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Drainage effects on carbon budgets of degraded peatlands in the north of the Netherlands

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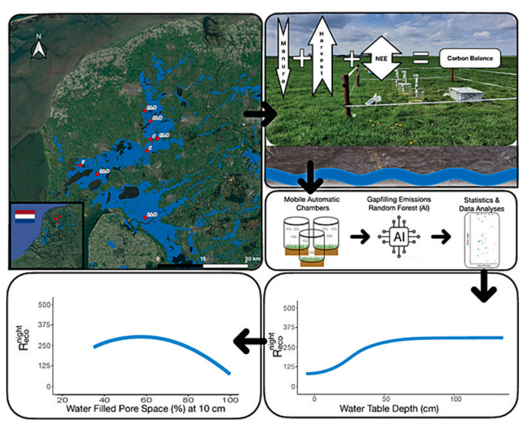
HIGHLIGHTS

- High spatial variation of carbon budgets using a network of automated chambers
- Daily water table depth relates to nightly ecosystem respiration only down to 50 cm.
- Year to year emission variation may result from soil moisture optimum of carbon loss.
- TIER 1 and TIER 2 approaches may neglect regional drivers of CO_2 peat emission.

GRAPHICAL ABSTRACT



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ABSTRACT

Peatlands store vast amounts of carbon (C). However, land-use-driven drainage causes peat oxidation, resulting in CO_2 emission. There is a growing need for ground-truthing CO_2 emission and its potential drivers to better quantify long-term emission trends in peatlands. This will help improve National Inventory Reporting and ultimately aid the design and verification of mitigation measures. To investigate regional drivers of CO_2 emission, we estimated C budgets using custom-made automated chamber systems measuring CO_2 concentrations corrected for carbon export and import. Chamber systems were rotated among thirteen degraded peatland pastures in Friesland (the Netherlands). These peatlands varied in water table depth (WTD), drainage-irrigation management (fixed regulated ditch water level (DWL), subsurface irrigation, furrow irrigation, or dynamic regulated DWL), and soil moisture. We investigated (1) whether drainage-irrigation management and related hydrological

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drivers could explain variation in C budgets, (2) how nighttime ecosystem respiration (R_{eco}^{night}) related to hydrological drivers, and (3) how C budgets compared with estimates from Tier 1 and Tier 2 models regularly used in National Inventory Reporting. Deep-drained peatlands largely overlapped with C budgets from shallow-drained peatlands. The variation in C budgets could not be explained with drainage-irrigation measures or annual WTD, likely because of high variation between sites. R_{eco}^{night} increased from 85 to 250 kg CO_2 ha^{-1} day^{-1} as the WTD dropped from 0 to 50 cm across all sites. A deeper WTD had no apparent effect on R_{eco}^{night}, which could be explained by the unimodal relationship we found between R_{eco}^{night} and soil moisture. Finally, C budgets estimated by Tier 1 emission factors and Tier 2 national models mismatched the between-site and between-year variation found in chamber-based estimated NECBs. To conclude, our study showed that shallow WTDs greatly determine C budgets and that regional C budgets, which can be accurately measure with periodic automated chamber measurements, are instrumental for model validation.

1. Introduction

Peatlands have historically been an important carbon (C) sink (Joosten and Clarke, 2002) and store around 600 Gt of C, nearly 30 % of all global soil C stocks (Yu et al., 2010). Currently, around 10 % of peatlands worldwide have been drained (Joosten, 2010), which causes peat oxidation. This is one of the main causes of peat degradation, thereby contributing to a large part of peatland carbon dioxide (CO_2) emissions, which add up to around 0.52 Gt C per year (Leifeld and Menichetti, 2018). Draining peatlands allows for the optimization of large-scale agriculture, such as mechanized dairy farming. However, global climate policies advocate for C emission reductions from all sectors (IPCC, 2023). Suggested mitigation actions for agriculture on drained/degraded peat soils involve raising the groundwater table, as it is generally accepted that a higher groundwater table depth (WTD) leads to lower peatland CO_2 emissions (Couwenberg, 2011; Drösler et al., 2013; Evans et al., 2021; Joosten, 2010; Tiemeyer et al., 2020). In addition to the active regulation of ditch surface water level (DWL) relative to field height of Dutch peatlands, several drainage-irrigation measures are being tested to reduce CO_2 emission. These include subsurface irrigation (SSI), in which subsurface drains connected to surrounding ditches facilitate water infiltration; furrow irrigation (FI), in which DWL is raised to effectuate water infiltration through the furrows, and dynamic DWL, in which DWL is actively heightened when this is not expected to impact trafficability and grass yield.

The link between WTD and CO_2 emission is also used to determine annual CO_2 budgets in models for National Inventory Reporting (NIR). The annual budgets estimated by the more basic Tier 1 IPCC emission factors (Drösler et al., 2013) are based on annual WTD, dividing peatland sites according to their drainage i.e. shallow-drained (<30 cm annual WTD) or deep-drained (> 30 cm annual WTD). The more advanced Tier 2 models for the Netherlands have DWL as an important input variable, which relates to WTD (Haahti et al., 2012). These models are the GLG model (which can also use annualWTD, van den Akker et al., 2008), which incorporates peat characteristics and is based on estimated carbon losses from land subsidence, and the recently developed SOMERS (Erkens et al., 2022), which is a combination of numerical models that incorporate the different processes involved in peatland CO_2 emission. However, drainage-irrigation management such as subsurface irrigation (SSI) has given mixed results (Tiemeyer et al., 2024; Aben et al., 2024; Boonman et al., 2022; Kruijt et al., 2023; Tiemeyer et al., 2021; Weideveld et al., 2021) and the nature of the relationship between water table and CO_2 emission is debated (Aben et al., 2024; Campbell et al., 2021; Couwenberg, 2011; Evans et al., 2021; Karki et al., 2019; Tiemeyer et al., 2020).

First, there are contrasting results regarding the linearity of such a relationship, with some studies showing a linear (Aben et al., 2024; Jurasinski et al., 2016; Evans et al., 2021; Fritz et al., 2017) and others a non-linear (Mäkiranta et al., 2009; Tiemeyer et al., 2020) association between CO_2 emission and WTD. While the existence of a relationship between CO_2 emission and WTDs between 0 and 50 cm is generally accepted, studies vary on whether deeper WTDs lead to further increases in emissions (Couwenberg, 2011; Tiemeyer et al., 2020). This is important to know, since the various drainage-irrigation mitigation measures usually raise the summer WTD outside of the 0 to 50 cm range.

Second, it is unclear how WTD affects soil moisture in deeply drained peatlands and how this affects CO_2 fluxes. It is likely that the highest CO_2 emission occurs at optimum soil moisture content (Mäkiranta et al., 2009; Moyano et al., 2013; Säurich et al., 2019; Byun et al., 2021), meaning high enough to avoid drought stress of microbes and low enough to facilitate soil gas transport (including supply of oxygen), indicating that the relationship between WTD and CO_2 emission is indirect and would show an optimum at a certain WTD. Possibly, at very low WTD, the soil—particularly the topsoil—can become very dry which is not optimal for soil organic matter oxidation (Mäkiranta et al., 2009; Fenner and Freeman, 2011; Byun et al., 2021), and on the other end, at a high WTD or fully submerged peat, soil organic matter cannot be oxidized due to the lack of oxygen. Management measures such as SSI, where drains can regularly rewet the peat (Weideveld et al., 2021), could also affect this relationship.

An important reason for these debates about the WTD-CO_2 flux relation is that the nature of CO_2 emissions from peatlands, which are highly variable and therefore require intensive measurements at every site, can lead to limitations in terms of design or methods. Many studies include relatively few sites (e.g., Campbell et al., 2021; Karki et al., 2019) which makes statistical analysis difficult. Also, Evans et al. (2021) show increased CO_2 emissions with decreased WTD. However, the dominant land-use type in this study changed along the WTD gradient, which complicates separating land-use effects from WTD effects. Finally, many studies are based on a limited number of light and dark measurements with manual chambers during the daytime (e.g., Tiemeyer et al., 2016; Weideveld et al., 2021), which are extrapolated using models for gross primary production (GPP) and ecosystem respiration (R_{eco}) to quantify the sites annual net ecosystem CO_2 exchange (NEE). This leads to large data gaps and raises the question of whether daytime dark measurements accurately represent R_{eco} as true R_{eco} may be lower during the night due to lower plant respiration (Fan et al., 2024). Still, major treatment effects will likely be found independent of the methods used for measuring CO_2 flux and gap-filling (Liu et al., 2022).

