

1 **Combined water table and temperature dynamics control CO<sub>2</sub>  
2 emission estimates from drained peatlands under rewetting and  
3 climate change scenarios**

4 Tanja Denager<sup>1</sup>, Jesper Riis Christiansen<sup>2</sup>, Raphael Johannes Maria Schneider<sup>1</sup>, Peter Langen<sup>3</sup>,  
5 Thea Quistgaard<sup>3</sup>, Simon Stisen<sup>1</sup>

6 <sup>1</sup> Department of Hydrology, Geological Survey of Denmark and Greenland, Copenhagen, Denmark

7 <sup>2</sup> Forest and Landscape Ecology, Department of Geoscience and Nature Management, Copenhagen University,  
8 Denmark

9 <sup>3</sup> Department of Environmental Science, Atmospheric Emissions & Modelling, Aarhus University, Roskilde,  
10 Denmark

11 *Correspondence to:* Tanja Denager (tad@geus.dk)

12

13 **Abstract:**

14 This study integrates process-based hydrological modeling and empirical CO<sub>2</sub> flux modeling at a daily  
15 temporal resolution to evaluate how peatland hydrology influence CO<sub>2</sub> emissions under scenarios of  
16 rewetting and climate change.

17 Following the calibration of a three-dimensional transient groundwater flow model for a peat-  
18 dominated catchment, daily groundwater table dynamics were simulated to represent hydrological  
19 conditions in drained peat soils. These simulations were coupled with an empirical CO<sub>2</sub> flux model,  
20 developed from a comprehensive daily dataset of groundwater table depth, temperature, and soil CO<sub>2</sub>  
21 flux measurements. The empirical CO<sub>2</sub> flux model captures a clear temperature-dependent response of  
22 soil CO<sub>2</sub> emissions to variations in groundwater table depth.

23 By applying this coupled modeling framework, we quantified CO<sub>2</sub> emissions at daily timescales. The  
24 results demonstrate that incorporating both temperature sensitivity and high-resolution temporal  
25 variability in water level significantly influences projections of CO<sub>2</sub> fluxes. Especially the co-occurrence  
26 of elevated air temperature and low groundwater table significantly influence CO<sub>2</sub> emissions under  
27 scenarios of rewetting and climate change. These insights highlight the importance of including  
28 changing climate conditions in future peatland management strategies for emission inventories.

29 The study illustrates the value of combining detailed hydrological simulations with emission models. It  
30 also emphasizes the need for detailed monitoring of greenhouse gas emissions across multiple sites  
31 and the development of robust empirical models that can be generalized and spatially upscaled.

32

33 **Introduction**

34 Drained peatlands are widely accepted as being net greenhouse gas (GHG) sources and rewetting of  
35 peatlands is considered an effective means of overall net GHG emission reduction (Leifeld et al., 2019).  
36 The depth of the groundwater table below the surface i.e. the water table depth (WTD) largely  
37 controls the annual emissions of carbon dioxide ( $\text{CO}_2$ ) and methane ( $\text{CH}_4$ ) from organic soils, where  
38 deeper WTD results in  $\text{CO}_2$  emissions and a shallow WTD increases  $\text{CH}_4$  emissions (Evans et al., 2021).  
39 Despite triggering  $\text{CH}_4$  emissions, rewetting of organic soils will still lead to a net long-term reduction  
40 of GHG emissions (Günther et al., 2020). However, current estimates of GHG emissions from drained  
41 and rewetted peatlands are still quite uncertain due to a lack of long-term monitoring and simplified  
42 modeling approaches.

43 Commonly adopted methodologies for estimating contribution of organic soils in national GHG  
44 inventories (Arents et al., 2018; Evans et al., 2021; Koch et al., 2023; Tiemeyer et al., 2020) are based  
45 on empirical response functions between long-term annual mean WTD estimates from data-driven  
46 machine learning (ML) models (Bechtold et al., 2014; Koch et al., 2023) and observed net ecosystem  
47 GHG budgets (Tiemeyer et al. 2020). Those methodologies allow regional upscaling and integration  
48 into national emission estimates.

49 However, significant variability in the observed net ecosystem carbon balance (NECB) used to derive  
50 the empirical relationship can be attributed to site-specific factors, including intra-annual (seasonal)  
51 WTD and temperature dynamics (Tiemeyer et al., 2020) caused by fluctuating climate. The current  
52 GHG inventory methods are not suited to account for extremes such as drought and flooding that have  
53 a profound, but temporally limited (days, weeks or months) impact on WTD. Especially the frequency  
54 and severity of droughts can have major impacts on the  $\text{CO}_2$  emissions as WTD increases together with  
55 temperature (Olefeldt et al., 2017). Therefore, temperature changes also directly impact GHG  
56 emissions, as soil  $\text{CO}_2$  and  $\text{CH}_4$  production are temperature sensitive. Currently, the impact of short-  
57 term compound events (e.g., simultaneous warm and dry conditions (Zscheischler et al., 2020) on  
58 annual  $\text{CO}_2$  emissions from peat soil is little known. Such events can lead to consequences like a deep  
59 groundwater table, highlighting the need for improved understanding of how climate variability and  
60 long-term change (Olefeldt et al., 2017) affect future  $\text{CO}_2$  emissions from both drained and rewetted  
61 peatlands.

62 For Denmark, it is generally expected that, as a result of climatic changes, annual mean WTD will  
63 decrease (water tables closer to surface). However, this decrease in annual mean WTD is primarily  
64 attributed to a decrease in WTD during the wetter winter months, while warmer future summers are  
65 anticipated to experience minimal decrease or even increase in summer WTD (water tables deeper  
66 below the surface) and more prolonged periods with increased WTD (Henriksen et al., 2023;  
67 Seidenfaden et al., 2022).

68 The ML and statistical models of annual mean WTD (Bechtold et al., 2014; Koch et al., 2023) utilized in  
69 current national GHG inventories (Gyldenkærne et al., 2025; Koch et al., 2023; Nielsen et al., 2025b;  
70 Tiemeyer et al., 2020) effectively reflect the spatial variability at the national scale, but most current  
71 ML WTD models are temporally invariant and account for neither inter-annual (between-year)  
72 variability nor seasonal or intra-annual variability in WTD or temperature. . To establish WTD- $\text{CO}_2$   
73 relations at intra-annual time scales, capable of capturing the impact of short-lived extreme events  
74 such as droughts and inundations, WTD time series at these finer temporal resolutions are required.  
75 For this, process-based transient 3D hydrological models capable of integrating unsaturated-saturated  
76 flow models to predict spatial and temporal variability of WTD are highly useful. Combined with the  
77 WTD- $\text{CO}_2$  relation we claim these model outputs can be used to calculate the  $\text{CO}_2$  emissions on daily,  
78 seasonal, and inter-annual timescales.

Such hydrological models provide the potential for improving our estimation of peatland hydrology and thereby the spatio-temporal WTD variability. Improved representation of temporal variability of WTD are needed for refining the current and future GHG estimates that cannot be derived using the simple application of IPCC default emission factors (IPCC, 2014). Process-based hydrological models offer the opportunity to assess the effect of different management strategies and environmental conditions, such as rewetting and climate change.

Process-based hydrological models are increasingly being applied to study dynamics of peatland hydrology (Mozafari et al., 2023). For instance, Land Surface Models (LSM) (Bechtold et al., 2019; Largeron et al., 2018; Shi et al., 2015; Yuan et al., 2021) are employed to analyze the soil–plant–atmosphere exchange processes of water, energy and carbon. However, most LSM's rely on a simplified conceptual representation of hydrologic processes and are characterized by coarse spatial scales.

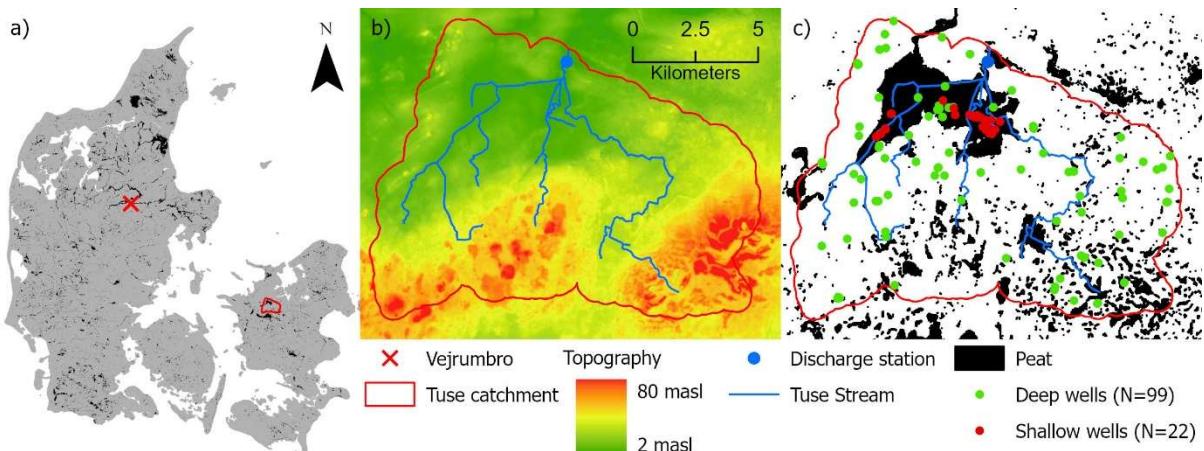
Of the studies applying fully integrated unsaturated-saturated flow models for peatland hydrology, some focus on site or field-scale models (Friedrich et al., 2023; Haahti et al., 2015; Java et al., 2021; Stenberg et al., 2018) while others apply the models at catchment scale (Ala-aho et al., 2017; Duranel et al., 2021; Friedrich et al., 2023; Jutebring et al., 2018; Lewis et al., 2013). A catchment scale approach with water balance closure is particularly important for climate change impact predictions, since the boundary conditions to the peatlands will also be affected by climate change. Similarly, the use of catchment scale models is important because impact evaluations of peatland management scenarios, such as rewetting, can also include impacts on streamflow and groundwater levels in neighboring areas.

The objectives of this study were to 1) estimate current and predict the future hydrology and soil CO<sub>2</sub> emissions in a Northern European drained peatland and 2) investigate the role of rewetting and climatic extremes on annual CO<sub>2</sub> emissions. To achieve these objectives, we used a transient physically-based hydrological 3D model to predict daily WTD for a case study area, the Tuse Stream catchment, representing a typical degraded Danish peatland. Secondly, we developed an empirical soil CO<sub>2</sub> flux (fCO<sub>2</sub>) model based on coupled CO<sub>2</sub> flux, WTD and temperature observations for a similar Danish peatland (Nielsen et al., 2025a), capable of making daily predictions. Combining the mechanistic hydrological model and the empirical emission model enabled the estimation of daily soil CO<sub>2</sub> fluxes under current conditions as well as scenarios of rewetting and future climate, while accounting for the impact of climatic variability and extremes.

## 110 Data and methodology

### 111 Study area

112 Tuse Stream catchment is located on the island of Zealand in the eastern part of Denmark (Figure 1a).  
113 The total area encompasses 107 km<sup>2</sup> of which 19 km<sup>2</sup> are peat soil. The areal extent of peat soil was  
114 determined using a national map of organic soils (Adhikari et al., 2014). The largest continuous peat  
115 area within the catchment is a 13 km<sup>2</sup> drained fen located in a river valley (Figure 1c) in the low-lying  
116 part of the catchment. The peat soil area is primarily used for agriculture. In small parts of the area,  
117 the drainage has been stopped to restore the natural hydrologic regime. The measured peat layer  
118 thickness extends from 0.4 to 3.5 meters, below which alluvial sand deposits are typically found.  
119 Generally, the deeper geology in the area can be characterized as clay-dominated glacial till deposits.  
120 The catchment is characterized by flat topography, with the southern part of the catchment being  
121 hillier. The climate conditions are humid and temperate. The catchment receives about 737 mm of  
122 precipitation per year (1990-2024) and has an annual mean temperature of 9°C (Scharling, 1999a, b).



123

124 *Figure 1: a) Location of Tuse Stream catchment and the Vejrumbro site, b) topography and stream network of Tuse Stream*  
 125 *catchment, masl: meter above sea level, c) location of organic soil and observation wells in the Tuse Stream catchment.*

126 Shallow WTD in the drained organic soils is monitored in 22 groundwater wells (2-3.5 meters deep)  
 127 (Figure 1c). The wells are fully screened and WTD is automatically logged with pressure transducers at  
 128 an hourly basis (aggregated to daily values) and verified with manual measurements. All WTD data are  
 129 available in the Danish National Well Database (Jupiter, 2025). In this study, we define the water table  
 130 depth (WTD) as positive when located below the surface and negative when above the surface.  
 131 Monitoring data includes additional point measurements and timeseries of groundwater head from 99  
 132 deep wells installed in mineral soils throughout the catchment (Figure 1c). In the model setup, water  
 133 extraction in 40 abstraction wells is included based on data from the Danish National Well Database in  
 134 May 2020 (Henriksen et al., 2020) and implemented as yearly mean abstraction evenly distributed on  
 135 the daily model timesteps. Daily discharge is monitored at the catchment outlet at Tuse Stream (Figure  
 136 1b).

### 137 Hydrological modelling

138 The focus of the hydrological modelling in this study is to adequately simulate shallow groundwater  
 139 levels and their dynamics for the peatland area in the Tuse Stream catchment. The fen peatland in  
 140 Tuse Stream catchment is largely fed by groundwater discharge from the upstream catchment,  
 141 emphasizing the need to develop a coupled groundwater surface water model at catchment scale. In  
 142 addition, the objective of utilizing the model for climate change impact assessments requires a  
 143 catchment scale approach with a deep groundwater component to represent changes in groundwater  
 144 and surface water discharge to the peatland as well as changes in the boundary conditions. The  
 145 catchment scale approach also facilitates the combined calibration and evaluation of the total water  
 146 balance and peatland WTD by constraining the model with observed streamflow at the outlet as well  
 147 as peatland groundwater level dynamics.

148 The model is set up as a transient, distributed, coupled surface-groundwater model and executed  
 149 within the hydrological modeling framework MIKE SHE (DHI, 2022; Graham and Butts, 2005). MIKE SHE  
 150 combines full 3D groundwater flow coupled with a gravity flow module in the unsaturated zone, 2D  
 151 overland flow and 1D river flow routing in streams (DHI, 2019) (Figure S1). The simplified gravity flow  
 152 module for unsaturated flow assumes a uniform vertical gradient and ignores capillary forces but  
 153 provides a suitable solution for the time varying recharge to the groundwater table based on  
 154 precipitation and evapotranspiration (DHI, 2022).

155 The model is a modified sub-model of the National Hydrological Model of Denmark (DK-model),  
 156 developed at the Geological Survey of Denmark and Greenland (GEUS) (Henriksen et al., 2020; Stisen  
 157 et al., 2019). The geological model is interpreted in a horizontal 100 meter grid. The numerical model is

158 calibrated in the same 100 meter resolution, with the saturated zone consisting of 11 computational  
159 layers of varying thickness. The top model layer has a uniform thickness of 2 meters, which is also  
160 applied to the peat layer areas. The bottom level of the groundwater model is defined by the  
161 prequaternary chalk that underlies the Island of Zealand, which in the Tuse Stream catchment is  
162 located in a depth of approximately 150-250 meters below surface.

163 The time-varying constant head boundary conditions at the sub-model boundary are defined from the  
164 operational National Hydrological Model setup (Henriksen et al., 2020). The observed forcing data of  
165 precipitation, temperature and reference evapotranspiration are provided by the Danish  
166 Meteorological Institute (DMI) as gridded daily data in 10 km resolution for precipitation and 20 km  
167 resolution for evapotranspiration and temperature (Scharling, 1999a, b; Stisen et al., 2011). The model  
168 employs a maximum timestep of one day, at which the meteorological variables are fed into the  
169 model. The model was provided with a hotstart file from an initial model run.

