show locations with  
619 small  $\Delta_{GHG,WTD}$  or with negligible water table drawdown. Spatial distributions of  $\Delta_{CO_2,WTD}$  and  
620  $\Delta_{CH_4,WTD}$  are provided in Supplementary Figures 25, 26 and the 95% intervals in Supplementary  
621 Figures 27, 28.

622

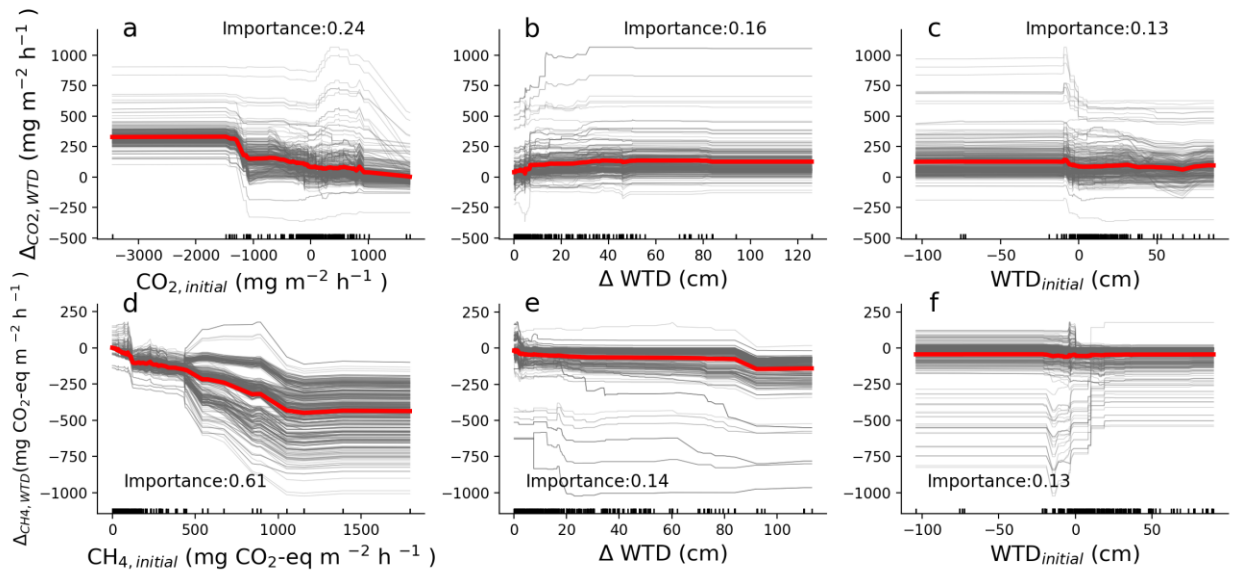
623 **Figures**

624 Figure 1.



625

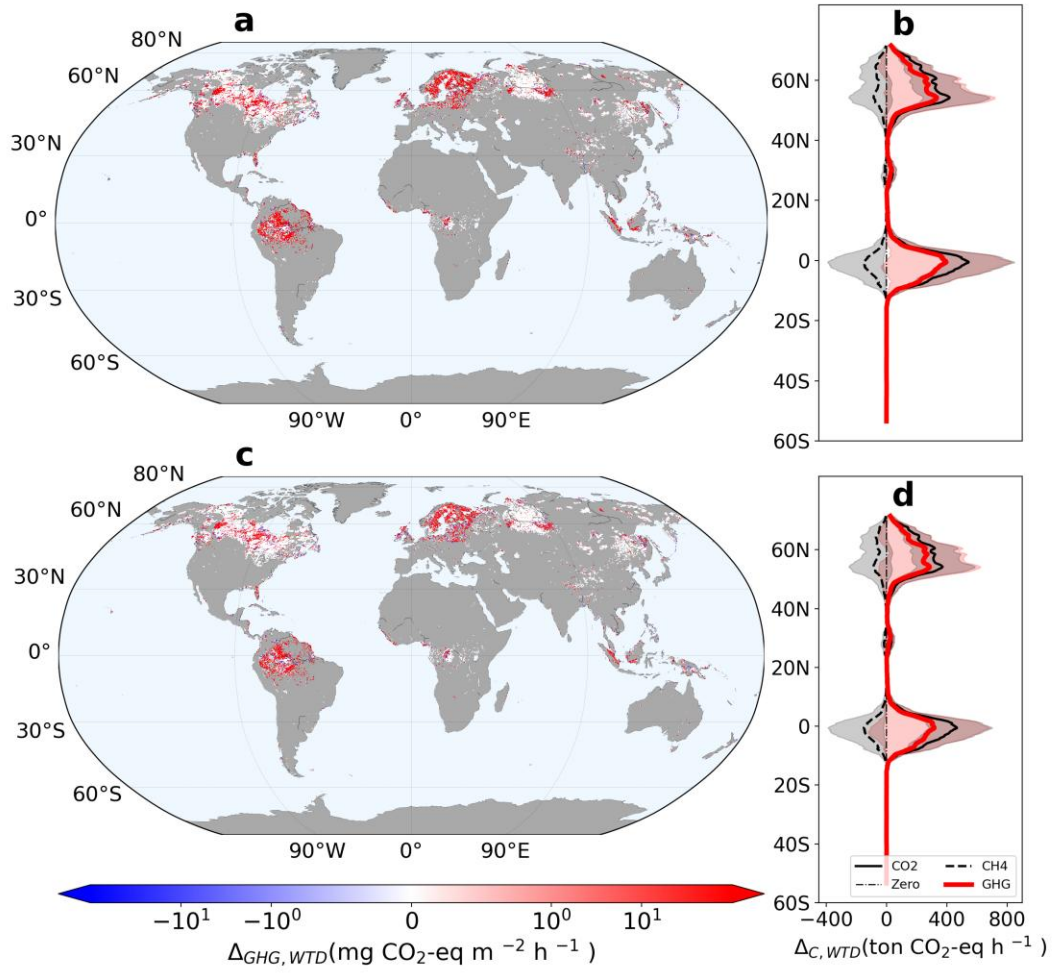
626 Figure 2.



627

628

629 Figure 3.



630

631