Here, we estimated the carbon (C) budgets for 2021 and 2022 from thirteen drained peatlands used as pastures in Friesland, the Netherlands, estimated from two and a half years of periodic, multi-day measurements of CO_2 concentrations with custom-made automated transparent chambers. The peatlands vary in annual field water table depth (WTD), drainage-irrigation management (fixed regulated DWL [control], SSI, FI, or dynamic DWL), and soil moisture. We ask the following questions:

(1) To what extent can drainage-irrigation management and related hydrological parameters explain variation in C budgets? We hypothesize that shallow-drained sites with higher regulated DWL emit less CO_2 than deep-drained sites, and that SSI, FI, and dynamic DWL lower CO_2 emission. Furthermore, based on the

results found by Evans et al., 2021 & Tiemeyer et al., 2016, we expect that deeper annual WTD leads to higher CO_2 emission.

(2) What is the relationship between nighttime ecosystem respiration (R_{eco}^{night}) and hydrological drivers of soil respiration in peatlands? R_{eco}^{night} was chosen because there is no photosynthesis during the night. We hypothesize that R_{eco}^{night} increases with deeper WTD, and that there is an optimum relationship between soil moisture and R_{eco}^{night}.

(3) How do the C budgets compare to Tier 1 and Tier 2 models used for NIR? We expect the average C budget of shallow-drained and deep-drained peatlands to approximate values of Tier 1 IPCC emission factors, and that NECBs estimated Tier 2 GLG and SOMERS correlate well with chamber-based C budgets.

2. Methods

2.1. Study area

The experiment took place in the province of Friesland, the Netherlands, which has a large area of peatland (89,000 ha, Provincie Fryslân, 2021). Friesland is known for relatively deep drainage and frequent occurrence of a clay layer on top of the peat compared to the rest of the Netherlands. The average annual air temperature is 10.1 °C and the average annual precipitation is 840 mm (KNMI, reference period 1999–2018). Approximately 62 % of the Frisian peatland is used as grassland (drained peatlands) for dairy farming (59,000 ha), generally with high grass and milk productivity. To achieve this high productivity, fixed ditch water levels in these drained peatlands are generally low leading to deep DWL (up to 120 cm below soil surface of the parcels), combined with intensive fertilization (>230 kg N ha^{-1} yr^{-1}), leading to high peat oxidation (Weideveld et al., 2021). The peat layer is between 80 and 200 cm thick, of which the top 30 cm is strongly humified (Von Post humidification scale: H8-H10), and which is often covered by a (carbon-rich) clay layer of 20–40 cm (Weideveld et al., 2021). The deeper peat (70–80 cm) is only moderately decomposed (Von Post humification scale H5-H7).

2.2. Experimental sites

Thirteen sites were set up at dairy farms across Friesland (Fig. 1), with the aim of having a representative overview of annual budgets of regional CO_2 emissions. The sites varied in land use intensity (extensive vs. highly intensive), thickness of the peat layer (between 80 and 200 cm), fixed ditch water level (DWL) as controlled by the water authorities (between 10 and 120 cm below soil surface), and drainage-irrigation management (Table 1). The sites include six control locations (no drainage-irrigation measures applied), three locations with subsurface irrigation (SSI) as described in Weideveld et al. (2021), three locations with furrow irrigation (FI), in which the ditch water level (DWL) was raised to bring about water infiltration via furrows, and one location with dynamic DWL, in which water levels of surrounding ditches are actively raised when this is not expected to negatively impact trafficability and grass yield. Locations 1, 2, 3, 5 and 8 had paired sites (Fig. 1, Table 1).Locations with paired sites include both a control site and a nearby site where a drainage-irrigation management measure was applied.

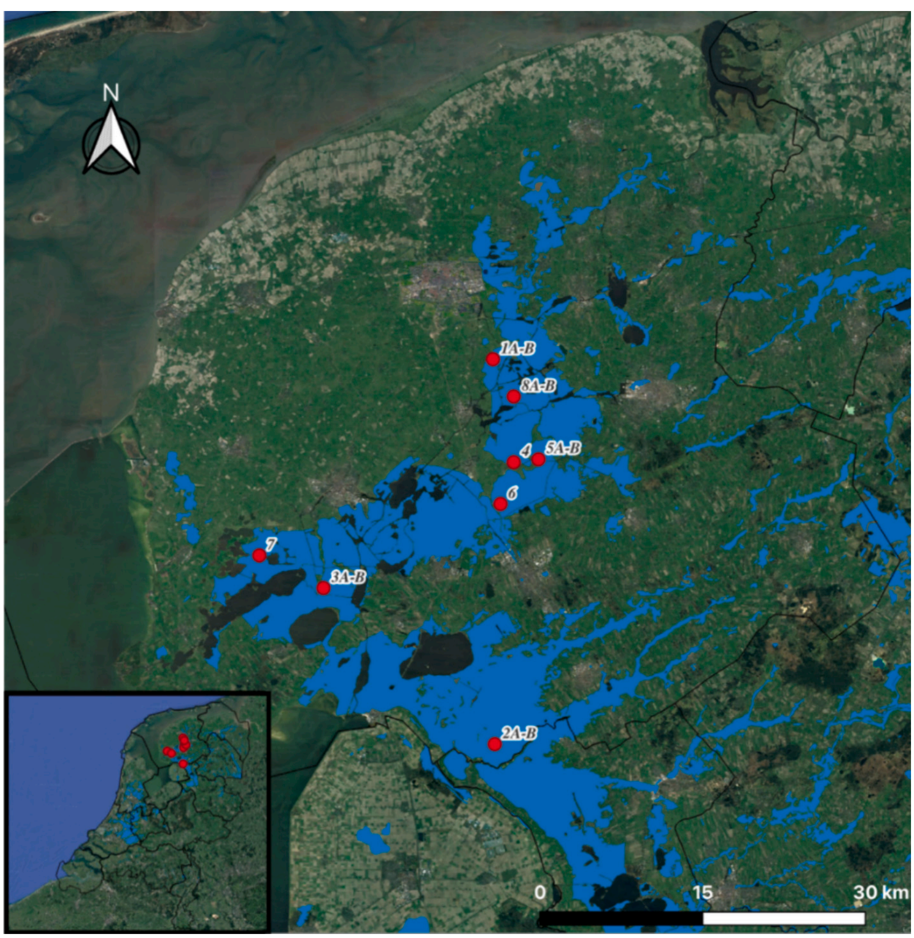

Fig. 1. Map showing measurement locations in Friesland, within the Netherlands. The blue color indicates peat areas, red dots indicate the locations and the black lines the provincial borders. Numbers and letters indicate the different locations.

Table 1

description of the sites, with soil type named according to the Dutch soil classification system: “Waardveen” on Carex and Phragmites remnants (kVc), “Koopveengronden” on Sphagnum remnants (hVs), “Koopveengronden” on Carex and Phragmites remnants (hVc) and “Weideveengronden” on Carex and Phragmites remnants (pVs). Drainage-irrigation measures are: none (control), Subsurface Irrigation (SSI), Furrow Irrigation (FI) and dynamic Ditch Water Level (d-DWL). DWL is regulated according to the decree by the water authority, which aims to maintain it year-round. A more extensive version can be found in Table S1.