170 Spatial and temporal distributions of root depth and LAI are based on classes (Figure S2 and Table S1)  
171 where the peat, forest, agricultural and open nature land use classes have yearly cycles of LAI and root  
172 depth (Figure S3). Likewise, soil type is spatially distributed (Figure S2) and based on the three classes  
173 peat, sand and clay (Table S2). In the vertical direction, the soil columns in the unsaturated zone  
174 module are divided into 40 cells from top to bottom; 30x0.1m, 5x1m and 5x5m. Technically, the  
175 unsaturated zone is parameterized to 33 m depth, but during simulation limited to the top of the  
176 simulated groundwater table. We implemented uniform vertical water retention characteristics of  
177 peat, while clay and sand water retention characteristics were defined separately for the depths 0-30  
178 cm (horizon A), 30-70 cm (horizon B) and >70 cm (horizon C). Soil parameterization is freely adapted  
179 from (Børgesen et al., 2009) and detailed in Table S3.

180 MIKE SHE allows incorporation of drainage systems, representing both artificial and natural drains. The  
181 drainage system bypasses the slow water movement in aquifers by providing a short-cut from e.g. the  
182 agricultural field to the nearest stream. The amount of water routed by drains from the saturated zone  
183 to local surface water bodies is calculated using a linear reservoir model, where the difference  
184 between groundwater head and drain level is multiplied by a drain time constant ( $dt$ ). The drain level is  
185 defined by a drain depth ( $dd$ ) set relative to surface level. Hence, drainage in any given model cell only  
186 occurs if the simulated groundwater level exceeds the drainage level (DHI, 2022). The drain time  
187 constant and drainage depth in each model grid cell are distributed across the model domain  
188 according to the five land use classes (Figure S2 and Table S1).

189 The model parameter sensitivity analysis and subsequent calibration prioritized parameters affecting  
190 the shallow WTD in the peat soil and the overall water balance in the catchment. A list of model  
191 parameters can be seen in Table S3. Parameter values not included in the calibration process are  
192 obtained from the National Hydrological Model parametrization.

### 193 Calibration method

194 We used the Pareto Archived Dynamically Dimensioned Search (PADDS) algorithm (Asadzadeh and  
195 Tolson, 2013) available within the optimization toolkit Ostrich (Matott, 2019). PADDS is a multi-  
196 objective optimizer and obtains the pareto front across multiple objective function groups, enabling  
197 post-weighting of individual objective functions. Throughout the calibration routine, Ostrich minimized  
198 the weighted sum of squared error (WSSE) of each of the objective function groups. The PADDS  
199 algorithm was run with the user settings of maximum 1000 iterations. The period 2010-2013 was used  
200 as a calibration spin-up period and the model performance was evaluated for the 2014-2023  
201 calibration period.

202 Calibration was performed against three objective function groups:  $KGE_{WTD\_modified}$ ,  $r_{spatial}$  and  
203  $KGE_qME_{head}ME_{amp}$ . The  $KGE_{WTD\_modified}$  objective group is used to optimize the model performance with  
204 respect to the WTD in peatlands.  $KGE$  is the Kling-Gupta Efficiency and consists of three terms: the  
205 Pearson correlation coefficient  $r$ , a term representing the measure of variability  $\alpha$  and a bias term  $\beta$ . In  
206  $KGE$ ,  $\beta$  is a unitless measure of the bias specified as the ratio between the sum of simulated and  
207 observed values ( $\beta = \sum_{sim}/\sum_{obs}$ ). As we use  $KGE$  to optimize the WTD (and not hydraulic head), the  
208 operational sign can be both negative (water table above surface/inundation) and positive (water  
209 table below surface), violating the idea of optimizing  $\beta$  as the ratio of sums of values with possibly  
210 alternating operational signs. Therefore, we are using  $KGE_{WTD\_modified}$  where  $\beta$  is replaced by the mean  
211 error (ME) (Table 1). This modification requires that the order of magnitude of the  $ME_{WTD}$  is  
212 comparable to the errors on the other terms in  $KGE$ . In our case this is ensured by the fact that the  
213 mean observed WTD values range between approximately 0.3-0.6 m, resulting in  $ME_{WTD}$  values  
214 typically below 0.5 m. Alternatively, the  $ME_{WTD}$  term could be scaled within the  $KGE_{WTD}$  equation.

215 The calibration using the  $KGE_{WTD\_modified}$  as objective function group aims at achieving the best overall  
216 agreement between simulated and observed WTD. However, during first calibration experiments, we  
217 found that this objective function group primarily focuses on the temporal dynamics of WTD. To  
218 improve the representation of the spatial variability of the mean WTD, the correlation coefficient  
219 ( $r_{spatial}$ ) was included as an additional objective function group (Table 1).

220  $KGE_qME_{head}ME_{amp}$  is an objective function group that combines three performance criteria: the Kling-  
221 Gupta Efficiency performance criterion for discharge ( $KGE_q$ ), the mean error of hydraulic head in  
222 deeper aquifers ( $ME_{head}$ ) and the mean error of annual amplitude of hydraulic head in the deeper  
223 aquifers ( $ME_{amp}$ ). For a detailed description of the implementation of  $ME_{amp}$  as objective function see  
224 (Henriksen et al., 2020). This objective function group was included to optimize the overall water  
225 balance and streamflow dynamics expressed through the discharge at the catchment outlet ( $KGE_q$ ), to  
226 match the general water level in the deeper aquifers across the catchment ( $ME_{head}$ ), and to match the  
227 natural seasonal variations in hydraulic head ( $ME_{amp}$ ). As the metrics of  $KGE_q$ ,  $ME_{head}$  and  $ME_{amp}$  are  
228 combined into one objective function group, we need to weigh the observations, to ensure that  $KGE_q$ ,  
229  $ME_{head}$  and  $ME_{amp}$  affect the objective group of  $KGE_qME_{head}ME_{amp}$  approximately equally. This was done  
230 based on WSSE from a model run with initial parameter values.

231

232

233

234

235

236

237

238

239

240

241 Table 1: Objective functions metrics. KGE stands for Kling-Gupta Efficiency.

Objective function group	Observations	No. of observation wells	Metric	Abbreviation	Equation	Range	Optimum value
KGE <sub>WTD_modifie<sub>d</sub></sub>	Daily WTD in shallow wells (in peat)	22	Modified KGE on WTD	KGE <sub>WTD_modifie<sub>d</sub></sub>	$1 - \sqrt{(r_{WTD} - 1)^2 + (\alpha_{WTD} - 1)^2 + (ME_{WTD})^2}$ Where, $ME_{WTD} = \frac{1}{n} \sum_{i=1}^n WTD_{simi} - WTD_{obsi}$	[-∞;1]	1
$r_{spatial}$	Mean WTD over the calibration period	22	Spatial correlation of the mean WTD	$r_{spatial}$	$r(\overline{WTD_{sim}}, \overline{WTD_{obs}})$	[-1;1]	1
KGE <sub>q</sub> ME <sub>head</sub> ME <sub>amp</sub>	Discharge	1	KGE on discharge	KGE <sub>q</sub>	$1 - \sqrt{(r_q - 1)^2 + (\alpha_q - 1)^2 + (\beta_q - 1)^2}$	[-∞;1]	1
	Hydraulic head in deep wells (in mineral soil)	66	Mean error on hydraulic heads	ME <sub>head</sub>	$\frac{1}{n} \sum_{i=1}^n head_{simi} - head_{obsi}$	[-∞;∞]	0
		8	Mean error on yearly amplitude of hydraulic heads	ME <sub>amp</sub>	$\frac{1}{n} \sum_{i=1}^n A_{simi} - A_{obsi}$	[-∞;∞]	0

242 WTD: water table depth [m], q: discharge [m/s], head: hydraulic head [m], A: amplitude [m]

243 A local sensitivity analysis based on initial parameter values from Table S4 was performed and values  
 244 of composite scaled sensitivity (CSS) were obtained. Selection of free calibration parameters were  
 245 based on the criterion that parameters were included if their CSS was larger than 0.05\*CSS of the  
 246 parameter with the highest CSS. The resulting 11 free parameters are indicated with grey in Table S4.  
 247 Other parameters were kept at the values listed in Table S4 or tied to the calibration parameters.

248 Hydrological simulations of historical and future climate  
 249 The calibrated hydrological model was run for the historical simulation period of 1990-2023 using  
 250 observed climate forcing data (Scharling, 1999a, b; Stisen et al., 2011). Future hydrological projections  
 251 are derived from simulations using the hydrological model forced by climate model projections,  
 252 including precipitation, air temperature ( $T_{air}$ ), and potential evapotranspiration. The resulting impacts  
 253 on groundwater levels, as simulated by the hydrological model, are evaluated. We used 17 climate  
 254 models (Table S5) with the Representative Concentration Pathway 8.5 (RCP8.5), which represents the  
 255 RCP scenario (2.6-8.5) leading to the highest emissions and strongest impact of climate change. The  
 256 climate model outputs are generated and bias corrected by Pasten-Zapata et al. (2019), and the Global  
 257 and Regional Circulation (GCM, RCM) models originate from the Euro-CORDEX project (Jacob et al.,  
 258 2014).

259 The climate simulations cover three 30-year periods: the reference period (1991-2020), the mid-  
 260 century (2041-2070) and the end-century (2071-2100). All 51 climate simulations (17 climate models ×  
 261 3 periods) were first run using the initial potential head from the national model climate simulations  
 262 (Henriksen et al., 2020). Subsequently, they were rerun using the mean potential head for the  
 263 respective 30-year period as the initial potential head.

264 Empirical CO<sub>2</sub> emission models

265 Implementation of annual CO<sub>2</sub> emission model

266 Recent studies established a functional relationship between the annual net ecosystem carbon balance

267 (NECB) for CO<sub>2</sub> and the mean annual WTD (Koch et al., 2023; Tiemeyer et al., 2020) by fitting a

268 nonlinear Gompertz function. Like in Koch et al. (2023) and Tiemeyer et al. (2020), this study considers

269 NECB as only CO<sub>2</sub> fluxes, excluding methane (CH<sub>4</sub>) and other carbon exports such as dissolved or

270 particulate organic carbon. We apply the WTD functional relationship for CO<sub>2</sub> from Koch et al. (2023),

271 which is fitted to Danish flux data, and refer to it as the *Annual WTD model*. The *Annual WTD model*

272 demonstrates a systematic relationship in which CO<sub>2</sub> flux from NECB increases with annual WTD in the

273 interval between 7 cm and 50 cm, above which an asymptotic level of 10 Mg CO<sub>2</sub>-C ha<sup>-1</sup> yr<sup>-1</sup> is reached

274 (Koch et al., 2023). The *Annual WTD model* is therefore not sensitive to changes in WTD deeper than

275 approximately 50 cm. At WTD levels less than 7 cm, the *Annual WTD model* suggests CO<sub>2</sub> uptake;

276 however, this element is not included in our analysis which only models CO<sub>2</sub> emission.

277 Derivation and implementation of daily CO<sub>2</sub> emission model

278 For our empirical model to predict daily soil CO<sub>2</sub> fluxes (fCO<sub>2</sub>) we assume that the WTD dependent

279 NECB (Tiemeyer et al. 2020, Koch et al. 2023) is driven mainly by the response of soil respiration to

280 WTD and T<sub>air</sub>, as gross primary photosynthesis (GPP) and aboveground autotrophic respiration is

281 mostly dependent on light availability and plant phenology (Rodriguez et al., 2024). This allows scaling

282 to match the NECB magnitude but maintains integrity in the regulation of WTD on soil CO<sub>2</sub> fluxes.

283 Using a unique and comprehensive coupled dataset (Nielsen et al., 2025a) of daily mean net soil CO<sub>2</sub>

284 fluxes, T<sub>air</sub> and WTD for six spatial replicate measurement points, we develop a coupled temperature

285 and WTD dependent empirical soil CO<sub>2</sub> flux model, hereafter referred to as the *Daily WTD-T<sub>air</sub> model*.

286 The model essentially scales the WTD-fCO<sub>2</sub> relation to T<sub>air</sub>. The dataset Nielsen et al. (2025a) is from a

287 drained fen, called Vejrumbro (Figure 1), with similar characteristics (soil type, climate, land use

288 history) as the peat area in the Tuse Stream catchment (see methodological details in Nielsen et al.

289 (2025a). The soil net CO<sub>2</sub> fluxes, WTD and T<sub>air</sub> were measured automatically for one year (2022-2023)

290 (Nielsen et al., 2025a) and we used a subset of fluxes measured for six spatial replicates 5-6 times per

291 day, resulting in a dataset of 10950 – 13140 individual fluxes covering 365 days (Nielsen et al., 2025a).

292 Implementation of CO<sub>2</sub> flux models

293 Spatially distributed net soil CO<sub>2</sub> fluxes are calculated at a 100-meter scale across the 13 km<sup>2</sup>

294 contiguous peatland area (Figure 1) with the *Annual WTD model* and the *Daily WTD-T<sub>air</sub> model*,

295 respectively, using WTD at a 100-meter scale (hectare scale) and a uniform T<sub>air</sub>. Afterwards the

296 spatially distributed soil CO<sub>2</sub> fluxes are aggregated to represent the spatial mean of the 13 km<sup>2</sup>

297 peatland area.

298 First, we applied the *Annual WTD model* and the *Daily WTD-T<sub>air</sub> model* for the historical simulation

299 period of 1990-2023, using spatiotemporal distributed WTD from the calibrated hydrological model.

300 Afterwards, the empirical CO<sub>2</sub> models are utilized on each of the 17 climate projections for T<sub>air</sub> and

301 WTD. Daily T<sub>air</sub> for the Tuse Stream catchment peatland area is taken directly from the 17 bias

302 corrected climate projections, while daily spatial WTD is a model output from the 17 hydrological

303 simulations, when running the hydrological model with the forcing data (precipitation, temperature

304 and evapotranspiration) from the 17 climate projections. Thereby, we are able to quantify the

305 variability in soil CO<sub>2</sub> flux among the 17 climate projections for each of the simulation periods and

306 among the 30 years within each of the simulation periods.

307 Design and application of rewetting scenarios  
308 For impact evaluations of peatland management scenarios on the annual CO<sub>2</sub> emissions, we define  
309 three rewetting scenarios: A, B and C. These scenarios are implemented through controlled  
310 modifications of the simulated WTD in peatland grid cells. This method of representing rewetting  
311 scenarios does not involve structural modifications to the hydrological model and assumes changes in  
312 WTD without accounting for process-based feedback mechanisms within the coupled surface–  
313 subsurface hydrological system. Therefore, the rewetting scenarios cannot be interpreted as real-life  
314 management practices. All rewetting scenarios were applied for 1990 to 2023, representing the  
315 climatology for this period and generating 34-year time series of rewetted WTD.

316 The scenarios are meant to illustrate different rewetting impacts on WTD, representing wetter winters  
317 (A), uniform shift in WTD (B) and wetter summers (C), but all with the same long-term mean WTD. In  
318 Scenario A, the daily groundwater table is elevated when it is above the long-term (34-year) mean  
319 water table resulting in unchanged water table levels during summer but an increase in winter.  
320 Scenario B uniformly raises the water table by a constant scalar, while Scenario C applies the same  
321 scalar increase to water table while simultaneously reducing the annual amplitude by half. The  
322 modifications of the simulated WTD are implemented using the following equations:

$$323 WTD_{i,rewet\ A} = \begin{cases} WTD_i, & \text{if } WTD_i \geq \overline{WTD} \\ WTD_i + 2.5 \cdot (\overline{WTD} - WTD_i), & \text{if } WTD_i < \overline{WTD} \end{cases} \quad [2]$$

324

$$325 WTD_{i,rewet\ B} = WTD_i - (\overline{WTD} - \overline{WTD_{rewet\ A}}) \quad [3]$$

326

$$327 WTD_{i,rewet\ C} = \overline{WTD_{rewet\ B}} + 0.5 \cdot (WTD_{i,rewet\ B} - \overline{WTD_{rewet\ B}}) \quad [4]$$

328

329 where  $WTD_{i,rewet\ A}$ ,  $WTD_{i,rewet\ B}$  and  $WTD_{i,rewet\ C}$  is the daily WTD in a grid cell for rewetting  
330 scenario A, B and C, respectively.  $WTD_i$  is the daily WTD in a grid cell from the calibrated hydrological  
331 model.  $\overline{WTD}$  is the long-term (34-year) mean WTD in a grid cell from the historical period of the  
332 calibrated hydrological model.  $\overline{WTD_{rewet\ A}}$  and  $\overline{WTD_{rewet\ B}}$  are long-term (34-year) mean WTD in a  
333 grid cell from the rewetting scenario A and B, respectively.