Map code	Location name	Drainage-irrigation management	Soil type	Peat thickness (cm)	Top layer	DWL (cm)	Land use
1A	1-ControlA	Control	kVc	220	40 cm clay	95	Biological/ grazing
1B	1-ControlB	Control	kVc	220	40 cm clay	135	Biological/ grazing
2A	2-Control	Control	hVs	120	Peat	35	High-intensity grazing
2B	2-SSI	SSI	hVs	125	Peat	40	High-intensity grazing
3A	3-Control	Control	kVs	105	30 cm clay	115	High-intensity grazing
3B	3-SSI	SSI	kVs	120	30 cm clay	40	High-intensity grazing
4	4-SSI	SSI	kVc	170	40 cm clay	45	Biological/ grazing
5A	5-Control	Control	hVs	110	30 cm clay	80	Extensive/ grazing
5B	5-FI	FI	hVs	150	30 cm clay	15	Extensive/ grazing
6	6-FI	FI	hVs	120	Peat mixed with clay	20	Extensive
7	7-FI	FI	kVs	160	30 cm clay	35	Biological/grazing
8A	8-Control	Control	pVc	230	20 cm clay	55	High-intensity grazing
8B	8-d-DWL	d-DWL	pVs	200	20 cm clay	60	High-intensity grazing

2.3. Experimental setup

At every location, we set up a 3 by 3 m measurement plot in which we regularly deployed automated cylinder-shaped chambers (height and inner diameter of 51 and 38.4 cm, respectively) for estimating net ecosystem exchange (NEE). We measured a combination of environmental parameters (supplementary fig. S.1) from June 2020 until December 2022. Annual carbon (C) budgets were determined for 2021 and 2022 and are the focus of this paper. Three PVC collars (height 20 cm, outer diameter 38 cm), meant for deployment of closed chambers (see below) were dug into the soil up to a depth of 15 cm, from east to west with 75 cm in between collars to avoid chambers shading each other.

To the north of the collars, a box was placed for the greenhouse gas measuring system and batteries, and two dip wells (one for a pressure sensor with logger and one for manual validation measurements) were placed to measure WTD. We also placed dip wells in nearby ditches to measure DWL. Water level in dip wells was monitored using ElliTrack-D water pressure loggers (Leiderdorp Instruments). DWL and WTD measured relative to a fixed value for the average soil surface, which was determined at the start of the experiment via D-GPS relative to a reference founded in the Pleistocene sand. WTD was used to calculate annual WTD and summer WTD (1 July until 30 September).

To the south of the collars, soil temperature and moisture probes were horizontally installed into the ground. Soil temperature was measured at depths of 2, 5, and 10 cm with a HOBO® pendant MX2201 probe and at 20 and 60 cm with a HOBO® STMBM002 probe. Soil moisture was measured at depths of 10 cm and 30 cm with a HOBO® SMDM005 probe. A photosynthetically active radiation (PAR) sensor (HOBO® S-LIA-M003) was installed at 1 m height on the fence surrounding the experimental set-up. Data from soil moisture and temperature sensors at 20 and 60 cm depth were collected with a HOBO® U30-NRC data logger on a 5-min interval.

Soil moisture data was rescaled to water-filled pore space (WFPS) by setting the top 5 % of all soil moisture data from the probes to full saturation (100 % WFPS) and dividing the remaining values by the mean soil moisture value of the top 5 % measurements. These values represent a percentage (0–100 %) of WFPS. Hereafter, this is referred to as estimated WFPS ($WFPS_e$) as it does not represent measured values.

2.4. Mowing and fertilization

To properly mimic management of the agricultural drained peatland, the experimental sites were also fertilized and mowed. All fertilization was done with fresh dairy manure (2.0 % N (SD ± 0.3 %), 35.5 % C (SD ± 2.3 %), C/N ratio 18.5 (SD ± 3.0) and 6.33 mg/g P (SD ± 0.18), measured as described below, from the 4-SSI location once or twice a year based on the fertilization scheme and quantity of the surrounding site farms (Table 1). Mowing occurred when grass height was over 30 cm. Grass yield was determined inside the collars as follows: Grass height was measured before and after cutting with a polystyrene disc (diameter 30 cm) and a ruler, after which grass was cut at around 3 cm above the soil. The grass and manure samples were then dried at 70 °C for at least 48 h until stable dry weight. Total nitrogen (TN) and total carbon (TC) were determined in milled, dry plant material and dried manure (3 mg) using an elemental CNS analyzer (NA 1500, Carlo Erba; Thermo Fisher Scientific, Franklin, USA). Paired sites were always fertilized and mowed on the same day.

2.5. CO_2 measurements

We calculated NEE between the soil-vegetation system and the atmosphere by analyzing concentration changes of CO_2 inside automated, transparent, closed chambers (photo in supplementary fig. S.2). The chambers (3 at each site) were transparent with a height and inner diameter of 51 and 38.4 cm, respectively, and a flat lid controlled by a stepper motor. They were placed on the aforementioned collars that had a seasonally fluctuating offset in chamber height. Collar heights above the surface (some 5 cm) were measured during chamber deployment to adjust the volume used in flux calculations and thereby correct for the seasonal fluctuation (see below). A multiplexer with an integrated pump (2.5 L min^{-1}; KNF NMP830KNDC-B 12 V) was used to control the chambers and facilitate gas circulation between chambers and a gas analyzer (LI-850, LI-COR®) via 10 m of polyurethane tubing (one way). Chambers were measured every 15 min with 3-min closures and 30-s flushing time in between. Concentrations of CO_2 and H_2O were logged every two seconds. Grass heights were recorded at the start of chamber deployment. A low-flow fan ensured well-mixed chamber air (Christiansen et al., 2011; Rochette and Hutchinson, 2005). The average of measurements of the three chambers was calculated per 30 min, which is the time interval usually used in Eddy Covariance (Vitale et al., 2020; S. Zhu et al., 2023), giving 48 estimates of NEE per day.

Chamber systems were rotated among locations, such that every location had 1 to 2 measurement campaigns per month. During each campaign, the chamber system was deployed for 2 to 3 days. This setup enables 1) measuring multiple locations at a frequency that allows for gap-filling of the days in which fluxes were not measured using continuously measured environmental variables as further described below; and 2) reducing the duration of potential artifacts on vegetation and soil as induced by the altered microclimate in the chamber (Boonman et al., 2022; Pumpanen et al., 2010).

2.5.1. Flux calculation and quality control

The CO_2 flux, representing the net ecosystem exchange (NEE, μmol m^{-2} s^{-1}), was calculated according to Eq. (1):

$$NEE = \frac{10V \cdot P_0 \left(1 - \frac{W0}{1000}\right) f_{0_{lin}}}{R \cdot S(T_0 + 273.15)} \tag{1}$$

where $f_{0_{lin}}$ represents the rate of change in water-corrected CO_2 mole fraction (μmol mol^{-1} s^{-1}) inside the closed chamber, V (cm^3) is the chamber volume, including the effect of (changes in) collar height, S (cm^2) is the soil surface area, T_0 (°C) is the air temperature measured inside the chamber after chamber closure (DS18B20 Digital temperature sensor), P_0 (kPa) is the air pressure measured by the barometric pressure sensor inside the multiplexer after closure (Adafruit BMP183 or BMP280), W_0 is the water vapor mole fraction as measured by the CO_2/H_2O analyzer (mmol mol^{-1}), and R (=8.314 Pa m^3 K^{-1} mol^{-1}) is the ideal gas constant. $f_{0_{lin}}$ is the linear regression with a regression window of 90 s, starting 40 s after chamber closure to account for disturbances caused by chamber closure, with a deadband of 15 s.

2.5.2. Quality check

Data points were deemed erroneous and removed when the analyzer's cell pressure or temperature was outside of the manufacturer's guaranteed spec range.

The flux data was manually checked per campaign, excluding points that did not meet the following three criteria: 1) an $R^2 > 0.9$ of the linear regression (except for sunrise and sunset) during spring, summer, and autumn, and $R^2 > 0.6$ during winter (when fluxes are lower and therefore R^2 is naturally lower, 2) the PAR-flux curve showed an expectable trend (based on grass height) and 3) absence of methodological errors (broken fan, malfunctioning lid etc.). Selecting data based on R^2 may have excluded some measurements which had changing cloud cover during the 90 s that changes in CO_2 concentration were recorded.

We admit that warming or cooling of the chamber headspace compared to ambient air temperature is an important filter criterion (some studies, such as Vaidya et al., 2021, discard flux data when warming exceeds 1.5 K). Nevertheless, a temperature correction for daytime NEE fluxes remains absent in our current analysis. No filtering for substantial changes in relative humidity was applied either. Incomplete mixing of the headspace in periods with relatively long grass may have occurred, but was not quantified nor corrected for. The potential greenhouse effect of periodically deployed chambers on grass growth and consequently on C export through harvesting biomass requires attention in future studies.

2.5.3. Gap-filling to determine NEE, R_{eco}, and GPP

Because only a limited number of days were measured during the campaigns, the remaining days had to be gap-filled based on these data. Gap-filling was performed with a Random Forest (RF) model because it performed well in previous studies (Mahabbati et al., 2021; Zhu et al., 2023). We did not choose to construct R_{eco} and GPP models to gap-fill NEE (as in e.g., Poyda et al., 2021; Weideveld et al., 2021) because these models (Lloyd-Taylor and Arrhenius) can include a large degree of bias (Liu et al., 2022). Also, our data was relatively similar to Eddy Covariance (EC) data because it consisted of high-frequency day- and night-time measurements with regular long gaps in between, and gap-filling for EC is generally performed with models such as RF and marginal distribution sampling (MDS) (Mahabbati et al., 2021).

The RF model was trained with the estimated NEE of all years (2020, 2021 and 2022) and the following environmental parameters as explanatory variables: PAR, air temperature, soil temperature at 20 cm depth, ground water temperature, day of the year, day−/nighttime flag, WTD, grass height, and days since mowing. We built 800 trees using three variables per split using the *randomforest* function from the ‘randomForest’ package (Breiman, 2001). To reduce uncertainty of an individual RF model, the median model over 250 model runs has been used. Days since mowing was added because we found that mowing strongly increased NEE, which only largely recovered after about a week. In case data from soil temperature at 20 cm depth (18 % missing) or PAR (48 % missing) were missing, they were gap-filled using a regression with environmental data from the nearest measurement location or from the meteorological weather station of the Royal Dutch Meteorological Institute in Leeuwarden, depending on the distance. Soil temperature at 20 cm depth was chosen because soil temperature at 5 and 10 cm depth had much more missing data (76 % and 68 %, respectively). Air temperature data from the SSI-4 site were used for all sites, as it was complete for the entire 2021 and 2022. Soil moisture was not included in gap-filling because there were large data gaps in these data due to faulty probes.

Ecosystem respiration (R_{eco}) and GPP were also calculated through gap-filling methods. To estimate R_{eco}, we trained an RF model with data from the night fluxes (PAR < 1) using the same environmental variables as for the full RF model. We then used the RF model to predict respiration during the day and night with the available environmental data. Only night data was used to predict R_{eco} for the full day, because during the night GPP = 0, and therefore the CO_2 emissions during the night are assumed to represent ecosystems respiration only, whereas daytime fluxes are a combination of ecosystem respiration and photosynthesis. The RF model for Reco was trained similarly to the RF model for NEE, using air temperature, soil temperature at 20 cm depth, ground water temperature, day of the year, WTD, grass height, and days since mowing as environmental variables, but excluding the PAR and day/night variables, as the model was trained on nighttime data only when PAR was <1. Although it is an established method to model daytime R_{eco} based on nighttime R_{eco} estimates, we are aware that it may lead to biased estimates as both the temperature response of R_{eco} and the temperature-controlled magnitude of R_{eco} can differ between day- and nighttime, for example, due to processes such as inhibited leaf respiration in light (Järveoja et al., 2020; Keenan et al., 2019). RF was used because this was shown to perform much better when calculating R_{eco} than using empirical models such as the Lloyd-Taylor modified Arrhenius function (Han et al., 2022). Subsequently, GPP during the day was calculated by subtracting the NEE from the R_{eco}. Importantly, some of the analyses in this paper focus only on the measurements of Reco taken in the field during the nighttime (R_{eco}^{night}) rather than including the values predicted by RF, as these provide the most concrete evidence of relationships between ecosystem respiration and environmental variables, and are not affected by possible bias in the RF model.

We performed an uncertainty analysis on this gap-filling using data from a different automated chamber system located in location 4-SSI that has largely been permanently deployed since 2021 (Aben et al., 2024), where year-round measurements have been taken, continuously measuring day and night fluxes.. To simulate a dataset, campaigns (2–3 days of consecutive measurements) were selected from a continuous dataset (measured concurrently at site 4-SSI). These campaigns were used to train the model and fill the artificial gaps based on the relationships established by the model. With gap filling, an annual NEE budget can be produced, which can be compared to the annual NEE budget of the measured values. As the measurement frequency was not equally distributed over the year and over all sites (supplementary table S.1) we tested four scenarios for different campaign intervals measuring: once a month, twice a month, four times per month and seasonally, where more measurement were taken in summer compared to winter (supplementary table S.2). Each scenario used the same total amount of data points throughout the full year. Based on this uncertainty analysis, an estimate can be made of the extent to which mobile measurements are suitable for determining annual budgets.

Second, the effect of removing campaigns from the dataset on the NEE resulting from the RF models was determined to assess sensitivity of random forest to input data. This was done as follows: for every campaign per location, a dataset was created in which this campaign was removed. Subsequently, the RF model was run 120 times for this new dataset, resulting in new gap-filling data and new annual NEE per year per location. Then, the variation between NEE per year per location with the different removed campaigns was determined by calculating the 95 % confidence interval.

2.6. Relationship annual C budgets and drainage-irrigation management

The gap-filled fluxes were used to calculate the annual NEE per location in 2021 and 2022. Similarly, annual budgets of R_{eco} and GPP were calculated using gap-filled values for R_{eco} and GPP. We use the Tiemeyer et al., 2016 definition for C budget, which accounts for C export via harvest and C import via manure, but not for the potential loss of C via leaching or lateral transfer and the potential emission of volatile organic C, methane, and carbon monoxide. Therefore, C budget was calculated by summing up annual NEE, C export through harvest (positive term), and C import through fertilization (negative term), which were determined as described above.

The average C budgets from the different sites were compared according to their annual WTD-class (shallow-drained or deep-drained). The 3-Control and 4-SSI sites were not included in this comparison because at 3-Control the old grass sod had been removed and new grass had been sown just before the start of the experiment, leading to a temporary built-up of soil carbon stocks often coinciding with very low NEE, and 4-SSI had a much lower number of campaigns compared to other sites, leading to much higher uncertainty as described above. When classifying sites as either shallow-drained or deep-drained, the two-year mean of WTD was used.

Furthermore, the individual C budgets were related to drainage-irrigation mitigation measures (regulated DWL (control), SSI, FI, and dynamic DWL), year (2021 and 2022), annual WTD, summer WTD, and (regulated) DWL, also excluding the 3-Control and 4-SSI locations. Differences between drainage-irrigation measures and years were tested with a repeated measures ANOVA using the *rstatix* package (Kassambara, 2020). Dynamic DWL was not tested because there was only one site. These results should be regarded with caution because the 4-SSI site was included to enable testing with the repeated measures ANOVA. The difference in C budget between 2021 and 2022 and the effects of annual WTD, summer WTD, and DWL were tested using a separate linear mixed-effects model with the *lme* function using the *nlme* package (v3.1–152; Pinheiro et al., 2021), with site as a random factor.

2.6.1. Relationship of R_{eco}^{night} with WTD and soil moisture

To investigate mechanisms potentially driving site-specific variation in CO_2 emission, we related WTD and soil moisture to R_{eco}^{night}. We parametrized nonlinear models for the response of R_{eco}^{night} to WTD and soil moisture. For the relationship between R_{eco}^{night} and WTD, a Gompertz function was fitted (eq. 2) as in Tiemeyer et al. (2020), using the *nlsLM* function of the minpack.lm package (Elzhov et al., 2023). The uncertainty in the predictions was estimated with bootstrapping ($n = 999$) using the *nlstools* function (Baty et al., 2015).

$$R_{eco}^{night}(WTD) = R_{eco_{min}}^{night} + R_{eco_{diff}}^{night} \cdot e^{-a \cdot e^{b \cdot WTD}} \quad (2)$$

where $R_{eco_{min}}^{night}$ is the lower asymptote, $R_{eco_{diff}}^{night}$ is the difference between upper and lower asymptotes, while a and b are fitting parameters for the displacement along the x-axis and the growth rate. An additional analysis was performed with the *nlme* function, using the *nlme* package (v3.1–152; Pinheiro et al., 2021), in which location was added as a random factor.

For the relationship between soil moisture and R_{eco}^{night}, a quadratic polynomial function was fitted to enable a comparison with Säurich et al. (2019), who also used this function. The function was also fitted with the *nlsLM* function. To improve interpretability of the soil moisture data, we pooled the data in bins of 5 % $WFPS_e$ by taking the average of all values within the bin (e.g., all values between 95 % and 100 % $WFPS_e$). Lines were fitted for the pooled data, including only pooled data points that included at least 5 values to avoid a very large effect on the quadratic model by single measurements.