334 Bootstrapping means of future climate CO<sub>2</sub> emissions

335 We applied a bootstrap resampling approach to estimate the uncertainty in the mean values of soil  
336 CO<sub>2</sub> flux. Specifically, we resampled the means over the 17 climate models, each containing 30 annual  
337 values, with replacement. This process was repeated 10,000 times to construct bias-corrected and  
338 percentile-based 95% confidence intervals around the bootstrapped means.

339

340 Results

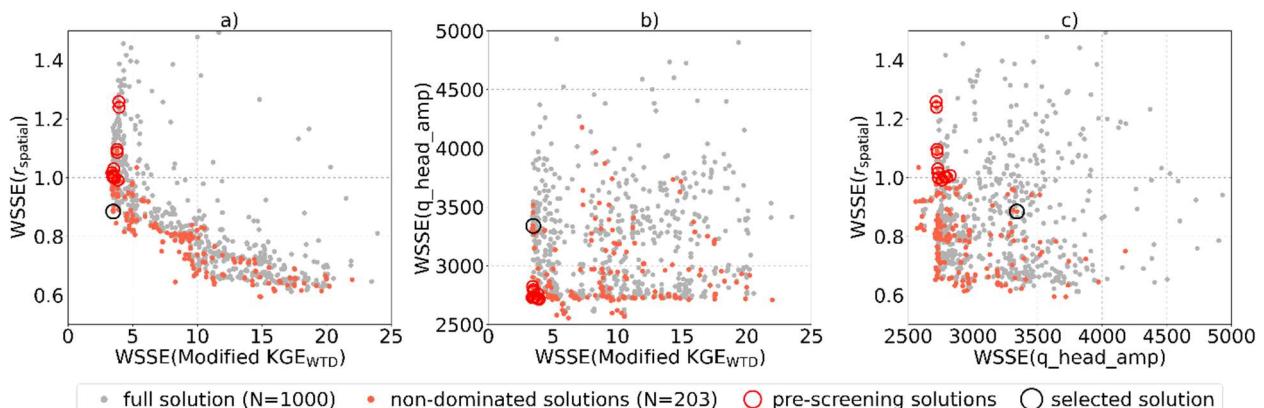
341 Hydrological model

342 Calibration of the hydrological model

343 The model calibration, running 1000 model evaluations based on three objective function groups,  
 344 using Ostrich ParaPADDS optimizer with 40 parallel model executions, took ~24 hours on a Xeon E-  
 345 4850 @2,20 GHz Server. The calibration resulted in 203 non-dominated solutions forming a three-  
 346 dimensional pareto front. Figure 2 presents scatterplots of the three objective functions, illustrating  
 347 the trade-offs between them. Especially, there is a clear trade-off between the two objective functions  
 348 addressing temporal dynamics ( $KGE_{WTD}$ ) and spatial dynamics ( $r_{spatial}$ ), as illustrated in Figure 2a.

349 The number of non-dominated solutions and the trade-offs illustrate that several parameter sets can  
 350 be considered and that an ensemble of parameter sets could be selected. For the purpose of further  
 351 analysis and climate change impact assessments, however, we select one balanced solution from the  
 352 non-dominated solutions, through a stepwise procedure. First, a pre-screening was performed with  
 353 performance criteria for WTD of  $KGE_{WTD}$  larger than 0.6, for discharge of  $KGE_{discharge}$  larger than 0.6 and  
 354 for hydraulic head in deeper wells of  $\pm 1$  m, for  $ME_{head}$  and  $ME_{amp}$ , respectively. Afterwards, the  
 355 balanced parameter set was selected as the solution with the highest spatial correlation ( $r_{spatial}$ ).

356 The selection procedure was designed to prioritize accurate simulation of the temporal dynamics of  
 357 peatland WTD, while maintaining strong performance across additional objective functions and  
 358 maximizing spatial correlation accuracy. Initial calibration efforts indicated that achieving a  $KGE_{WTD}$   
 359 value greater than 0.6 was necessary to ensure an adequate alignment between the simulated and  
 360 observed WTD time series.



361  
 362 *Figure 2: Scatterplots of WSSE (weighted sum of squared errors) for the three objective function groups in the calibration.*  
 363 *Pareto front for 1000 model evaluations.*

364 Hydrological model performance

365 Model performance metrics for the selected solution are summarized in Table 2. The  $q\_head\_amp$   
 366 objective function is separated into individual contributions from the metrics  $KGE_q$ ,  $ME_{head}$  and  $ME_{amp}$ .  
 367 Additionally, Table 2 shows the three metrics which make up the modified  $KGE_{wtd}$ :  $r_{wtd}$ ,  $\alpha_{wtd}$  and  $ME_{wtd}$ .  
 368 In general, the model performs well with a  $KGE_{wtd}$  in peat of 0.64, a  $KGE_q$  of 0.63, a  $ME_{head}$  for the deep  
 369 wells of 0.75 m and a  $ME_{amp}$  for the deep wells of 0.51 m for the selected solution. However, the  
 370 correlation coefficient for the spatial variability ( $r_{spatial}$ ) is poor with a value of 0.06. The model  
 371 optimization achieves solid metrics on all the three components of  $KGE_{wtd}$ . The mean bias of WTD  
 372 across all shallow peatland observation wells ( $ME_{wtd}$ ) is only 8 cm (Table 2).

373 Table 2: Hydrological model performance

Name of metric	Abbreviation	Unit	Selected solution
Modified KGE on WTD	$KGE_{WTD,modified}$	-	0.64
Correlation coefficient WTD	$r_{WTD}$	-	0.83
Measure of variance	$\alpha_{WTD}$	-	0.14
Mean error of WTD	$ME_{WTD}$	m	0.08
Spatial correlation of the mean WTD	$r_{spatial}$	-	0.06
KGE on discharge	$KGE_q$	-	0.63
Mean error on the hydraulic heads	$ME_{head}$	m	0.75
Mean error on amplitude of the hydraulic heads	$ME_{amp}$	m	0.51

374

375 Though the model obtains a relatively small mean error, it largely underestimates the spatial variability  
 376 in WTD. The observed mean WTD variability across the 22 monitoring wells ( $SD = 16.5$  cm) is  
 377 considerably higher than that observed in the simulations ( $SD = 6.8$  cm). Even though the model  
 378 performance on  $KGE_{WTD}$  was generally good, it proved difficult to reproduce the spatial variation in  
 379 mean WTD.

380 To investigate the underestimation of spatial variability in WTD, we analyzed several spatial variables  
 381 considered relevant for explaining the observed variability in WTD: peat thickness, topography and  
 382 proximity to water bodies. However, no clear correlation was found between these spatial variables  
 383 and the mean observed WTD or model bias, as all had a correlation coefficient smaller than 0.34. See  
 384 Table S6.

385 Historical simulations of water table depth

386 The simulated WTD, generated by the calibrated hydrological model driven by historical climate for the  
 387 period 1990-2023, adequately represent both the observed seasonal patterns of WTD and their short-  
 388 term responses to precipitation events. Figure 3 shows the time series of WTD from two individual  
 389 monitoring wells as a typical example of the temporal match between observed and simulated WTD.

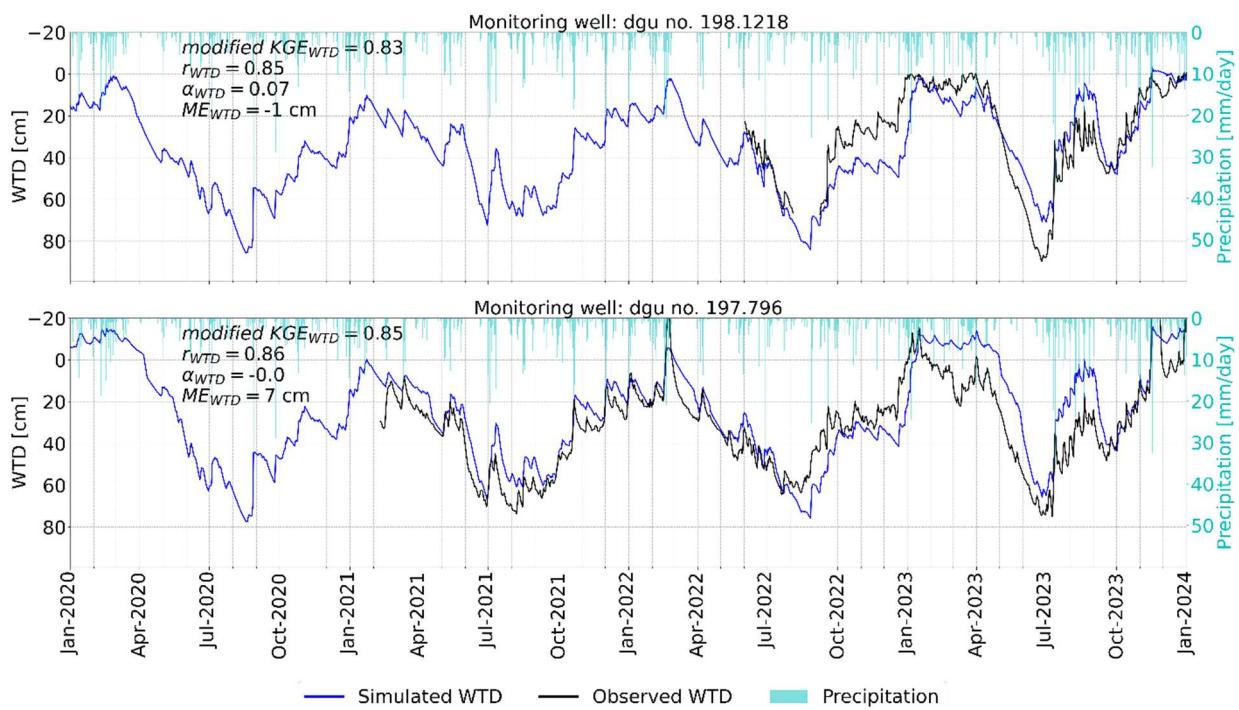


Figure 3: Example of observed and simulated timeseries for water table depth (WTD) for monitoring wells dgu no. 198.1218 and dgu no. 197.796. Including metrics for these wells.

393 Meteorological climate predictions  
 394 Changes in precipitation, temperature and evapotranspiration patterns in future climate projections  
 395 for Denmark generally indicate an increase in both temperature and annual precipitation. Table 3  
 396 presents the mean air temperature, mean annual precipitation and mean potential evapotranspiration  
 397 derived from the 17 climate projections across the three simulation periods.

398 *Table 3: Mean  $\pm$  SD (n=17) of annual air temperature, precipitation and potential evapotranspiration from the 17 climate*  
 399 *models during the three simulation periods.*

	Unit	Reference period (1991-2020)	Mid-century period (2041-2070)	End-of-century period (2071-2100)
Mean annual air temperature	°C	8.9 $\pm$ 0.7	10.6 $\pm$ 0.8	12.1 $\pm$ 0.8
Mean annual precipitation	mm yr <sup>-1</sup>	780 $\pm$ 121	837 $\pm$ 130	906 $\pm$ 152
Mean annual potential evapotranspiration	mm yr <sup>-1</sup>	621 $\pm$ 25	678 $\pm$ 27	727 $\pm$ 27

400

401 Hydrological climate predictions  
 402 Climate simulations using the hydrological model indicate a decreasing trend in mean annual WTDs  
 403 (Table 4), resulting in a shallower annual mean groundwater table in future climate conditions. Both  
 404 summer and winter mean WTDs are projected to be closer to the surface, suggesting generally wetter  
 405 conditions. The mean annual amplitude of WTD remains unchanged under future climate scenarios  
 406 (Table 4), indicating that there is no greater seasonal drawdown of the water table during summer,  
 407 although the duration of the drawdown period may be extended.

408 *Table 4: Statistics of WTD when using the hydrological model for climate simulations. Mean  $\pm$  SD (n=17) over the 17 climate*  
 409 *models during the three simulation periods. Summer is June, July and August, Winter is December, January and February. The*  
 410 *amplitude is based on the monthly means of WTD to avoid outliers.*

	Unit	Reference period (1991-2020)	Mid-century period (2041-2070)	End -of-century period (2071-2100)
Mean annual WTD	cm	31 $\pm$ 1	27 $\pm$ 2	24 $\pm$ 3
Mean summer WTD	cm	47 $\pm$ 1	40 $\pm$ 3	34 $\pm$ 3
Mean winter WTD	cm	18 $\pm$ 2	14 $\pm$ 4	10 $\pm$ 3
Mean annual WTD amplitude	cm	51 $\pm$ 2	50 $\pm$ 4	52 $\pm$ 4

411

## 412 Derivation of empirical daily soil CO<sub>2</sub> flux model

413 An analysis of the Vejrumbro dataset indicated a clear temperature dependency on the relation  
 414 between soil CO<sub>2</sub> flux (fCO<sub>2</sub>) and WTD. The Vejrumbro dataset was resampled to daily means of WTD,  
 415 T<sub>air</sub> and soil CO<sub>2</sub> flux across the six spatial replicate measurement points omitting data from days with  
 416 less than 24 flux measurements. This resulted in a dataset with 231 daily observations for each of fCO<sub>2</sub>,  
 417 WTD and T<sub>air</sub> distributed evenly over a year. Traditionally, empirical emission models for ecosystem  
 418 respiration (R<sub>eco</sub>) are fitted to soil temperature. However, due to the strong linear relationship  
 419 between daily soil temperature and daily air temperature at the Vejrumbro site ( $r = 0.96$ , p-value <  
 420 0.001) (Figure S4), T<sub>air</sub> was used as a proxy for soil temperature when fitting the *Daily WTD-T<sub>air</sub> model*.  
 421 This use of air temperature also facilitates upscaling and omits the need for projecting soil  
 422 temperatures under climate change scenarios.

423 To investigate how the WTD-fCO<sub>2</sub> relation scales with temperature, we binned daily soil CO<sub>2</sub> flux into  
 424 five temperature intervals: <4°C (n=39), 4-8°C (n=32), 8-12°C (n=52), 12-16°C (n=70) and >16°C (n=38)  
 425 and applied a linear regression model ( $y=ax$ ) with the intercept constrained at zero within each  
 426 temperature bin. The regressions were constrained to pass through the origin, reflecting the

427 assumption that soil  $\text{CO}_2$  flux is zero when the WTD is zero. Thereby, the relationship between  $f\text{CO}_2$   
 428 and WTD within each temperature bin was modeled using a linear regression of the form:

429  $f\text{CO}_2 = a \cdot \text{WTD}$  [5]

430 where  $f\text{CO}_2$  represents soil  $\text{CO}_2$  flux [ $\text{Mg CO}_2\text{-C ha}^{-1} \text{ day}^{-1}$ ],  $a$  denotes the fitted slope and WTD is water  
 431 table depth [cm], with positive values indicating depths below the surface.