2.6.2. Comparison with Tier 1 and Tier 2 models

To compare the estimated C budget from our data with Tier 1 and Tier 2 models, C budgets were calculated according to IPCC emissions factors (Tier 1, Drösler et al., 2013), and the SOMERS and GLG models (Tier 2, Erkens et al., 2022; van den Akker et al., 2008). The IPCC emission factors were based on the average WTD of sites, and sites with a WTD higher than 0.35 m were classified as "shallow-drained nutrient-rich grasslands", while locations with deeper WTD were classified as "deep-drained nutrient-rich grasslands", which give C budgets of 13.2 and 22.4 t CO_2 ha^{-1} yr^{-1} respectively (Drösler et al., 2013). The SOMERS- and GLG-based C budgets were determined based on the regulated DWL as maintained by the Frisian water authority.

SOMERS 1.0 (Erkens et al., 2022) uses a combination of region (province of Friesland), drainage-irrigation management (e.g., is SSI used or not) and regulated DWL to calculate C budget. The model uses a combination of several numerical models about processes related to water and carbon based on data from five peat locations in the Netherlands, one of which is in Friesland. To calculate SOMERS C budgets, soil type, distance to nearest ditch, drainage-irrigation management, summer DWL, and winter DWL are entered into a sheet specific for the region according to the SOMERS calculation rules (Erkens et al., 2022, https://www.nobveenweiden.nl/rekenregels/).

The GLG model (van den Akker et al., 2008) made use of characteristics of the fibric peat layer, presence or absence of a clay layer, and regulated DWL, according to eq. (3) for peat with a clay layer and eq. (4) for peat without a clay layer:

$$C\ budget_{GLG_{clay}} = F \cdot (15.5 \cdot DWL - 3.5) \cdot \rho_{so} \cdot fr_{os} \cdot fr_c \cdot 44/12 \quad (3)$$

$$C\ budget_{GLG_{no\ clay}} = F \cdot (15.5 \cdot DWL + 2.7) \cdot \rho_{so} \cdot fr_{os} \cdot fr_c \cdot 44/12 \quad (4)$$

With $C\ budget_{GLG_{clay}}$ and $C\ budget_{GLG_{no\ clay}}$ in tons CO_2 ha^{-1} yr^{-1} and where $F = 1$, DWL of the location (m), ρ_{so} is bulk density of the peat (kg m^{-3}), fr_{os} is organic matter content of the peat (−), and fr_c is the carbon fraction of the organic matter (−). Organic matter content was determined via loss on ignition of peat samples. Peat samples were incinerated for 4 h at 550 °C. Total nitrogen (TN) and total carbon (TC) were determined in soil material (9–23 mg) using an elemental CNS analyzer (NA 1500, Carlo Erba; Thermo Fisher Scientific, Franklin, USA). As the GLG model estimates C budgets using the deeper fibric peat layer, we used the peat parameters measured at a depth of 55 to 85 cm, thus excluding the clay layer which is very different from the peat.

All analyses were performed in R-4.3.1 (R Core Team, 2019).

3. Results

In this research, we determined the quantity and drivers of CO_2 emission in thirteen drained peatlands in the Friesland region for two years with different drainage, peat thickness, and water management.

The uncertainty analysis of the artificial data gaps on a continuously measured site showed that an approach with two campaigns per month in the growing season and one campaign per month outside of the growing season led to low variation in NEE (Fig. 2, 95 % confidence interval for annual NEE ± 1.5 t CO_2 ha^{-1} yr^{-1}), comparable to a setup with two or four campaigns per month (95 % confidence interval ± 2 t CO_2 ha^{-1} yr^{-1} and ± 1.6 t CO_2 ha^{-1} yr^{-1} respectively). In contrast, the variation was higher with one campaign per month (±3 t CO_2 ha^{-1} yr^{-1}), likely because of capturing less variation caused by harvest and fertilization events. Most sites had a measurement frequency in between

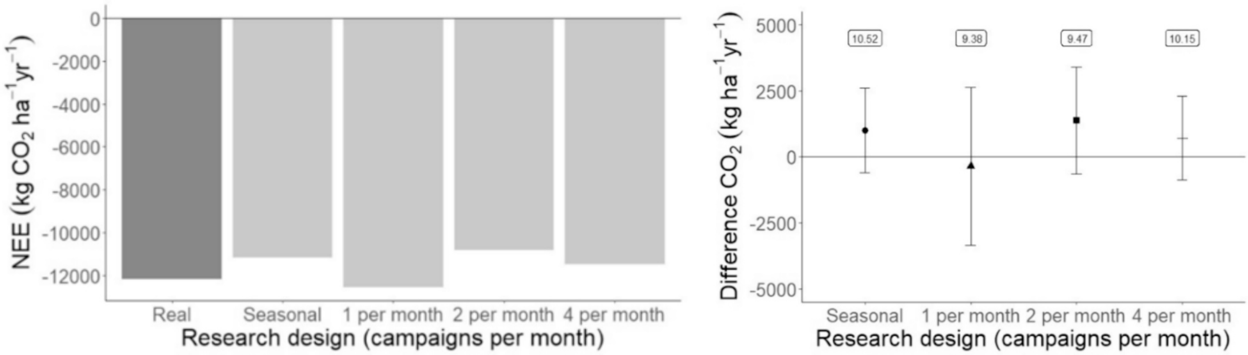

Fig. 2. Estimate and variation in mobile measurement simulation. A) NEE for each of the scenarios. The dark grey bar results from including all data points, as well as gap filling when data was not available. Light grey bars result from the various scenarios. It should be noted that C import through manure application and C export through grass harvesting are not included, resulting in negative values. B) The NEE difference with the estimate, as well as the variation between model runs. The label above each error bar shows the percentage of data included in each of the runs.

the seasonal scenario and the scenario with one campaign per month (supplementary table S.1). However, because one site was measured much less frequently for logistical reasons (4-SSI), this location is further marked with an asterisk in all results.

The sites had variable carbon (C) budgets, ranging from −0.1 t CO_2 ha^{-1} yr^{-1} up to 33.3 t CO_2 ha^{-1} yr^{-1} (Table 2). When sites were clustered based on annual WTD class (shallow-drained <30 cm annual WTD or deep-drained >30 cm annual WTD, Fig. 3A), no differences in C budget were found. The mean C budget of shallow-drained sites was similar to the mean C budget of deep-drained locations (14.69 vs 14.68 t CO_2 ha^{-1} yr^{-1}, excluding 3-Control and 4-SSI, see Fig. 3A), which is close to the IPCC emission factor for shallow-drained peatlands (13.19 t CO_2 ha^{-1} yr^{-1}) but much lower than the IPCC emission factor for deep-drained peatlands (22.35 t CO_2 ha^{-1} yr^{-1}). On average, NEE contributed negatively to C budget (average − 3.5 t CO_2 ha^{-1} yr^{-1}), ranging from −19.5 to 9 t CO_2 ha^{-1} yr^{-1} (Table 2), giving an average Root Mean Square Error of 20.78 kg ha^{1} d^{-1} and Mean Absolute Error of 11.89 kg ha^{-1} d^{-1} (supplementary fig. S.4). C export (positive term) through harvest was the largest term contributing to the average C budget (average 23.3 ± 6.6 SD t CO_2 ha^{-1} yr^{-1}), while C import (negative term) through manure application was much less (−5.1 ± 2.9 SD t CO_2 ha^{-1} yr^{-1}). Harvest also correlated strongly with GPP (supplementary fig. S.5).

A repeated measures ANOVA did not show an explanatory effect of drainage-irrigation management for the variation in C budget (Fig. 3B, $F_{2,8} = 0.67$, $p = 0.54$). Although the average C budgets of sites with furrow irrigation (FI) (10.5 t CO_2 ha^{-1} yr^{-1}) and sub surface irrigation (SSI) (12.5 t CO_2 ha^{-1} yr^{-1}, excluding 4-SSI) were slightly lower than the average C budget of control sites (16.6 t CO_2 ha^{-1} yr^{-1}), there was also high variability within treatments with, e.g., a high C budget for one SSI location (29.8 t CO_2 ha^{-1} yr^{-1} for 2-SSI in 2021) and a low C budget for one control locations (−0.1 t CO_2 ha^{-1} yr^{-1} for Control-2 in 2022). The single dynamic DWL site (8-d-DWL) had an above average C budgets in both 2021 and 2022 (20.6 and 31.4 t CO_2 ha^{-1} yr^{-1}).

Table 2
Annual Carbon Budgets (CB), NEE, R_{eco}, GPP, harvest, and applied manure for different locations for different years in t ha^{-1} y^{-1}. The 3-Control and 4-SSI locations are marked with an asterisk due to unique conditions; 3-control had a new grass layer sown just before the start of the experiment, leading to a very low NEE, whereas 4-SSI had a much lower number of campaigns compared to other locations.

Location	Treatment	Year	CB	NEE ± 95 % CI	R_{eco}	GPP	Harvest	Manure	Annual WTD	IPCC_EF	IPCC_EF	SOMERS CB	GLG CB
			t CO_2 ha^{-1} yr^{-1}						cm		t CO_2 ha^{-1} yr^{-1}		
1-ControlA	Control	2021	15.4	−6.3 ± 0.42	54.6	−60.9	26.1	−4.5	25.7	Shallow	13.19	19.1	17.1
	Control	2022	6.4	−6.7 ± 0.30	53.1	−59.9	17.6	−4.5	42.0	Deep	22.35	19.1	17.2
1-ControlB	Control	2021	10	−6.7 ± 0.32	57.2	−63.9	21.1	−4.5	39.0	Deep	22.35	20.25	4.6
	Control	2022	−0.1	−19.5 ± 0.42	49.6	−69.1	23.9	−4.5	64.1	Deep	22.35	20.25	5.2
2-Control	Control	2021	33.3	9.6 ± 0.36	89.3	−79.7	30	−6.4	36.6	Deep	22.35	8.8	11.2
	Control	2022	12.9	0.8 ± 0.33	64	−63.3	18.5	−6.4	62.3	Deep	22.35	8.8	11.9
2-SSI	SSI	2021	29.8	0.7 ± 0.37	71.2	−70.5	35.5	−6.4	28.5	Shallow	13.19	8.8	10.3
	SSI	2022	8.4	−7.6 ± 0.35	63.7	−71.3	22.4	−6.4	58.5	Deep	22.35	8.8	10.8
3-Control*	Control	2021	7.6	−17 ± 0.27	62.2	−79.2	32.2	−7.6	24.7	Shallow	13.19	5.6	6.6
	Control	2022	0.6	−14.3 ± 0.31	55.1	−69.4	25.3	−10.3	54.4	Deep	22.35	5.6	6.6
3-SSI	SSI	2021	14.9	−5.2 ± 0.36	72.4	−77.6	27.7	−7.6	21.0	Shallow	13.19	31.18	36
	SSI	2022	0.1	−13.1 ± 0.28	59.2	−72.3	23.6	−10.3	43.0	Deep	22.35	31.18	36
4-SSI*	SSI	2021	24.1	−1.3 ± 0.88	72.2	−73.5	31.2	−5.7	25.9	Shallow	22.35	7.15	4.1
	SSI	2022	21.8	1.4 ± 1.14	74.3	−73	20.4	0	35.3	Deep	22.35	7.15	4.1
5-Control	Control	2021	19.1	0.2 ± 0.30	71.8	−71.6	21.5	−2.5	29.0	Shallow	13.19	27.1	12.4
	Control	2022	25.8	9 ± 0.46	75.7	−66.8	19.4	−2.6	55.9	Deep	22.35	27.1	12.4
5-FI	FI	2021	4.2	−13.4 ± 0.45	53.2	−66.7	20.2	−2.5	16.6	Shallow	13.19	13.2	1.1
	FI	2022	6	−4.2 ± 0.38	58.3	−62.5	12.9	−2.6	32.5	Deep	22.35	13.2	0
6-FI	FI	2021	4.9	−4.1 ± 0.44	51.9	−56.1	10.9	−1.9	18.4	Shallow	13.19	3.3	8.4
	FI	2022	11.7	−3.3 ± 0.27	51.8	−55.3	17.5	−2.4	34.3	Deep	22.35	3.3	8.1
7-FI	FI	2021	13.3	−4.9 ± 0.26	78.8	−83.7	23.9	−5.7	28.3	Shallow	13.19	9.15	1.1
	FI	2022	16	−0.9 ± 0.33	76.3	−77.3	21.5	−4.5	37.3	Deep	22.35	9.15	2.5
8-Control	Control	2021	14.8	−3.5 ± 0.63	56.2	−59.8	23.5	−5.1	18.4	Shallow	13.19	12.5	7.1
	Control	2022	17.3	0.5 ± 0.67	63.7	−63.3	24.6	−7.7	37.2	Deep	22.35	12.5	6.9
8-d-DWL	dynamic DWL	2021	31.4	−0.7 ± 0.20	70.4	−71	37.2	−5.1	18.9	Shallow	13.19	15.4	3.7
	dynamic DWL	2022	20.6	−5 ± 0.28	65.5	−70.5	33.4	−7.7	33.0	Deep	22.35	15.4	2.3

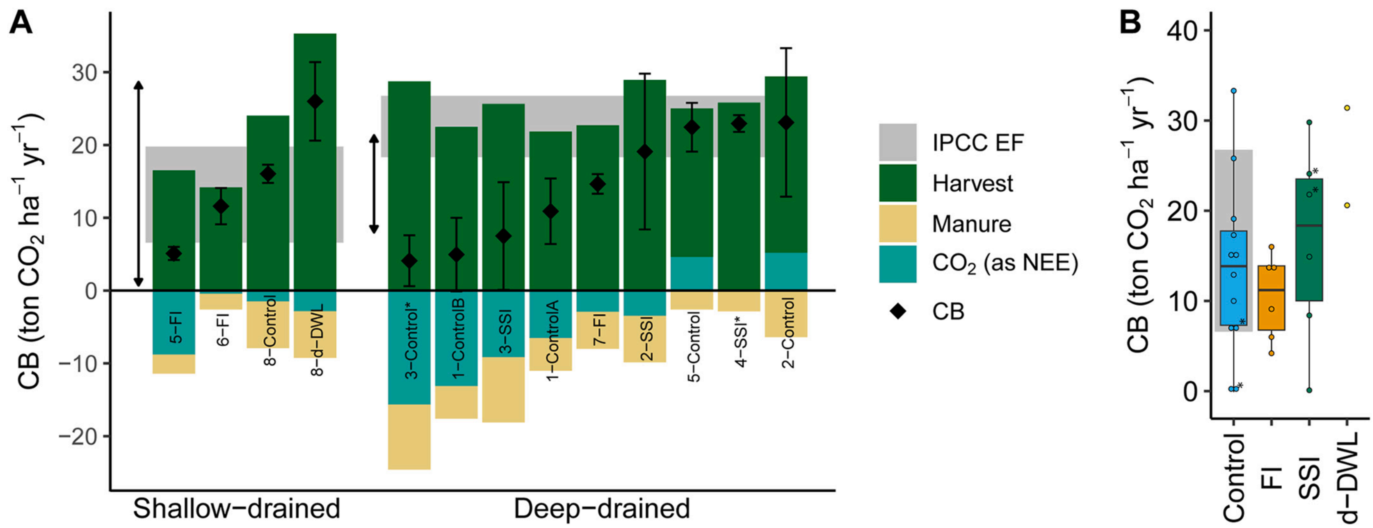

Fig. 3. Carbon Budget (CB) in t CO_2 ha^{-1} yr^{-1} per (A) measurement site and (B) drainage-irrigation measure. Measurement sites in Fig. 3A are categorized by drainage according to IPCC standards for annual WTD using the avarage of the two years in which they were measured. Points show the average CB, the error bars show the minimum and maximum values of the CB per location for 2021 and 2022 combined. Colors show the contribution of different C imports and exports on CB per year. Arrows indicate a 95 % confidence interval for the average CBs of shallow-drained (<30 cm annual WTD) and deep-drained (>30 cm annual WTD) sites, grey bars indicate IPCC emission factors for shallow-drained and deep-drained nutrient-rich grasslands. In Fig. 3B, colors indicate drainage-irrigation measures and the grey bar is the range for IPCC EFs. In both panels, the 3-Control and 4-SSI sites are marked with an asterisk due to unique conditions; 3-control had a new grass layer sown just before the start of the experiment, whereas 4-SSI had a much lower number of campaigns compared to other locations.