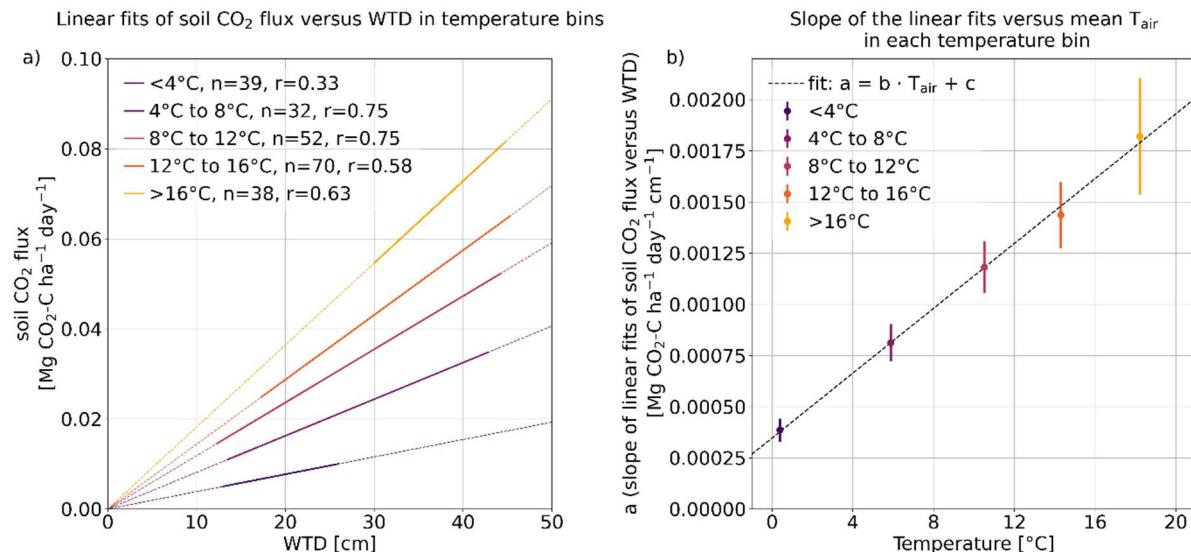
432 This analysis revealed an increasing slope, i.e. sensitivity of soil  $\text{CO}_2$  flux to changes in WTD, with rising  
 433 temperature (Figure S5 and Figure 4a), indicating that the WTD-  $f\text{CO}_2$  slope ( $a$ ) can be modelled as a  
 434 linear function of temperature ( $T_{\text{air}}$ ) (Figure 4b):

435  $a = b \cdot T_{\text{air}} + c$  [6]

436 Combining these relationships yields a simple model of the soil  $\text{CO}_2$  flux:

437  $f\text{CO}_2 = b \cdot T_{\text{air}} \cdot \text{WTD} + c \cdot \text{WTD}$  [7]

438 where  $T_{\text{air}}$  [ $^{\circ}\text{C}$ ] is the temperature,  $b$  [ $\text{Mg CO}_2\text{-C ha}^{-1} \text{ day}^{-1} \text{ cm}^{-1} \text{ }^{\circ}\text{C}^{-1}$ ] and  $c$  [ $\text{Mg CO}_2\text{-C ha}^{-1} \text{ day}^{-1} \text{ cm}^{-1}$ ] are  
 439 empirical constants.



440

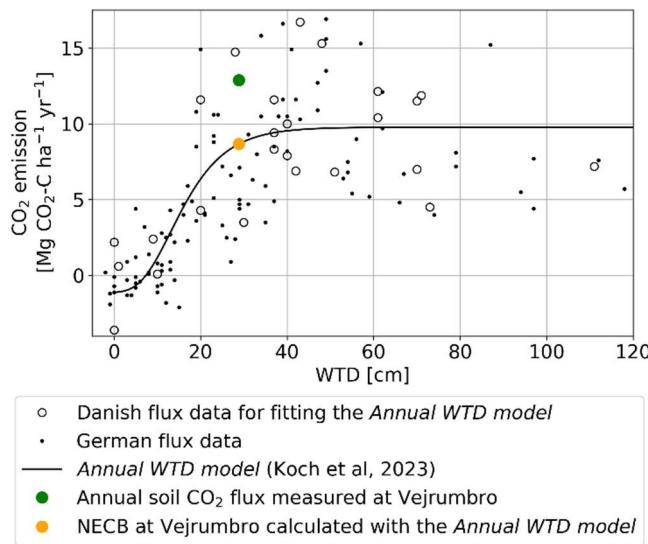
441 Figure 4: Left: linear models of soil  $\text{CO}_2$  flux vs. water table depth (WTD) in air temperature bins. The thicker segment of the  
 442 line represents the range of data used to derive the fitted model.  $n$  is the number of daily observations of soil  $\text{CO}_2$  flux in each  
 443 temperature bin.  $r$  is Person correlation coefficient. Raw data behind the linear regressions can be seen at Figure S5. Right:  
 444 Slope (incl. uncertainty) (of the linear fit of soil  $\text{CO}_2$  flux versus WTD) versus observed mean temperature in each temperature  
 445 bin.

446 Having established a suitable form of the empirical soil  $\text{CO}_2$  flux equation, we used nonlinear least  
 447 squares fit to estimate the  $b$  and  $c$  parameters based on the daily soil  $\text{CO}_2$  flux,  $T_{\text{air}}$  and WTD (without  
 448 temperature bins). This method minimizes the residual sum of squares between the observed soil  $\text{CO}_2$   
 449 flux and the *Daily WTD-T<sub>air</sub> model*. The resulting fitted model demonstrated a significant correlation to  
 450 the observed data ( $r = 0.78$ ,  $p$ -value < 0.001,  $\text{RMSE} = 0.021 \text{ Mg CO}_2\text{-C ha}^{-1} \text{ day}^{-1}$ ) (Figure S6) with daily  
 451 soil  $\text{CO}_2$  flux increasing in response to rising WTD and  $T_{\text{air}}$  (Figure S7). The fitted empirical constants are  
 452 as follows:  $b = 8.32 \cdot 10^{-5} \text{ Mg CO}_2\text{-C ha}^{-1} \text{ day}^{-1} \text{ cm}^{-1} \text{ }^{\circ}\text{C}^{-1}$ ,  $c = 3.33 \cdot 10^{-4} \text{ Mg CO}_2\text{-C ha}^{-1} \text{ day}^{-1} \text{ cm}^{-1}$ .

453 The *Daily WTD-T<sub>air</sub> model* predicts the highest soil  $\text{CO}_2$  flux under conditions of simultaneously high  $T_{\text{air}}$   
 454 and WTD, where a high WTD refers to a water table located furthest below the surface (dry  
 455 conditions). The multiplicative *Daily WTD-T<sub>air</sub> model* demonstrated a moderate fit to the soil  $\text{CO}_2$  flux  
 456 data, with a  $R^2$  of 0.61. To assess the individual contributions of the predictor variables, we also

457 computed the  $R^2$  between CO<sub>2</sub> flux and  $T_{air}$  and WTD separately. This was done using a constructed  
 458 dataset that included all combinations of WTD and  $T_{air}$  within the model range. This resulted in  $R^2$   
 459 values of 0.34 for  $T_{air}$  and 0.54 for WTD (Table S7). These values reflect the explanatory power of each  
 460 variable in isolation.

461 Despite the significant variability in the observed net ecosystem carbon balance (NECB) used for the  
 462 *Annual WTD model* (Figure 5) it is considered to represent a robust mean as it is based on multiple  
 463 sites and years for Danish and German conditions. Compared to the *Annual WTD model* both the  
 464 measured soil CO<sub>2</sub> flux (12.9 Mg CO<sub>2</sub>-C ha<sup>-1</sup> yr<sup>-1</sup> (green circle)) and the *Daily WTD-T<sub>air</sub>* simulated soil CO<sub>2</sub>  
 465 flux (13.6 Mg CO<sub>2</sub>-C ha<sup>-1</sup> yr<sup>-1</sup> (not shown)) at Vejrumbro are above the corresponding fitted value of  
 466 NECB (8.7 Mg CO<sub>2</sub>-C ha<sup>-1</sup> yr<sup>-1</sup> (orange circle)) based on an annual WTD of 29 cm, but still within the  
 467 range of observed NEBCs used for fitting the *Annual WTD model* (Figure 5). This may be explained by  
 468 the methodology of flux measurements at Vejrumbro that did not consider GPP (CO<sub>2</sub> uptake) and  
 469 therefore are expected to result in higher net CO<sub>2</sub> fluxes. In order to align the *Daily WTD-T<sub>air</sub> model* to  
 470 the level of the *Annual WTD model* where GPP is included, a scaling factor based on the above  
 471 differences ( $f_{scaling} = 0.64$ ) was applied to equation 7 to account for lack of GPP in the soil CO<sub>2</sub> fluxes  
 472 used for empirical model development. Applying this scaling factor, we seek to avoid the risk of  
 473 overestimating emissions when applying the *Daily WTD-T<sub>air</sub> model* at other locations.



474  
 475 *Figure 5: The Annual WTD model together with the Danish flux data of annual NECB and WTD data underlaying the model*  
 476 *(Koch et al., 2023). German flux data are included for comparison (Tiemeyer et al., 2020). Colored circles are measured and*  
 477 *calculated soil CO<sub>2</sub> flux and NECB for the Vejrumbro dataset, so the colored circles represent the year 2022-2023.*

478 The Vejrumbro dataset used for fitting the *Daily WTD-T<sub>air</sub> model* was limited to a maximum WTD of 47  
 479 cm and maximum  $T_{air}$  of 21°C (Figure S7). Outside this range, the predictions of the *Daily WTD-T<sub>air</sub>*  
 480 *model* exhibits increased uncertainty. At the same time, it is generally understood that the upper  
 481 portion of the peat layer drives the net CO<sub>2</sub> emissions observed at the surface. Therefore, the  
 482 extrapolation of WTD in the *Daily WTD-T<sub>air</sub> model* must be constrained. The *Daily WTD-T<sub>air</sub> model*  
 483 should be sensitive within a WTD range comparable to the expected daily variation in the *Annual WTD*  
 484 *model*, which also reaches an fCO<sub>2</sub> asymptotic at deeper water tables. In the *Annual WTD model*, the  
 485 Annual NECB reaches 90% of its maximum asymptotic level at a mean annual WTD of 30 cm (Figure 5).  
 486 The mean annual WTD results from intra-annual (within year) WTD variation described by the annual  
 487 amplitude. The mean annual amplitude (based on monthly means) is 65 cm, across the 22 observed  
 488 WTD time series in the Tuse Stream catchment used for calibrating the hydrological model. We  
 489 assume that a mean annual WTD of 30 cm originates from an annual WTD variation with a similar

490 amplitude. Therefore, we assume that the WTD range of the *Daily WTD-T<sub>air</sub> model* is  $30 + 65/2$  cm =  
491 62.5 cm. For the T<sub>air</sub> range, it is assumed that the sensitivity continues until 25°C, which is a daily  
492 average value very rarely occurring, even in future climate projections. Thus, when applying the *Daily*  
493 *WTD-T<sub>air</sub> model*, daily WTD values and T<sub>air</sub> values were truncated, setting WTD and T<sub>air</sub> to 62.5 cm and  
494 25°C, respectively, when exceeding those thresholds.

495 In both the *Daily WTD-T<sub>air</sub> model* and the *Annual WTD model*, CO<sub>2</sub> fluxes are constrained so that the  
496 model does not simulate negative fluxes or carbon uptake(Gyldenkærne et al., 2025).

497 CO<sub>2</sub> emissions from peatlands

498 CO<sub>2</sub> emissions throughout the historical simulation period

499 The long-term mean of the emission factor for the Tuse Stream catchment peat area is  $8.0 \pm 0.8$  Mg  
500 CO<sub>2</sub>-C ha<sup>-1</sup> yr<sup>-1</sup> (mean  $\pm$  SD, n=34) when using the *Annual WTD model* and  $8.8 \pm 1.6$  Mg CO<sub>2</sub>-C ha<sup>-1</sup> yr<sup>-1</sup>  
501 (mean  $\pm$  SD, n=34) when using the *Daily WTD-T<sub>air</sub> model* (Table 5).

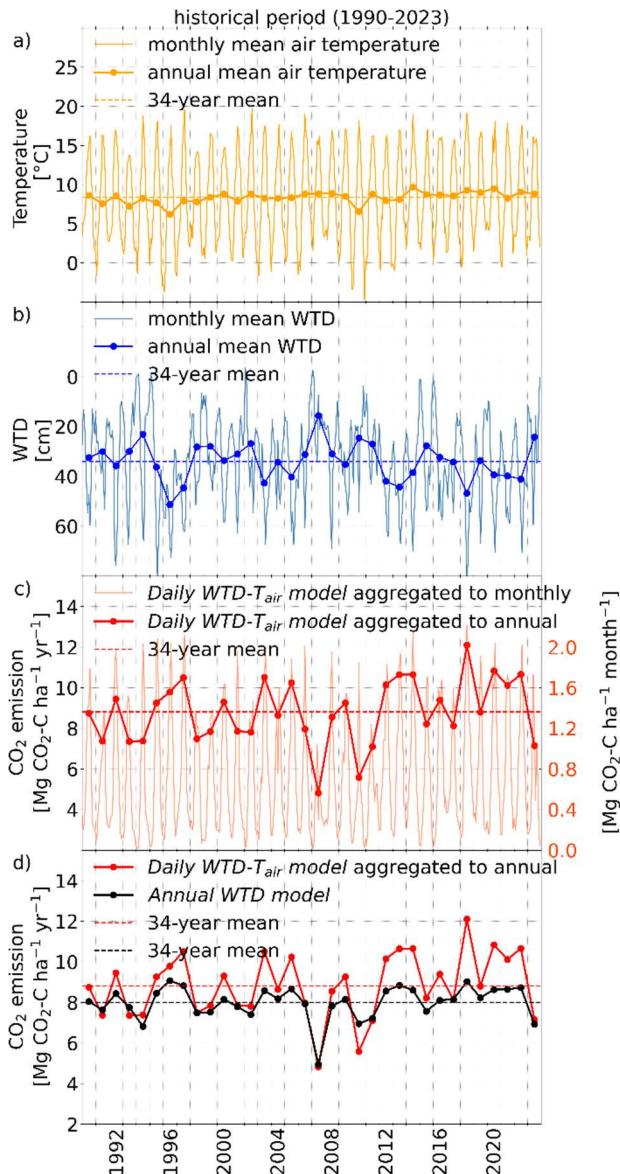
502 *Table 5: Long-term mean water table depth (WTD), long-term mean annual WTD amplitude (based on monthly means of WTD*  
503 *to avoid outliers) and long-term soil CO<sub>2</sub> flux, throughout the historical period and the three modified 34-year WTD time series*  
504 *of rewetting scenarios. Mean  $\pm$  SD is based on the 34 years of the historical period (1990-2023).*

	Unit	Historical period (1990-2023)	Rewetting scenario A	Rewetting scenario B	Rewetting scenario C
Mean WTD	cm	$34 \pm 8$	$14 \pm 18$	$14 \pm 8$	$14 \pm 4$
Mean annual WTD amplitude	cm	$51 \pm 11$	$110 \pm 28$	$51 \pm 11$	$26 \pm 5$
CO <sub>2</sub> emission from <i>Daily WTD-T<sub>air</sub> model</i> aggregated to annual	Mg CO <sub>2</sub> -C ha <sup>-1</sup> yr <sup>-1</sup>	$8.8 \pm 1.6$	$7.7 \pm 2.0$	$5.2 \pm 1.5$	$4.4 \pm 0.8$
CO <sub>2</sub> emission from <i>Annual WTD model</i> aggregated to annual	Mg CO <sub>2</sub> -C ha <sup>-1</sup> yr <sup>-1</sup>	$8.0 \pm 0.8$	$4.6 \pm 3.0$	$4.3 \pm 2.0$	$4.4 \pm 1.2$

505  
506 Figure 6 shows T<sub>air</sub>, as wells as the spatial mean of WTD and CO<sub>2</sub> emissions across the peatland, as  
507 simulated by the *Daily WTD-T<sub>air</sub> model* and the *Annual WTD model* during the historical period. The  
508 CO<sub>2</sub> emissions calculated with the *Daily WTD-T<sub>air</sub> model* (red line in Figure 6c, 6d) depend on both the  
509 observed daily temperature variability (orange line in Figure 6a) and simulated intra-annual (seasonal)  
510 WTD variability (blue line in Figure 6b), while the CO<sub>2</sub> emission calculated with the *Annual WTD model*  
511 (black points in Figure 6d) only depends on the inter-annual (annual means) WTD (blue points in Figure  
512 6b) and not the temperature.