When comparing paired sites, the 5-FI site had a much lower C budget than the 5-Control site (Table 2, 5.1 vs 22.5 t CO_2 ha^{-1} yr^{-1}), which was coupled with a strong effect of FI on WTD (supplementary fig. S.6). The 2-SSI site also had a lower C budget than the 2-Control site (19.1 vs 23.1 t CO_2 ha^{-1} yr^{-1}), although this difference was smaller, possibly because the effect on WTD was also smaller. SSI also heightened WTD in 3-SSI compared to 3-Control (supplementary fig. S.6), but because of the new grass sod in 3-Control these C budgets cannot be fairly compared. Finally, the 8-d-DWL site had a higher C budget than the 8-Control site (26.0 vs 16.1 t CO_2 ha^{-1} yr^{-1}), although it did have slightly higher WTD (Table 2, supplementary fig. S.6).

Contrary to expectations that a higher WTD leads to lower emissions, the colder, wetter year 2021 (supplementary fig. S.7), during which all sites had higher annual WTD and summer WTD (supplementary table S.4, fig. S.8), showed a trend towards having higher C budgets ($F_{1,10}$ = 3.94, p = 0.075, Fig. 4A). Furthermore, C budgets did not correlate to annual WTD, summer WTD, or regulated DWL (p > 0.1 for all, Fig. 4B—D).

In contrast, R_{eco}^{night} showed a relationship with WTD where R_{eco}^{night} increased at relatively shallow WTD between 0 and 50 cm (Fig. 5A, supplementary table S.5). However, at deeper WTD than 50 cm, there was no further increase in R_{eco}^{night}. A similar pattern was visible when looking at individual measurements (supplementary fig. S.9), which also shows the temperature response of CO_2 emissions. When looking at sites separately (supplementary fig. S.10), most individual sites show a similar pattern, although for some sites, the relationship was more linear. Importantly, WTD was often 50 cm or deeper in summer for most sites (supplementary table S.4, fig. S.8).

The quadratic relationship between water-filled pore space (WFPS$_e$, estimated based on soil moisture; see Methods) at −10 and − 30 cm and R_{eco}^{night} shows an optimum soil moisture content range at which most CO_2 was emitted (Fig. 5). This optimum was most pronounced for soil moisture at 10 cm depth (Fig. 5A) and less pronounced for soil moisture at 30 cm depth (Fig. 5C), as also highlighted by the stronger evidence

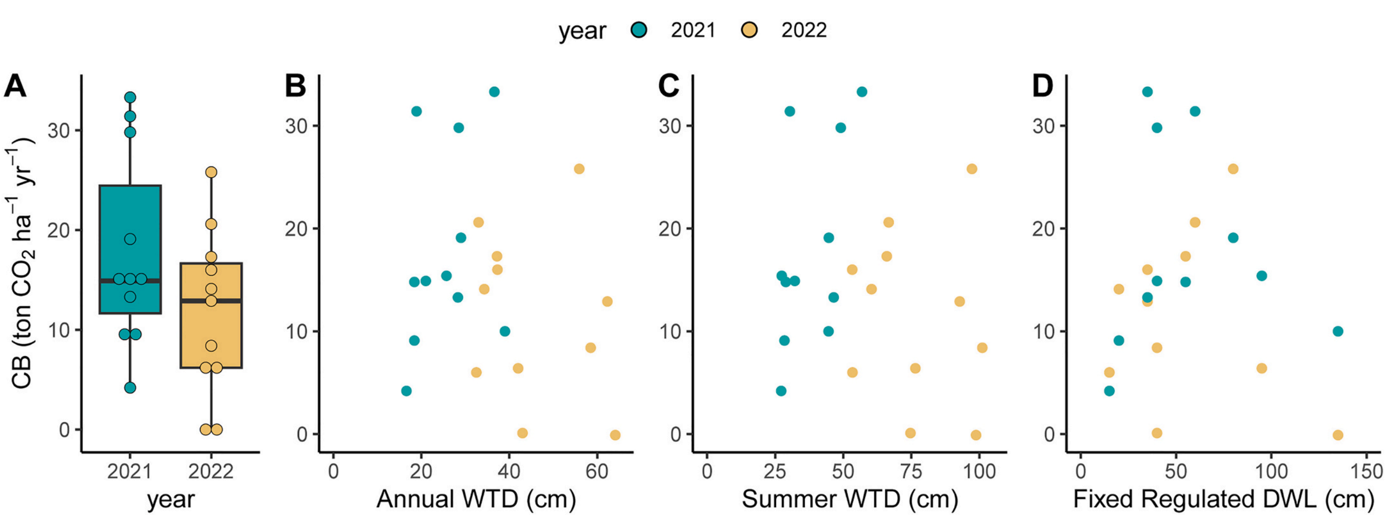

Fig. 4. (A) difference between Carbon Budgets (CB) in 2021 and 2022 (excluding 3-Control and 4-SSI), and relationship between CB and (B) annual Water Table Depth (WTD), (C) summer WTD, and (D) fixed regulated Ditch Water Level (DWL). Blue represents 2021, yellow represents 2022 and N = 22.

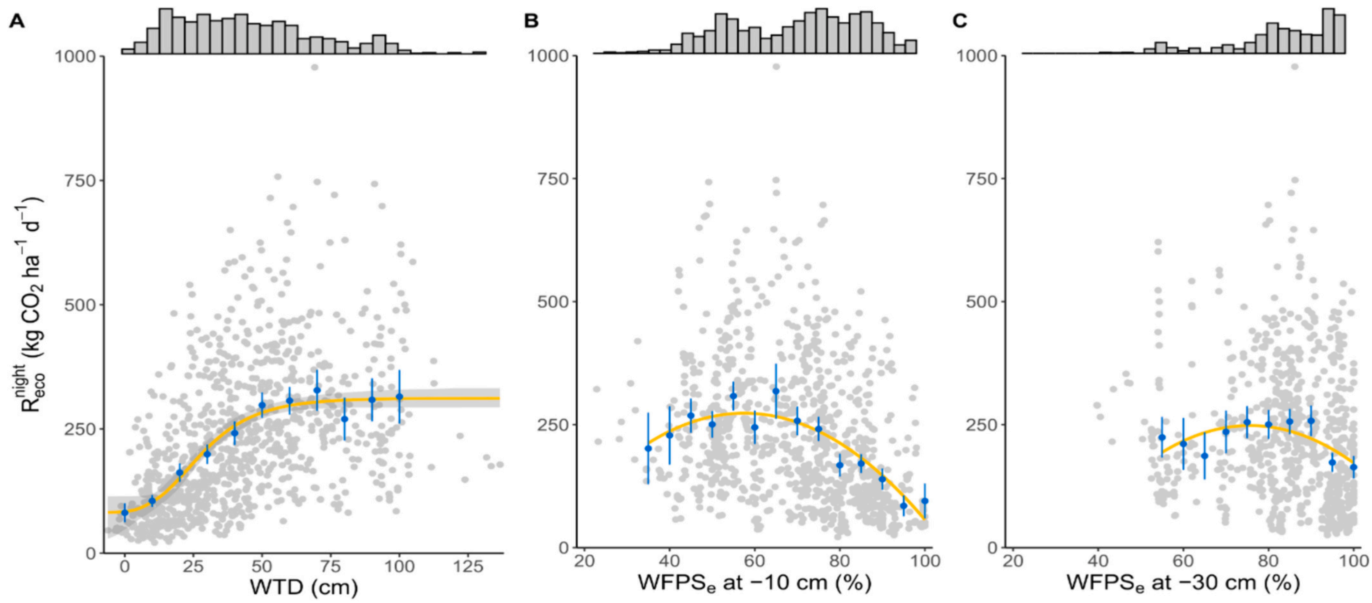

Fig. 5. A) Relationship between WTD and R_{eco}^{night} averaged per night. Grey points show R_{eco}^{night} average per night, blue points show the pooled data in bins of 10 cm WTD. Error bars show a 95 % confidence interval of pooled data in bins of 10, only including pooled data with at least five data points. The histogram shows the density of measurements for a certain WTD. The yellow line is according to a fitted Gompertz function, as shown in eq. (3) and also used in Tiemeyer et al. (2020). Parametrized values are $R_{eco_{min}}^{night} = 84$, $R_{eco_{diff}}^{night} = 229$, a = 5.2, and b = −0.073. Additionally, the Gompertz function was also fitted with the nlme function including site as a random effect (supplementary fig. S.10). B & C) Relationship between estimated water-filled pore space (WFPS$_e$) and average R_{eco}^{night} at a soil depth of (B) 10 cm and (C) 30 cm. Grey dots show individual measurements, blue dots show WFPS$_e$ binned into 5 % intervals, where each bin contains a minimum of five observations. Confidence intervals for binned values are shown, yellow lines are fitted according to quadratic polynomial functions, of which the parameter estimates and *p*-values are shown in supplementary tables S.6 and S.7.

that the parameter estimates deviated from zero (supplementary table S.6 and S.7). WFPS$_e$ at 10 cm depth ranged from 20 to 100 % with an optimum at 60 %, while WFPS$_e$ at 30 cm depth ranged from 40 to 100 % with an optimum at 75 %.