513 Inter-annual (between years) variation in CO<sub>2</sub> emission is substantially larger when using the *Daily*  
514 *WTD-T<sub>air</sub> model* ( $SD = 1.6$  Mg C-CO<sub>2</sub> ha<sup>-1</sup> yr<sup>-1</sup>) compared to the *Annual WTD model* ( $SD = 0.8$  Mg C-CO<sub>2</sub>  
515 ha<sup>-1</sup> yr<sup>-1</sup>) (Figure 6d), as the former captures extreme events, such as periods of high temperature or  
516 deep groundwater tables, as well as compound events involving the simultaneous occurrence of both.  
517 In contrast, the *Annual WTD model* is insensitive to temperature and the intra-annual (within year)  
518 timing of deep WTD. Moreover, the *Annual WTD model* imposes an upper limit of 10 Mg CO<sub>2</sub>-C ha<sup>-1</sup>  
519 yr<sup>-1</sup> for annual emissions (Koch et al., 2023) (Figure 5). During the summer of 2018, a compound  
520 extreme event occurred, characterized by both high temperatures and deep groundwater table. The  
521 annual CO<sub>2</sub> flux for this year shows a 34% increase when estimated using the *Daily WTD-T<sub>air</sub> model*  
522 compared to the *Annual WTD model*. This discrepancy arises from the *Daily WTD-T<sub>air</sub> model*'s ability to  
523 account for the prolonged duration of concurrent high temperatures and deep groundwater table  
524 conditions throughout the summer (Figure 6d). Conversely, in 2010, the *Daily WTD-T<sub>air</sub> model*  
525 estimates significantly lower annual CO<sub>2</sub> emissions compared to the *Annual WTD model* (Figure 6d).  
526 This difference is due to the emission model's ability to account for the effects of prolonged periods of  
527 low temperatures during the autumn and spring of 2010, leading to a mean annual temperature below

528 the long-term mean, despite summer temperatures being consistent with other years (Figure 6a).  
 529 Examples of years with extreme events primarily driven by either WTD or  $T_{air}$  include 1996, which  
 530 experienced a significant summer decline in groundwater table (Figure 6b), and 1997, which was  
 531 characterized by elevated summer temperatures (Figure 6a). However, neither of these events led to  
 532 CO<sub>2</sub> emissions as high as those simulated during the compound event of both high temperatures and  
 533 deep water table in 2018 (Figure 6).



534  
 535 Figure 6: Air temperature ( $T_{air}$ ), water table depth (WTD) and soil CO<sub>2</sub> emission for the historical simulation period 1990-2023.

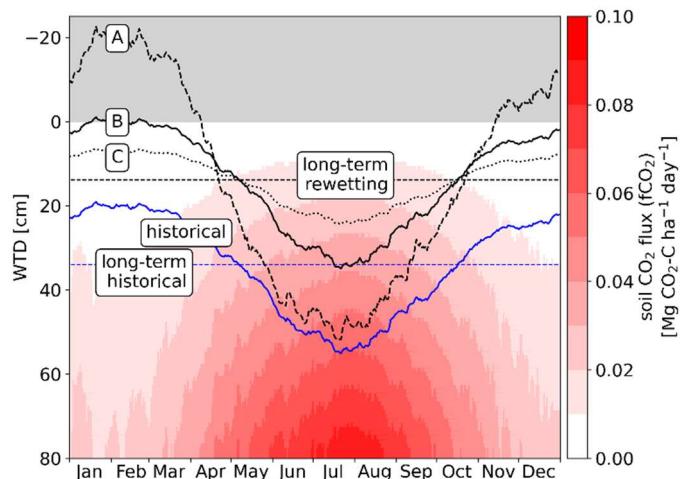
536 CO<sub>2</sub> emissions under different rewetting scenarios  
 537 The rewetting scenarios represent an adjustment to the WTD simulated by the hydrological model  
 538 over the 34-year historical period, thereby reflecting the climatological conditions prevailing during  
 539 that time. Across all three rewetting scenarios, the long-term (34-year) mean WTD was raised by 20  
 540 cm, from 34 cm to 14 cm below the surface, ensuring a consistent long-term annual mean WTD among  
 541 the rewetting scenarios (Table 5). Accordingly, the application of the *Annual WTD model* for estimating  
 542 CO<sub>2</sub> fluxes result in CO<sub>2</sub> emissions between  $4.3 \pm 1.2 \text{ Mg C-CO}_2 \text{ ha}^{-1} \text{ yr}^{-1}$  (mean  $\pm$  SD, n=34) and  $4.6 \pm 3.0$   
 543  $\text{Mg C-CO}_2 \text{ ha}^{-1} \text{ yr}^{-1}$  (mean  $\pm$  SD, n=34) across all rewetting scenarios (Table 5). The mean annual soil CO<sub>2</sub>  
 544 flux from the three rewetting scenarios, as calculated using the *Annual WTD model*, are similar but not

545 identical. This is because the *Annual WTD model* is applied to each of the 34 individual annual mean  
546 WTD values rather than to a single long-term mean WTD. The SD of CO<sub>2</sub> emissions calculated using the  
547 *Annual WTD model* in scenario C is markedly lower than in rewetting scenario A and B, reflecting the  
548 lower inter-annual (between years) variability in mean annual WTD observed for this scenario (Table  
549 5).

550 In contrast to the *Annual WTD model*, the *Daily WTD-T<sub>air</sub> model* captures the simultaneous occurrence  
551 of low groundwater table and high T<sub>air</sub> during the summer months. Application of this emission model  
552 indicates that raising the groundwater table during summer months (rewetting scenario C) yields the  
553 greatest reduction potential in soil CO<sub>2</sub> emissions (Table 5), leading to a 50% decrease in the mean  
554 value, from  $8.8 \pm 1.6$  to  $4.4 \pm 0.8$  Mg C-CO<sub>2</sub> ha<sup>-1</sup> yr<sup>-1</sup> (mean  $\pm$  SD, n=34) (Table 5). In contrast,  
555 management scenarios that primarily target increase in winter water table (rewetting scenario A)  
556 exhibit only marginal emission reduction potential (Table 5).

557 A visual representation of daily soil CO<sub>2</sub> emissions in relation to mean daily temperature during the 34-  
558 year historical period under different WTD conditions (Figure 7) reveals that high summer  
559 temperatures are a key driver of CO<sub>2</sub> emissions. WTD observations from the Tuse catchment peatland  
560 indicate that, during shorter periods in the warm summer months, the WTD can exceed 80 cm (Figure  
561 3). These periods with very low summer water table contribute substantially to total CO<sub>2</sub> emissions  
562 (Figure 7).

563 A rewetting scenario that mainly generates wetter winter conditions (rewetting scenario A) has very  
564 limited CO<sub>2</sub> emission reduction. All three scenarios assume that even under rewetting, the peatland  
565 WTD will follow a climate driven seasonality and that obtaining zero WTD in summer periods will be  
566 difficult by classical nature-based solutions. Rewetting scenario C, which features the greatest increase  
567 in summer WTD, achieves the largest reduction in CO<sub>2</sub> emissions (Figure 7). Permanent wet conditions  
568 with WTD at zero would be required to obtain zero CO<sub>2</sub> emission with the developed *Daily WTD-T<sub>air</sub>*  
569 *model*, but under such conditions, methane emissions would also come into play and plant growth  
570 would be severely limited.



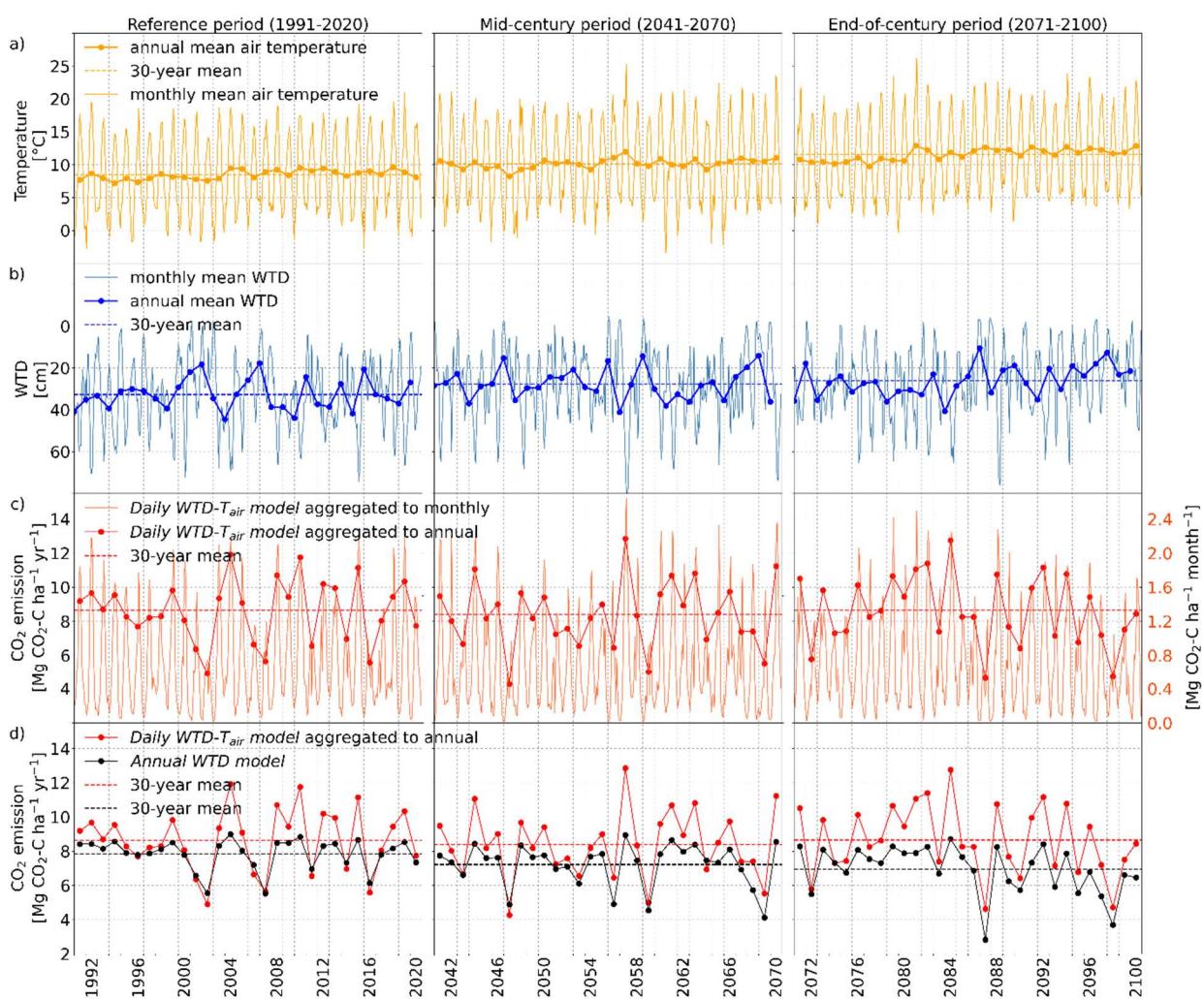
571  
572 *Figure 7: Colormap: Visual representation of the annual distribution of daily surface soil CO<sub>2</sub> flux (fCO<sub>2</sub>, CO<sub>2</sub> exchange with*  
573 *atmosphere) under mean daily temperature during the historical period (1990-2023) and for different water table depths*  
574 *(WTD). Curves: solid blue line: simulated daily mean WTD during the historical period and corresponding long-term (34-year)*  
575 *mean WTD, black lines: daily mean WTD for each of the modified 34-year WTD time series of rewetting scenarios (A, B and C)*  
576 *and the corresponding long-term (34-year) mean WTD.*

577 CO<sub>2</sub> emissions across future climate simulation periods  
578 Figure 8 shows the same variables as Figure 6 but based on a representative climate model simulation  
579 instead of the observed climate record, offering a typical example of the development of temperature,

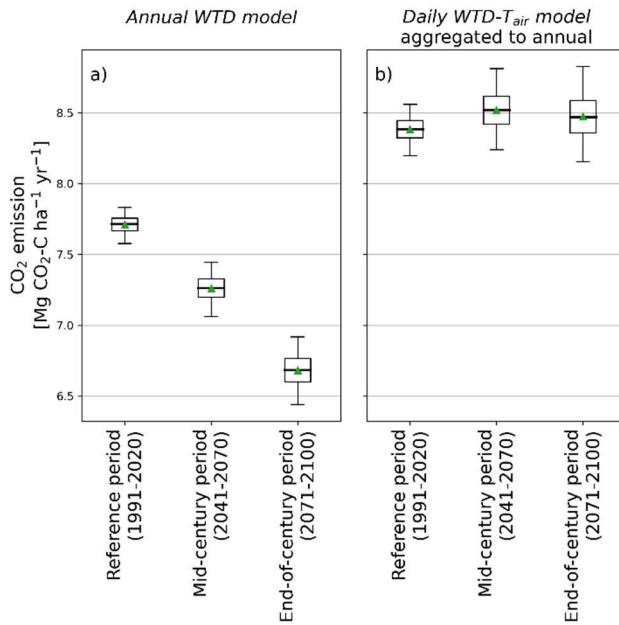
580 WTD and soil CO<sub>2</sub> flux through the reference, mid-century and end-of-century periods based on the  
 581 RCP 8.5 pathway.

582 The future climate simulations show an increase in both the annual mean temperature and  
 583 groundwater levels combined with higher maximum summer temperature (Figure 8a, 8b, Table 3,  
 584 Table 4). The bootstrap mean of soil CO<sub>2</sub> flux calculated with the *Annual WTD model* over all climate  
 585 models predicts a decreasing trend in soil CO<sub>2</sub> flux under future climate conditions (Figure 9a,  
 586 horizontal dotted black line in Figure 8d), driven by an inter-annual (between years) mean WTD closer  
 587 to surface (Table 4, Figure 8b). However, this decreasing trend is countered by the inclusion of T<sub>air</sub>  
 588 effects when applying the *Daily WTD-T<sub>air</sub> model* (Figure 9b, horizontal dotted red line in Figure 8c and  
 589 8d).

590 The wider confidence intervals in the mean annual CO<sub>2</sub> emissions for the future periods with both CO<sub>2</sub>  
 591 emission model (Figure 9) indicate that the inter-annual (between years) soil CO<sub>2</sub> fluxes become more  
 592 variable in future climate. Furthermore, the confidence intervals for the individual periods are wider  
 593 for the *Daily WTD-T<sub>air</sub>* (Figure 9b) compared to the *Annual WTD model* (Figure 9a), which is expected as  
 594 variations in T<sub>air</sub> and not only WTD is included as with the *Daily WTD-T<sub>air</sub> model*. This demonstrates that  
 595 the *Daily WTD-T<sub>air</sub> model* captures extreme events, including periods of high temperature or deep  
 596 groundwater table, whether these events occur simultaneously (compound event) or independently.



597  
 598 Figure 8: Example of air temperature (T<sub>air</sub>), water table depth (WTD) and soil CO<sub>2</sub> flux for future climate simulation with  
 599 climate model projection no. 5 (Table S6).



600  
601 *Figure 9: Boxplot showing the distribution of bootstrap means of soil CO<sub>2</sub> emissions according to the Daily WTD-T<sub>air</sub> model and*  
602 *Annual WTD model during future climate. Green triangles and horizontal lines indicate the mean and the median of the*  
603 *bootstrap mean, respectively. Boxes show the 25<sup>th</sup> and 75<sup>th</sup> percentiles. Whiskers indicate the 95% confidence intervals.*  
604 *Outliers are not shown.*

605 The results presented in Figure 9 suggest that the impact on CO<sub>2</sub> emissions caused by future increases  
606 in T<sub>air</sub> and increases in water tables cancel each other out when using the *Daily WTD-T<sub>air</sub> model*. To  
607 investigate this further, we analyze how the combination of T<sub>air</sub> and WTD shift between the reference  
608 and the end-of-century periods, despite relatively stable total CO<sub>2</sub> emission.

609 We wish to identify the specific combination of T<sub>air</sub> and WTD that are associated with the majority of  
610 the CO<sub>2</sub> emission. Due to the non-linear response of soil CO<sub>2</sub> flux to environmental drivers in the *Daily*  
611 *WTD-T<sub>air</sub> model*, a large fraction of total emissions is generated on relatively few days. To quantify this,  
612 we calculated p50, defined as the proportion of days required to account for 50% of the total annual  
613 soil CO<sub>2</sub> flux (fCO<sub>2</sub>). This was achieved by ranking the daily values of fCO<sub>2</sub>, WTD, and T<sub>air</sub> in ascending  
614 order according to fCO<sub>2</sub>. Subsequently, the ranked fCO<sub>2</sub> values were cumulatively summed to obtain  
615 their percentile distribution (Figure S8). The procedure was first applied to fCO<sub>2</sub>, WTD, and Tair data  
616 from the historical simulation period, with the resulting percentile curves shown in Figure S8. Over the  
617 historical simulation period, 50% of the total fCO<sub>2</sub> (fCO<sub>2,p50</sub>) was generated within 22% of the days (p50  
618 = 22%), while the value of fCO<sub>2,p50</sub> and corresponding WTD<sub>p50</sub> and T<sub>air,p50</sub> are estimated to be 4.15·10<sup>-2</sup>  
619 g CO<sub>2</sub>-C ha<sup>-1</sup> day<sup>-1</sup>, 47 cm and 13.8 °C (Table 6 and Figure S8).

620 Similar estimates are derived from the three timeslots from the climate models (reference, mid-  
621 century and end-of-century climate simulation periods) using the 17 different climate models. For the  
622 future, 50% of the total fCO<sub>2</sub> is expected to occur within approximately 21 ± 1 % (mean ± SD, n=17) of  
623 the days (Table 6). The daily soil CO<sub>2</sub> flux associated to p50 (fCO<sub>2,p50</sub>) and p50 are nearly identical  
624 across both the historical and future climate simulations periods (Table 6). As also shown in Figure 9b,  
625 the magnitude and temporal distribution of fCO<sub>2</sub> are predicted to remain unchanged in the future.  
626 While the value of fCO<sub>2,p50</sub> remains relatively constant around 4·10<sup>-2</sup> Mg CO<sub>2</sub>-C ha<sup>-1</sup> day<sup>-1</sup> for future  
627 climate periods, the corresponding WTD<sub>p50</sub> and T<sub>air,p50</sub> values change as a result of changing climate  
628 moving towards higher temperatures (17 °C) and shallower groundwater table (40 cm).

629 Figure 10 provides a graphical representation of fCO<sub>2</sub> obtained from the *Daily WTD-T<sub>air</sub> model*, with the  
630 colormap illustrating the daily fCO<sub>2</sub> corresponding to different combinations of T<sub>air</sub> and WTD. The daily

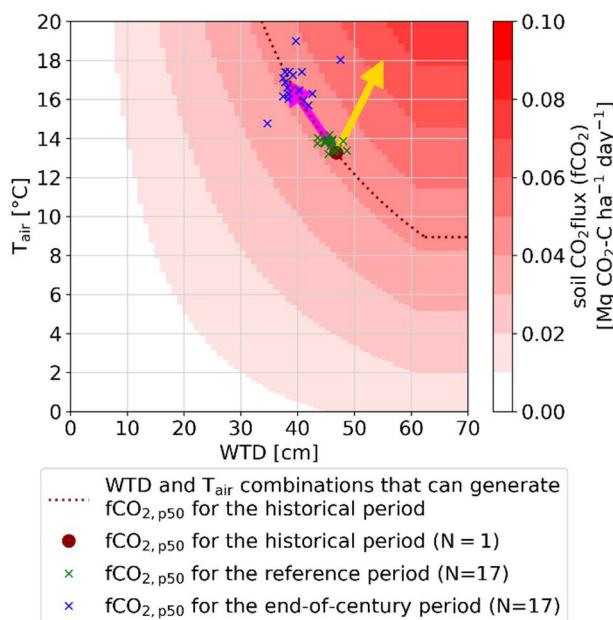
631  $fCO_{2, p50}$  ( $4.15 \cdot 10^{-2}$  g  $CO_2\text{-C ha}^{-1} day^{-1}$  for the historical period (Table 6)) can be achieved through  
 632 various combinations of  $T_{air}$  and WTD (dark red dotted line in Figure 10). The values of  $T_{air, p50}$  and  
 633  $WTD_{p50}$  corresponding to  $fCO_{2, p50}$  for the Tuse Stream catchment peatland are plotted as a dark red  
 634 point. As expected, the  $fCO_{2, p50}$  values for the reference periods of the 17 climate models (green  
 635 crosses at Figure 10) are closely aligned with that of the historical period. It is evident that the  $fCO_{2, p50}$   
 636 values for the end-of-century climate conditions (blue crosses at Figure 10) shift along the direction  
 637 indicated by the pink arrow (along the red dotted line), reflecting a trend toward higher temperatures  
 638 and lower WTD (i.e. water levels closer to the surface surface). This indicates that the mean daily  $fCO_2$   
 639 (Table 6) and the long-term  $fCO_2$  remains constant in the future (Figure 9b), as a result of a  
 640 counterbalance between impacts of rising temperatures and rising groundwater levels.

641 The pink arrow at Figure 10 illustrates the characteristic impact of climate change in Denmark,  
 642 reflecting the concurrent increase in air temperature and shallow groundwater levels (Schneider et al.,  
 643 2022). In contrast, other regions in Europe are experiencing declining groundwater level trends to  
 644 climate change (Wunsch et al., 2022). Consequently,  $CO_2$  emissions from peatlands in these regions  
 645 are expected to shift in the direction indicated by the yellow arrow in Figure 10, towards considerably  
 646 larger emission rates.

647 *Table 6: p50 is the fraction of days required to reach 50% of the total soil  $CO_2$  flux ( $fCO_2$ ).  $fCO_{2, p50}$  is the daily soil  $CO_2$  flux  
 648 associated with p50.  $WTD_{p50}$  and  $T_{air, p50}$  are the water table depth (WTD) and air temperature ( $T_{air}$ ) corresponding to  $fCO_{2, p50}$ ,  
 649 respectively. Mean  $\pm$  SD is based on 17 climate model simulations.*

		Historical simulation period (1990-2023)	Climate simulation periods		
	Unit		Reference period (1991-2020)	Mid-century period(2041-2070)	End-of-century period (2071-2100)
p50	% days	22	$21 \pm 1$	$21 \pm 1$	$21 \pm 1$
$fCO_{2, p50}$	$Mg\ CO_2\text{-C ha}^{-1} day^{-1}$	$4.15 \cdot 10^{-2}$	$4.03 \cdot 10^{-2} \pm 9.89 \cdot 10^{-4}$	$4.00 \cdot 10^{-2} \pm 3.24 \cdot 10^{-3}$	$4.03 \cdot 10^{-2} \pm 3.65 \cdot 10^{-3}$
$T_{air, p50}$	°C	13.8	$14 \pm 0.3$	$15 \pm 0.6$	$17 \pm 1.0$
$WTD_{p50}$	cm	47	$46 \pm 1$	$42 \pm 3$	$40 \pm 3$

650



651  
 652 *Figure 10: Colormap: Visual representation of the Daily WTD- $T_{air}$  model output, illustrating soil  $CO_2$  flux ( $fCO_2$ ) as function of  
 653 daily water table depth (WTD) and air temperature ( $T_{air}$ ). The dark red dotted line represents combinations of  $T_{air}$  and WTD  
 654 that corresponds  $fCO_2$  at  $p50$  ( $fCO_{2, p50}$ ), where  $p50$  is the fraction of days required to reach 50% of the total accumulated  $fCO_2$   
 655 during the historical period. Green crosses are  $fCO_{2, p50}$  for the reference period of the 17 climate simulations. Purple crosses*

656 are  $fCO_{2, p50}$  for the end-of-century climate simulation period of the 17 climate simulations. The pink and yellow arrows  
657 indicate different future trends in  $T_{air}$  and WTD and the associated trend in  $CO_2$  emissions under climate change. Specific to  
658 Denmark, the pink arrow indicates increases in  $T_{air}$  and decrease in WTD, other regions might experience increase in both  $T_{air}$   
659 and WTD and an associated large increase in  $CO_2$  emissions (yellow arrow).

660 Discussion

661 Peatland management under changing climate

662 In 2023, CO<sub>2</sub> emissions from drained organic soils in croplands and grasslands was estimated to have  
663 accounted for 6.7% of Denmark's total emissions, including those from the Land Use, Land-Use Change  
664 and Forestry (LULUCF) sector (Nielsen et al., 2025b). Returning peatland organic soils to their natural  
665 hydrological state is a cost-effective GHG reduction strategy (IPCC, 2014; Kirpotin et al., 2021;  
666 Tanneberger et al., 2021; Wilson et al., 2016). Therefore, national policies (Regeringen, 2024) and the  
667 European Union's Nature Restoration Law (Regulation (EU) 2024/1991, 2024) seek to improve the  
668 management of peatlands and achieve climate neutrality targets under the urgent Green Transition  
669 agenda. To mitigate agricultural GHG emissions Danish ministerial agreements were initiated in 2024,  
670 targeting the restoration of 140,000 hectares of peatland (Regeringen, 2024). However, there is a need  
671 to strengthen the scientific evidence for mitigation measures to facilitate cost-effective policies.  
672 Quantitative predictions of fluxes such as the numbers presented in this study, supports prioritization  
673 and design of peatland rewetting strategies by estimating their CO<sub>2</sub> emission reduction potentials  
674 accounting for future climate variability impact on CO<sub>2</sub> emissions.

675 Integration of the process-based hydrological model of the Tuse Stream catchment with the  
676 empirically derived *Daily WTD-T<sub>air</sub> model* of soil CO<sub>2</sub> flux developed in this study revealed that emission  
677 simulations at daily timesteps produce greater variability in soil CO<sub>2</sub> fluxes compared to emission  
678 estimates derived from annual WTD means. This increased variability is attributed to the daily model's  
679 ability to account for short-term compound events, especially the simultaneous occurrence of elevated  
680 air temperatures and low groundwater levels.

681 More importantly, incorporating temperature dependence and higher temporal resolution into the  
682 CO<sub>2</sub> emissions model significantly alters the projected trends of CO<sub>2</sub> emission under both rewetting  
683 and changing climate conditions.

684 Nature-based approaches represent the most common real-world rewetting strategies, aiming to  
685 restore peatlands towards their natural hydrological regime. At a minimum, such rewetting requires  
686 terminating tillage activities and eliminating artificial drainage for instance by blocking of drainpipes  
687 and ditches. The rewetting scenarios implemented in this study, represented as simple modifications  
688 to WTD, are not reflective of practical management interventions - except perhaps in a few rare and  
689 costly restoration projects that involve installing artificial impermeable membranes along peatlands  
690 edges (Naturstyrelsen, 2022). However, the outcome of this study can serve as a reference for  
691 discussions on realistic expectations on CO<sub>2</sub> emission reductions from rewetted peatlands.

692 The rewetting analyzed in this study showed how different rewetting scenarios with varying seasonal  
693 amplitudes in WTD suggest significantly different emission reduction potential even with identical  
694 annual mean WTD. The results illustrate that increasing the groundwater table during warm periods is  
695 key to obtaining CO<sub>2</sub> emission reductions, whereas rewetting strategies that mainly raise winter water  
696 table without significantly affecting the summer levels offer limited mitigation benefits. This highlights  
697 the importance of not only targeting annual reductions in WTD but particularly designing rewetting  
698 strategies to increase the summer water table and avoid critically low water levels during droughts and  
699 warm periods. Achieving such rewetted conditions may include larger forced control of WTD than  
700 what is currently being practiced for most existing rewetting schemes, where the WTD remain subject  
701 to climate seasonality impact. Such nature-based solutions are not likely to reduce CO<sub>2</sub> emissions to  
702 the degree that current emission reduction policies target.

703

704 Also, projections of CO<sub>2</sub> emissions under different climate change scenarios were altered greatly by  
705 introducing temperature sensitivity and enhanced temporal resolution into the CO<sub>2</sub> emissions  
706 modeling framework. Here our results show that, while the projected rise in groundwater tables in  
707 isolation would lead to lower CO<sub>2</sub> emissions in future (when using the *Annual WTD model*), the *Daily*  
708 *WTD-T<sub>air</sub> model* revealed that anticipated increases in T<sub>air</sub> are likely to cancel out these reductions,  
709 resulting in CO<sub>2</sub> emissions on a level comparable to current levels. This is an important finding, since it  
710 suggests that increasing temperatures alone will likely increase CO<sub>2</sub> emissions, and that water level rise  
711 driven by climate change or rewetting initiatives might just counteract this trend. Rewetting measures  
712 would need to be substantially intensified to ensure climate resilience and achieve meaningful  
713 reductions in CO<sub>2</sub> emissions. Additionally, outside the specific case of Danish peatlands located in a  
714 region that is susceptible to a future wetter climate, other regions might project both increasing  
715 temperatures and lower groundwater tables, and in such cases climate change will significantly  
716 increase emissions without any rewetting. We acknowledge that the chosen Representative  
717 Concentration Pathway (RCP8.5) represents the scenario leading to the strongest impact of climate  
718 change and that additional, milder climate scenarios could have been included.

719 Hydrological simulation of groundwater levels in peat soil with process-based models  
720 Existing large scale CO<sub>2</sub> emission estimates, such as national inventories from organic soils  
721 (Gyldenkærne et al., 2025; Nielsen et al., 2025b), typically combine empirical emission models and  
722 data-driven ML approaches for estimating annual WTD (Bechtold et al., 2014; Koch et al., 2023;  
723 Tiemeyer et al., 2020). These approaches appear robust and suited for upscaling but are limited in  
724 their ability to represent the impact of sub-annual variability in temperature and WTD, which are  
725 issues that become increasingly important when analyzing effects of rewetting and climate change. In  
726 contrast to most data-driven approaches, hydrological models enable a climate-driven representation  
727 of WTD temporal dynamics and the underlying hydrological processes. Moreover, the use of physically  
728 based hydrological models has the distinct advantage of enabling scenario-based analyses, such as the  
729 evaluation of alternative land use strategies and the projection of future hydrological conditions under  
730 climate change scenarios. Utilizing hydrological models that generate high-resolution time series of  
731 WTD, it is possible to quantify impacts of WTD dynamics, including water levels, temporal variability  
732 and seasonal amplitudes, on changes in CO<sub>2</sub> emissions.

733 That said we acknowledge that the rewetting scenarios in the present study are applied using  
734 simplified adjustments to the simulated WTD, rather than being modeled through a detailed, process-  
735 based hydrological framework. Ideally, future assessments should apply catchment-scale models to  
736 evaluate peatland management interventions, such as rewetting, thereby enabling analysis of their  
737 broader hydrological impacts, including effects on streamflow and groundwater levels in neighboring  
738 areas. A unique feature of the present study is that the hydrological model of Tuse Stream catchment is  
739 developed in the same modelling framework as the National Hydrological Model of Denmark  
740 (Henriksen et al., 2020; Stisen et al., 2019). The National Hydrological Model is continuously updated  
741 with new data and operates in near real-time. This integration enables a link between the lessons  
742 learned from the Tuse Stream catchment-scale model and the National Hydrological Model of  
743 Denmark, thereby improving the representation of peatland hydrology and contributing to the  
744 refinement of future national GHG inventories.

745 As a continuation of this study, we will further investigate the spatial variability of WTD and extent  
746 hydrological model to include additional peatland-dominated catchments. Additionally, we will utilize  
747 the National Hydrological model to simulate WTD across all Danish peatlands.

748 Selection, fit and transferability of daily CO<sub>2</sub> emission model  
749 Detailed process-based terrestrial ecosystem models that simulate biogeochemical cycles and  
750 vegetation are available (Bona et al., 2020; Oikawa et al., 2017; Wu and Blodau, 2013). Such modelling  
751 schemes rely largely on multiple parameters related to plant and soil biogeochemistry which are not  
752 generally attainable, thereby limiting the possibility to generalize and upscale.

753 As an alternative a range of empirical models with varying levels of complexity has been developed to  
754 describe ecosystem respiration; however, the most commonly applied formulation is the Lloyd–Taylor  
755 model (Lloyd J., Taylor, 1994), in which temperature acts as the sole independent variable. Structural  
756 complexity in empirical equations is increased through the integration of various other environmental  
757 variables, for example, hydrological variables such as WTD (Rigney et al., 2018). Recent alternative  
758 empirical approaches for estimating CO<sub>2</sub> emissions for organics soils include response functions linking  
759 average annual WTD to annual emissions (Arents et al., 2018; Evans et al., 2021; Tiemeyer et al., 2020),  
760 such as the *Annual WTD model* (Koch et al., 2023) used in this study.

761 To evaluate alternative empirical emission models alongside our *Daily WTD-T<sub>air</sub> model*, we fitted three  
762 different empirical formulations from Rigney et al. (2018) to the Vejrumbro soil CO<sub>2</sub> flux data (Table  
763 S7). Each of the three empirical formulations incorporated both temperature and WTD as independent  
764 variable. The model fitting resulted in R<sup>2</sup> values comparable to those obtained from fitting the *Daily*  
765 *WTD-T<sub>air</sub> model* developed in this study (Table S7).

766 Studying the explanatory power of each independent variable of WTD and T<sub>air</sub> in isolation in the other  
767 empirical emission models, revealed that models in which WTD and T<sub>air</sub> are incorporated as additive  
768 terms, rather than as interdependent (e.g., multiplicative) terms (as in eq. 6 and 8 in Rigney et al.,  
769 (2018)), often exhibit coefficients of determination (R<sup>2</sup>) that are excessively dominated by either WTD  
770 or T<sub>air</sub> (Table S7). This indicates that such model formulations may inadequately capture the joint or  
771 synergistic effects of these variables on the dependent variable. The challenge likely stems from the  
772 fact that both WTD and T<sub>air</sub> exhibit similar seasonal patterns, which may lead the regression to  
773 primarily fit one of the additive terms containing either WTD or T<sub>air</sub>. Empirical models that incorporate  
774 WTD and T<sub>air</sub> as multiplicative terms (such as equation 7 in Rigney et al. (2018) and the *Daily WTD-T<sub>air</sub>*  
775 model developed in this study) demonstrate a more balanced distribution of explanatory power  
776 between each independent variable (Table S7). Nevertheless, equation [7] in Rigney et al. (2018)  
777 remains predominantly influenced by the T<sub>air</sub> component (Table S7). A more balanced distribution of  
778 explanatory power between temperature and WTD is desirable, given that both variables are  
779 recognized as key drivers of soil CO<sub>2</sub> flux dynamics, which is achieved better with the *Daily WTD-T<sub>air</sub>*  
780 than with any of the empirical models in Table S7.

781 We acknowledge that the *Daily WTD-T<sub>air</sub> model* does not reproduce many of the highest observed fCO<sub>2</sub>  
782 values (Figure S6 and S7). In addition to identifying a relationship between fCO<sub>2</sub> and WTD, which was  
783 used to derive the *Daily WTD-T<sub>air</sub> model* (Figure S5), we studied the temperature sensitivity within  
784 WTD bins to better understand the model's inability to reproduce the highest observed fCO<sub>2</sub> values.  
785 Specifically, we binned the daily fCO<sub>2</sub> into four WTD intervals: <20 cm (n=73), 20 to 40 cm (n=37), 30 to  
786 40 cm (n=77) and >40 cm (n=44) (Figure S9). We identified a potential relationship between fCO<sub>2</sub> and  
787 temperature within WTD bins (Figure S9). This result is expected given the strong interdependence  
788 among fCO<sub>2</sub>, temperature and WTD, all of which exhibit comparable seasonal dynamics. The high  
789 observed fCO<sub>2</sub> values cannot be captured by a simple empirical model based solely on T<sub>air</sub> and WTD,  
790 particularly because both high and low fCO<sub>2</sub> occur under similar T<sub>air</sub> and WTD conditions (Figure S5, S7  
791 and S9). Consequently, the *Daily WTD-T<sub>air</sub> model* represents a compromise that captures part of the  
792 variability while preserving a realistic mean response.

793 In this study, we demonstrate the need for the development of emission models operating on a sub-  
794 annual timescale. It highlights the necessity of creating scalable generalized models based on  
795 temperature, WTD and possibly other predictors. The development of such models requires data from  
796 a large number of sites with continuous and temporally dense measurement, in order to integrate  
797 information in a manner similar to models based on annual WTD. We recognize that currently, models  
798 based on annual WTD are likely the most robust for upscaling to national level and current conditions.

799 The simulated soil CO<sub>2</sub> flux at Vejrumbro, estimated using the *Daily WTD-T<sub>air</sub> model* (13.6 Mg CO<sub>2</sub>-C ha<sup>-1</sup> yr<sup>-1</sup>), aligns well with flux measurements from Danish and German sites (Figure 5). This agreement  
800 suggests a comparable magnitude of emissions across geographically distinct locations of similar  
801 characteristics, such as soil type and land use history.

803 We acknowledge that the *Daily WTD-T<sub>air</sub> model* is derived from a single dataset, and that other  
804 emission models also provide valid fits of WTD and T<sub>air</sub>. Furthermore, we recognize that empirical  
805 emission models are highly dependent on the specific data to which they are fitted. Acknowledging the  
806 limited data behind the *Daily WTD-T<sub>air</sub> model* utilized in this study, the goal has not been to accurately  
807 estimate the peatland emission budget, which will be uncertain due to the reliance on a single site.  
808 However, the objective has been to illustrate the impact and insights gained from applying emission  
809 models at a daily timescale and how this has significant impact on the conclusions that can be made  
810 regarding effects of rewetting and climate change. The decision to utilize the *Daily WTD-T<sub>air</sub> model* for  
811 rewetting and climate modeling scenarios is motivated by the simplicity of the relationship and its  
812 direct derivation from the Vejrumbro data, which clearly demonstrates a temperature-dependent  
813 relationship between soil CO<sub>2</sub> flux and WTD. The limited availability of multiple high-temporal-  
814 resolution GHG emission datasets broadly restricts the ability to generalize and upscale empirical GHG  
815 emission models at a daily timescale. Therefore, we consider the *Daily WTD-T<sub>air</sub> model* to be the most  
816 reliable option currently available. Future research should validate the performance of emission  
817 models on intra-annual (within years) data with continuous measured CO<sub>2</sub> data.

818 A promising methodology for future applications, as well as for integrating a Tier 3 framework,  
819 involves coupling a process-based hydrological model with process-based emission models or an  
820 empirically derived daily emission model, such as the one developed in this study, to enable detailed  
821 simulations of GHG emissions that capture short-term dynamics and compound environmental effects.

822

823

824 Conclusion

825 This study demonstrates the feasibility of simulating the temporal dynamics of the peatland water  
826 balance and shallow groundwater table depth (WTD) using a catchment-scale distributed hydrological  
827 model. Accurately modelling shallow WTD is critical for reliable projections of CO<sub>2</sub> emissions from  
828 peatlands. We combined simulations of shallow WTD from the calibrated hydrological model with two  
829 empirical CO<sub>2</sub> emission models 1) an annual WTD-CO<sub>2</sub> relationship and 2) a daily WTD-CO<sub>2</sub> model  
830 accounting for the temperature effect on soil CO<sub>2</sub> production. This approach was used to estimate net  
831 soil CO<sub>2</sub> emissions for the historical period (1991-2020), the mid-century period (2041-2070) and the  
832 end-of-century period (2071-2100). This demonstrated that projections of soil CO<sub>2</sub> emissions are highly  
833 sensitive to the complexity and temporal resolution of the emission model applied. Specifically,  
834 models that incorporate both temperature and WTD dynamics at a daily timescale results in vastly  
835 different conclusion regarding impacts of climate change and rewetting. Regarding climate change  
836 impacts, we show that a daily temperature and WTD based emission model predict increased  
837 emissions due to temperature changes, which can be counter balanced (in the Danish case) or  
838 amplified depending on the future trend in WTD. Our results also demonstrate that rewetting  
839 strategies aimed at raising the groundwater table during the warm summer period offer a CO<sub>2</sub>  
840 emission reduction potential of up to 50%, whereas approaches focused primarily on increasing winter  
841 water table levels result in only marginal reductions. The combination of process-based hydrological  
842 model simulations and a daily-resolution empirical CO<sub>2</sub> emission model used in this study captures the  
843 influence of short-term compound climate events—such as simultaneous high temperatures and low  
844 WTD—which substantially alters projected emission trends compared to simpler approaches. Such  
845 refined approaches are essential for developing adaptive, climate-resilient peatland restoration  
846 policies and improving national greenhouse gas inventories. The findings underscore the importance  
847 of moving beyond static, annual WTD thresholds in peatland management by incorporating dynamic  
848 hydrological simulations. Instead, rewetting strategies should prioritize maintaining elevated summer  
849 groundwater table levels to buffer against drought-induced emission peaks.

850 Supplement link

851 ...

852 Author contributions

853 All authors contributed to the conception and design of the study. TD conducted the analysis and  
854 drafted the manuscript, with input and revisions from all co-authors.

855 Competing interests

856 The authors declare that they have no conflict of interest.

857 Acknowledgements

858 We would like to thank Independent Research Fund Denmark for supporting the project PEAtlands and  
859 Climate-driven variability in groundwater depth – Impacts on greenhouse gas Emissions.

860 References

861 Adhikari, K., Hartemink, A. E., Minasny, B., Bou Kheir, R., Greve, M. B., and Greve, M. H.: Digital  
862 mapping of soil organic carbon contents and stocks in Denmark, PLoS One, 9,  
863 <https://doi.org/10.1371/journal.pone.0105519>, 2014.

864 Ala-aho, P., Soulsby, C., Wang, H., and Tetzlaff, D.: Integrated surface-subsurface model to investigate

865 the role of groundwater in headwater catchment runoff generation: A minimalist approach to  
866 parameterisation, *J. Hydrol.*, 547, 664–677, <https://doi.org/10.1016/j.jhydrol.2017.02.023>, 2017.

867 Arents, E. J. M. M., van der Kolk, J. W. H., Hengeveld, G. M., Lesschen, J. P., Kramer, H., Kuikman, P. J.,  
868 and Schelhaas, M. J.: Greenhouse gas reporting for the LULUCF sector in the Netherlands -  
869 Methodological background, updata 2018, Wageningen, WOt-technical report 113., 2018.

870 Asadzadeh, M. and Tolson, B.: Pareto archived dynamically dimensioned search with hypervolume-  
871 based selection for multi-objective optimization, *Eng. Optim.*, 45, 1489–1509,  
872 <https://doi.org/https://doi.org/10.1080/0305215X.2012.748046>, 2013.

873 Autio, A., Aho, P. A., Ronkanen, A. K., Rossi, P. M., and Kløve, B.: Implications of Peat Soil  
874 Conceptualization for Groundwater Exfiltration in Numerical Modeling: A Study on a Hypothetical  
875 Peatland Hillslope, *Water Resour. Res.*, <https://doi.org/10.1029/2019WR026203>, 2020.

876 Bechtold, M., Tiemeyer, B., Laggner, A., Leppelt, T., Frahm, E., and Belting, S.: Large-scale  
877 regionalization of water table depth in peatlands optimized for greenhouse gas emission upscaling,  
878 *Hydrol. Earth Syst. Sci.*, 18, 3319–3339, <https://doi.org/10.5194/hess-18-3319-2014>, 2014.

879 Bechtold, M., Lannoy, G. J. M. De, Koster, R. D., Reichle, R. H., Mahanama, S. P., Bleutens, W.,  
880 Bourgault, M. A., Brümmer, C., Burdun, I., Desai, A. R., Devito, K., Grünwald, T., Grygoruk, M.,  
881 Humphreys, E. R., Klatt, J., Kurbatova, J., Lohila, A., Munir, T. M., Nilsson, M. B., Price, J. S., Röhl, M.,  
882 Schneider, A., and Tiemeyer, B.: PEAT-CLSM: A Specific Treatment of Peatland Hydrology in the NASA  
883 Catchment Land Surface Model, *J. Adv. Model. Earth Syst.*, 2130–2162,  
884 <https://doi.org/10.1029/2018MS001574>, 2019.

885 Bechtold, M., Lannoy, G. J. M. De, Reichle, R. H., Roose, D., Balliston, N., Burdun, I., Devito, K.,  
886 Kurbatova, J., Strack, M., Zarov, E. A., States, U., Hydrology, W., Sciences, B., and Climate, G.: Improved  
887 Groundwater Table and L-band Brightness Temperature Estimates for Northern Hemisphere Peatlands  
888 Using New Model Physics and SMOS Observations in a Global Data Assimilation Framework, *Remote  
889 Sens. Environ.*, 246, 2020.

890 Bleutens, W., Zarov, E., and Schmitz, O.: A high-resolution transient 3-dimensional hydrological model  
891 of an extensive undisturbed bog complex in West Siberia, *Mires Peat*, 26, 1–25,  
892 <https://doi.org/10.19189/MaP.2019.OMB.StA.1769>, 2020.

893 Bona, K. A., Shaw, C., Thompson, D. K., Hararuk, O., Webster, K., Zhang, G., Voicu, M., and Kurz, W. A.:  
894 The Canadian model for peatlands (CaMP): A peatland carbon model for national greenhouse gas  
895 reporting, *Ecol. Modell.*, 431, 109164, <https://doi.org/10.1016/j.ecolmodel.2020.109164>, 2020.

896 Børgesen, C. D., Waagepetersen, J., Iversen, T. M., Grant, R., Jacobsen, B., and Elmhold, S.:  
897 Midtvejsevaluering af vandmiljøplan III - Hoved- og baggrundsnotater, 2009.

898 Bradley, C.: Simulation of the annual water table dynamics of a foodplain wetland, *Narborough Bog* ,  
899 UK, *J. Hydrol.*, 261, 150–172, 2002.

900 DHI: MIKE HYDRO - River - User Guide, Hørsholm, Denmark, 2019.

901 DHI: MIKE SHE - User Guide and Reference Manual, Hørsholm, Denmark, 2022.

902 Duranel, A., Thompson, J. R., Birmingham, H., Durepaire, P., Garambois, S., Wyns, R., and Cubizolle, H.:  
903 Modelling the hydrological interactions between a fissured granite aquifer and a valley mire in the  
904 Massif Central, France, *Hydrol. Earth Syst. Sci.*, 25, 291–319, 2021.

905 Evans, C. D., Peacock, M., Baird, A. J., Artz, R. R. E., Burden, A., Callaghan, N., Chapman, P. J., Cooper,  
906 H. M., Coyle, M., Craig, E., Cumming, A., Dixon, S., Gauci, V., Grayson, R. P., Helfter, C., Heppell, C. M.,  
907 Holden, J., Jones, D. L., Kaduk, J., Levy, P., Matthews, R., McNamara, N. P., Misselbrook, T., Oakley, S.,  
908 Page, S. E., Rayment, M., Ridley, L. M., Stanley, K. M., Williamson, J. L., Worrall, F., and Morrison, R.:

909 Overriding water table control on managed peatland greenhouse gas emissions, *Nature*, 593, 548–552,  
910 <https://doi.org/10.1038/s41586-021-03523-1>, 2021.

911 Friedrich, S., Gerner, A., Gabrielle, C., and Disse, M.: Scenario-based groundwater modeling of a raised  
912 bog with Mike She, *EGU Gen. Assem.* 2023, Vienna, Austria, 24–28 Apr 2023, EGU23-15608,  
913 <https://doi.org/https://doi.org/10.5194/egusphere-egu23-15608>, 2023.

914 Jupiter: <https://www.geus.dk/produkter-ydelser-og-faciliteter/data-og-kort/national-boringsdatabase-jupiter>, last access: 12 April 2025.

916 Graham, D. N. and Butts, M. B.: Flexible Integrated Watershed Modeling with MIKE SHE, in: *Watershed  
917 Models*, edited by: Singh, V. P. and Frevert, D. K., CRC Press, 245–272,  
918 <https://doi.org/10.1201/9781420037432.ch10>, 2005.

919 Günther, A., Barthelmes, A., Huth, V., Joosten, H., Jurasinski, G., Koebsch, F., and Couwenberg, J.:  
920 Prompt rewetting of drained peatlands reduces climate warming despite methane emissions, *Nat.  
921 Commun.*, 11, 1–5, <https://doi.org/10.1038/s41467-020-15499-z>, 2020.

922 Gyldenkærne, S., Callisen, L. W., Greve, M. H., Beucher, A. M., Weber, P. L., Elsgaard, L., Lærke, P. E.,  
923 Stisen, S., Koch, J., and Levin, G.: Opgørelse af CO<sub>2</sub>-emissioner fra organiske jorde, Aarhus Universitet,  
924 DCE – Nationalt Center for Miljø og Energi, Fagligt notat nr. 2025|01, 29pp pp., 2025.

925 Haahti, K., Warsta, L., Kokkoneen, T., Younis, B. B., and Koivusalo, H.: Distributed hydrological modeling  
926 with channel network flow of a forestry drained peatland site, *Water Resour. Res.*, 246–263,  
927 <https://doi.org/10.1002/2015WR018038>.Received, 2015.

928 Henriksen, H. J., Kragh, S. J., Gotfredsen, J., Ondracek, M., M, van, T., Jakobsen, A., Schneider, R., Koch,  
929 J., Troldborg, L., Rasmussen, P., Pasten-Zapata, E., and Stisen, S.: Dokumentationsrapport vedr.  
930 modelleverancer til Hydrologisk Informations- og Prognosesystem, 2020.

931 Henriksen, H. J., Schneider, R., Koch, J., Ondracek, M., Troldborg, L., Seidenfaden, I. K., Kragh, S. J.,  
932 Bøgh, E., and Stisen, S.: A New Digital Twin for Climate Change Adaptation, Water Management, and  
933 Disaster Risk Reduction (HIP Digital Twin), *Water (Switzerland)*, 15,  
934 <https://doi.org/10.3390/w15010025>, 2023.

935 IPCC: 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories :  
936 Wetlands, edited by: Hiraishi, T., Krug, T., Tanabe, K., Srivastava, N., Baasansuren, J., Fukuda,  
937 M.Troxler, T. G., Published: IPCC, Switzerland, Switzerland, 2014.

938 Jacob, D., Petersen, J., Eggert, B., Alias, A., Christensen, O. B., Bouwer, L. M., Braun, A., Colette, A.,  
939 Déqué, M., Georgievski, G., Georgopoulou, E., Gobiet, A., Menut, L., Nikulin, G., Haensler, A.,  
940 Hempelmann, N., Jones, C., Keuler, K., Kovats, S., Kröner, N., Kotlarski, S., Kriegsmann, A., Martin, E.,  
941 van Meijgaard, E., Moseley, C., Pfeifer, S., Preuschmann, S., Radermacher, C., Radtke, K., Rechid, D.,  
942 Rounsevell, M., Samuelsson, P., Somot, S., Soussana, J. F., Teichmann, C., Valentini, R., Vautard, R.,  
943 Weber, B., and Yiou, P.: EURO-CORDEX: New high-resolution climate change projections for European  
944 impact research, *Reg. Environ. Chang.*, 14, 563–578, <https://doi.org/10.1007/s10113-013-0499-2>,  
945 2014.

946 Jaros, A., Rossi, P. M., Ronkanen, A., and Kløve, B.: Parameterisation of an integrated groundwater-  
947 surface water model for hydrological analysis of boreal aapa mire wetlands, *J. Hydrol.*, 575, 175–191,  
948 <https://doi.org/10.1016/j.jhydrol.2019.04.094>, 2019.

949 Java, O., Kohv, M., and Lõhmus, A.: Performance of a bog hydrological system dynamics simulation  
950 model in an ecological restoration context: Soomaa case study, Estonia, *Water (Switzerland)*, 13,  
951 <https://doi.org/10.3390/w13162217>, 2021.

952 Jutebring, E., Johansson, E., Sjöberg, Y., Huseby, R., and Laudon, H.: Groundwater-surface water

953 interactions across scales in a boreal landscape investigated using a numerical modelling approach, *J.  
954 Hydrol.*, 560, 184–201, <https://doi.org/10.1016/j.jhydrol.2018.03.011>, 2018.

955 Kirpotin, S. N., Antoshkina, O. A., Berezin, A. E., Elshehawi, S., Feurdean, A., Lapshina, E. D., Pokrovsky,  
956 O. S., Peregón, A. M., Semenova, N. M., Tanneberger, F., Volkov, I. V., and Volkova, I. I.: Great Vasyugan  
957 Mire: How the world 's largest peatland helps addressing the world 's largest problems, *Ambio*, 50,  
958 2038–2049, <https://doi.org/10.1007/s13280-021-01520-2>, 2021.

959 Koch, J., Elsgaard, L., Greve, M. H., Gyldenkærne, S., Hermansen, C., Levin, G., Wu, S., and Stisen, S.:  
960 Water-table-driven greenhouse gas emission estimates guide peatland restoration at national scale,  
961 *Biogeosciences*, 20, 2387–2403, <https://doi.org/https://doi.org/10.5194/bg-20-2387-2023>, 2023.

962 Lambert, C., Larocque, M., Gagné, S., and Garneau, M.: Aquifer-Peatland Hydrological Connectivity and  
963 Controlling Factors in Boreal Peatlands, *Front. Earth Sci.*, 10,  
964 <https://doi.org/10.3389/feart.2022.835817>, 2022.

965 Largeron, C., Krinner, G., Ciais, P., and Brutel-Vuilmet, C.: Implementing northern peatlands in a global  
966 land surface model: Description and evaluation in the ORCHIDEE high-latitude version model (ORC-HL-  
967 PEAT), *Geosci. Model Dev.*, 11, 3279–3297, <https://doi.org/10.5194/gmd-11-3279-2018>, 2018.

968 Leifeld, J., Wüst-Galley, C., and Page, S.: Intact and managed peatland soils as a source and sink of  
969 GHGs from 1850 to 2100, *Nat. Clim. Chang.*, 9, 945–947, <https://doi.org/10.1038/s41558-019-0615-5>,  
970 2019.

971 Lewis, C., Albertson, J., Zi, T., Xu, X., and Kiely, G.: How does afforestation affect the hydrology of a  
972 blanket peatland? A modelling study, *Hydrol. Process.*, 3588, 3577–3588,  
973 <https://doi.org/10.1002/hyp.9486>, 2013.

974 Lloyd J., Taylor, J. A.: On the Temperature Dependence of Soil Respiration, *Funct. Ecol.*, 8, 315–323,  
975 1994.

976 Matott, L. S.: OSTRICH – An Optimization Software Toolkit for Research Involving Computational  
977 Heuristics Documentation and User 's Guide, Version 17.12.19, New York, 2019.

978 Mozafari, B., Bruen, M., Donohue, S., Renou-wilson, F., and Loughlin, F. O.: Peatland dynamics: A  
979 review of process-based models and approaches Science of the Total Environment Peatland dynamics :  
980 A review of process-based models and approaches, *Sci. Total Environ.*, 877,  
981 <https://doi.org/10.1016/j.scitotenv.2023.162890>, 2023.

982 Naturstyrelsen: Lavbundsprojekt Ringfenner, Detail- og Myndighedsprojekt, 2022.

983 Nielsen, A. S., Larsen, K. S., Lærke, P. L., Rodriguez, A. F., Pullens, J. W. M., Petersen, R. J., and  
984 Christiansen, J. R.: A full year of continuous net soil and ditch CO<sub>2</sub>, CH<sub>4</sub>, N<sub>2</sub>O fluxes, soil hydrology and  
985 meteorology for a drained fen in Denmark, *Earth Syst. Sci. Data Discuss.* [preprint],  
986 <https://doi.org/10.5194/essd-2025-123>, 2025a.

987 Nielsen, O.-K., Plejdrup, M. S., Winther, M., Nielsen, M., Gyldenkærne, S., Mikkelsen, M. H.,  
988 Albrektsen, R., Hjelgaard, K., Fauser, P., Bruun, H. G., Levin, G., Callisen, L. W., Andersen, T. A.,  
989 Johannsen, V. K., Nord-Larsen, T., Vesterdal, L., Stupak, I., Scott-Bentsen, N., Rasmussen, E., Petersen,  
990 S. B., Baunbæk, L., and Hansen, M. G.: Denmark's National Inventory Document 2025. Emission  
991 Inventories 1990-2023 - Submitted under the United Nations Framework Convention on Climate  
992 Change and the Paris Agreement, 2025b.

993 Oikawa, P. Y., Jenerette, G. D., Knox, S. H., Sturtevant, C., Verfaillie, J., Dronova, I., Poindexter, C. M.,  
994 Eichelmann, E., and Baldocchi, D. D.: Evaluation of a hierarchy of models reveals importance of  
995 substrate limitation for predicting carbon dioxide and methane exchange in restored wetlands, *J.  
996 Geophys. Res. Biogeosciences*, 122, 145–167, <https://doi.org/10.1002/2016JG003438>, 2017.

997 Olefeldt, D., Euskirchen, E. S., Harden, J., Kane, E., McGuire, A. D., Waldrop, mark P., and Turetsky, M.  
998 R.: A decade of boreal rich fen greenhouse gas fluxes in response to natural and experimental water  
999 table variability, *Glob. Chang. Biol.*, 23, 2428–2440, <https://doi.org/10.1111/gcb.13612>, 2017.

1000 Pasten-Zapata, E., Sonnenborg, T. O., and Refsgaard, J. C.: Climate change: Sources of uncertainty in  
1001 precipitation and temperature projections for Denmark, *Geol. Surv. Denmark Greenl. Bull.*, 43, 1–6,  
1002 <https://doi.org/10.34194/GEUSB-201943-01-02>, 2019.

1003 Regeringen: Aftale om et Grønt Danmark - Aftale mellem regeringen, Landbrug & Fødevarer,  
1004 Danmarks Naturfredningsforening, Fødevareforbundet NNF, Dansk Metal, Dansk Industri og  
1005 Kommunernes Landsforening - 24. juni 2024, 2024.

1006 Regulation (EU) 2024/1991: of the European Parliament and of the Council of 24 June 2024 on nature  
1007 restoration and amending Regulation (EU) 2022/869, Official Journal of the European Union, 2024.

1008 Rigney, C., Wilson, D., Renou-Wilson, F., Müller, C., Moser, G., and Byrne, K. A.: Greenhouse gas  
1009 emissions from two rewetted peatlands previously managed for forestry, *Mires Peat*, 21, 1–23,  
1010 <https://doi.org/10.19189/MaP.2017.OMB.314>, 2018.

1011 Rodriguez, A. F., Pullens, J. W. M., Christiansen, J. R., Larsen, K. S., and Lærke, P. E.: Modeling of  
1012 greenhouse gas emissions from paludiculture in rewetting peatlands is improved by high frequency  
1013 water table data, *Egusph.* [preprint], <https://doi.org/10.5194/egusphere-2024-3030>, 2024.

1014 Rossi, P. M., Ala-aho, P., and Doherty, J.: Impact of peatland drainage and restoration on esker  
1015 groundwater resources: modeling future scenarios for management, *Hydrogeol. J.*, 1131–1145,  
1016 <https://doi.org/10.1007/s10040-014-1127-z>, 2014.

1017 Scharling, M.: Klimagrid Danmark - Nedbør, lufttemperatur og potentiel fordampning 20X20 & 40x40  
1018 km - Metodebeskrivelse, Danish Meteorological Institute, 1999a.

1019 Scharling, M.: Klimagrid Danmark Nedbør 10x10 km (ver. 2) - Metodebeskrivelse, Danish  
1020 Meteorological Institute, 1999b.

1021 Schneider, R., Koch, J., Troldborg, L., Henriksen, H. J., and Stisen, S.: Machine learning-based  
1022 downscaling of modelled climate change impacts on groundwater table depth, 2022.

1023 Seidenfaden, I. K., Sonnenborg, T. O., Stisen, S., and Kidmose, J.: Quantification of climate change  
1024 sensitivity of shallow and deep groundwater in Denmark, *J. Hydrol. Reg. Stud.*, 41, 101100,  
1025 <https://doi.org/10.1016/j.ejrh.2022.101100>, 2022.

1026 Shi, X., Thornton, P. E., Ricciuto, D. M., Hanson, P. J., Mao, J., Sebestyen, S. D., Griffiths, N. A., and  
1027 Bisht, G.: Representing northern peatland microtopography and hydrology within the Community Land  
1028 Model, *Biogeosciences*, 12, 6463–6477, <https://doi.org/10.5194/bg-12-6463-2015>, 2015.

1029 Stenberg, L., Haahti, K., Hökkä, H., Launiainen, S., and Nieminen, M.: Hydrology of Drained Peatland  
1030 Forest: Numerical Experiment on the Role of Tree Stand Heterogeneity and Management, *For. MDPI*,  
1031 1–19, <https://doi.org/10.3390/f9100645>, 2018.

1032 Stisen, S., Sonnenborg, T. O., Troldborg, L., and Refsgaard, J. C.: Evaluation of Climate Input Biases and  
1033 Water Balance Issues Using a Coupled Surface – Subsurface Model, *Vadose Zo. J.*, 10,  
1034 <https://doi.org/10.2136/vzj2010.0001>, 2011.

1035 Stisen, S., Ondracek, M., Troldborg, L., Schneider, R. J. M., and van Til, M. J.: National Vandressource  
1036 Model - Modelopstilling og kalibrering af DK-model 2019, De nationale geologiske undersøgelser for  
1037 Danmark og Grønland (GEUS), Rapport 2019/31, 2019.

1038 Tanneberger, F., Abel, S., Couwenberg, J., Dahms, T., Gaudig, G., Günther, A., Kreyling, J., Peters, J.,  
1039 Pongratz, J., and Joosten, H.: Towards net zero CO<sub>2</sub> in 2050: An emission reduction pathway for

1040 organic soils in germany, Mires Peat, 27, 1–17, <https://doi.org/10.19189/MaP.2020.SNPG.StA.1951>,  
1041 2021.

1042 Thompson, C., Devito, K. J., and Mendoza, C. A.: Hydrologic impact of aspen harvesting within the  
1043 subhumid Boreal Plains of Alberta, *Hydrol. Process.*, 3924–3937, <https://doi.org/10.1002/hyp.13301>,  
1044 2018.

1045 Tiemeyer, B., Freibauer, A., Borraz, E. A., Augustin, J., Bechtold, M., Beetz, S., Beyer, C., Ebli, M.,  
1046 Eickenscheidt, T., Fiedler, S., Förster, C., Gensior, A., Giebels, M., Glatzel, S., Heinichen, J., Hoffmann,  
1047 M., Höper, H., Jurasiński, G., Laggner, A., Leiber-Sauheitl, K., Peichl-Brak, M., and Drösler, M.: A new  
1048 methodology for organic soils in national greenhouse gas inventories: Data synthesis, derivation and  
1049 application, *Ecol. Indic.*, 109, 105838, <https://doi.org/10.1016/j.ecolind.2019.105838>, 2020.

1050 Wilson, D., Blain, D., Couwenber, J., Evans, C., Murdiyarso, D., Page, S., Renou-Wilson, F., Rieley, J.,  
1051 Strack, M., and Tuittila, E. S.: Greenhouse gas emission factors associated with rewetting of organic  
1052 soils, *Mires Peat*, 17, 1–28, <https://doi.org/10.19189/MaP.2016.OMB.222>, 2016.

1053 Wu, Y. and Blodau, C.: PEATBOG: A biogeochemical model for analyzing coupled carbon and nitrogen  
1054 dynamics in northern peatlands, *Geosci. Model Dev.*, 6, 1173–1207, <https://doi.org/10.5194/gmd-6-1173-2013>, 2013.

1055 Wunsch, A., Liesch, T., and Broda, S.: Deep learning shows declining groundwater levels in Germany  
1056 until 2100 due to climate change, *Nat. Commun.*, 13, 1–13, <https://doi.org/10.1038/s41467-022-28770-2>, 2022.

1057 Yuan, F., Wang, Y., Ricciuto, D. M., Shi, X., Yuan, F., Brehme, T., Bridgman, S., Keller, J., Warren, J. M.,  
1058 Griffiths, N. A., Sebestyen, S. D., Hanson, P. J., Thornton, P. E., and Xu, X.: Hydrological feedbacks on  
1059 peatland CH<sub>4</sub> emission under warming and elevated CO<sub>2</sub>: A modeling study, *J. Hydrol.*, 603, 127137,  
1060 <https://doi.org/10.1016/j.jhydrol.2021.127137>, 2021.

1061 Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., van den Hurk, B.,  
1062 AghaKouchak, A., Jézéquel, A., Mahecha, M. D., Maraun, D., Ramos, A. M., Ridder, N. N., Thiery, W.,  
1063 and Vignotto, E.: A typology of compound weather and climate events, *Nat. Rev. Earth Environ.*, 1,  
1064 333–347, <https://doi.org/10.1038/s43017-020-0060-z>, 2020.

1065

1066

1067

1068