When comparing the C budgets in this project to C budgets estimated with Tier 1 and Tier 2 models (Fig. 6), it is visible that the amount of variation in our dataset is best captured by Tier 2 models, whereas Tier 1 models assume a fixed value based only on annual WTD (Fig. 6A, Table 2). However, when comparing C budgets per site-year estimated by SOMERS (Fig. 6C) and GLG (Fig. 6D) with our data, there is no clear relationship. Furthermore, the average C budget estimated by the GLG model was substantially lower than in our data (7.6 vs 14.7 t CO_2 ha^{-1} yr^{-1}), while the average C budget estimated by SOMERS was lower (13.0 t CO_2 ha^{-1} yr^{-1}). Interestingly, while in our data we found no relationship between annual WTD and C budget, the Tier 1 and Tier 2 models have comparable relationships with increasing C budget at increasing WTD (Fig. 6B). Because the Tier 2 models used regulated DWL as an input variable, the relationship between C budget and regulated DWL is even more pronounced for these models, especially for SOMERS (supplementary fig. S.11 A).

4. Discussion

4.1. General findings

We used custom-built automated transparent chambers that were regularly rotated among sites to quantify CO_2 fluxes and carbon (C) budgets of thirteen Frisian drained peatlands in 2021 and 2022 with different water table depth (WTD), drainage-irrigation management, and soil moisture. We found that this method could give accurate results with low 95 % confidence intervals when measuring seasonally, which was similar to our setup. Contrary to expectation, variation in C budgets seemed independent from drainage-irrigation management. Shallow-drained and deep-drained sites had similar average C budgets, while sites with furrow irrigation (FI) and sub surface irrigation (SSI) did not have statistically lower C budgets than control sites, possibly because of high within-treatment variation in C budgets and the small sample size. Also, we found no relationship between variation in C budget and annual WTD. In contrast, R_{eco}^{night} increased from 85 to 250 kg CO_2 ha^{-1} day^{-1} as the daily WTD dropped from 0 to 50 cm across all sites. A deeper WTD had no apparent effect on R_{eco}^{night}, which could be explained by the quadratic relationship we found between R_{eco}^{night} and soil moisture, as further discussed below. Finally, C budgets estimated by Tier 1 (IPCC EF) and Tier 2 models (SOMERS and GLG) mismatched the between-site variation found in chamber-based estimated C budgets. Across all sites, drainage-irrigation mitigation measures, and years, Tier 1 and Tier 2 approaches can differ substantially from the C budget estimates presented here.

4.2. Measuring CO_2 emission with periodic automatic chamber measurements

In this study we used a novel method to determine CO_2 emission from peatlands, by using automatic chambers rotated among sites in campaigns of 2–3 days. Then, a random forest (RF) model was used to determine CO_2 emission on days without measurements based on environmental parameters. An uncertainty analysis, using data from a site where automated chambers were placed permanently, showed a low confidence interval when these campaigns were carried out seasonally, measuring once per month outside the growing season and twice per month in the growing season, similar to our setup. The reason for this was likely that having a higher frequency of campaigns in the growing season better captured harvest and fertilization events.

This analysis showed that our method enables to measure multiple sites, allowing for a high spatial coverage of peatland areas, while having enough data to accurately determine annual CO_2 emission. This method is much less costly and less labor-intensive than measuring the

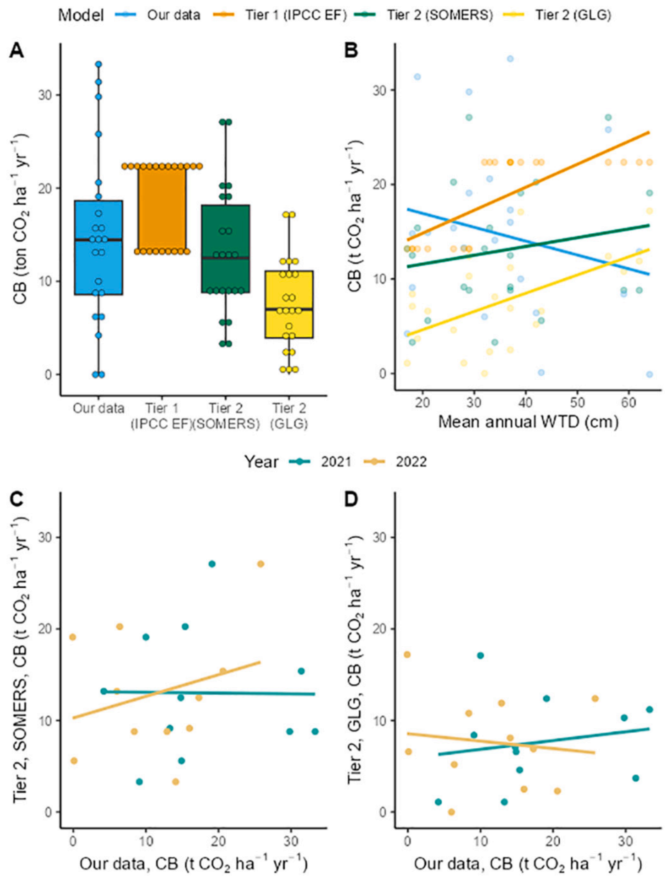

Fig. 6. Comparison of Carbon Budgets (CB) estimated in this project with CBs estimated by Tier 1 (IPCC emission factors, Drösler et al., 2013) and Tier 2 (SOMERS and GLG, Erkens et al., 2022; van den Akker et al., 2008) models. (A) boxplot showing CBs estimated by the different methods. (B) Comparison of relationship between annual WTD and the CB from the different models. (C and D) comparison between individual CBs estimated by Tier 2 models (SOMERS and GLG) and CBs estimated in this project. For Fig. 6A and B, colors indicate method; for Fig. 6C and D, colors indicate years.

same number of sites continuously with automatic chambers (e.g., Aben et al., 2024) that disturb the vegetation, need continuous site maintenance, and require a high number of greenhouse gas analyzers and automatic chambers. Furthermore, gap-filling CO_2 fluxes with a RF model based on day and night measurements is likely much more accurate than gap-filling CO_2 fluxes with GPP and Reco models based on light and dark measurements with manual chambers (Liu et al., 2022). Thus, the method used in our study presents a good trade-off between site disturbance, cost, labor intensity and accuracy.

4.3. Between-site and between-year variation in carbon budget and relation to drainage-irrigation management

Annual C budgets of CO_2 emission differed substantially between sites and years, as found in earlier studies (Schrier-Uijl et al., 2014; Tiemeyer et al., 2016; Weideveld et al., 2021). The between-site and between-year variation was seemingly not explained by drainage-irrigation management nor annual WTD. There were no clear differences between the average C budget from shallow-drained or deep-drained peatlands, and sites with drainage-irrigation mitigation measures (SSI, FI, and dynamic DWL) did not have significantly different C budgets from control sites, possibly because of high variability within treatments and low sample size. While a significant effect of SSI on C budgets has been found in some cases (Boonman et al., 2022; Aben et al., 2024), this effect is not consistent throughout literature (Tiemeyer et al., 2021; Weideveld et al., 2021). Control sites also had high variation and included both the sites with the lowest and highest C budget (−0.1 and 33 t CO_2 ha^{-1} yr^{-1}), although Tiemeyer et al. (2016) found much larger variation in C budgets (~3 to 69 t CO_2 ha^{-1} yr^{-1} for nutrient-rich grasslands on organic soils). Our highest C budget of 33 t CO_2 ha^{-1} yr^{-1} was found in location 2-Control, which is one of the sites without a clay layer, which can potentially explain why this budget was so high (van den Akker et al., 2012). We expect the low budget of −0.1 t CO_2 ha^{-1} yr^{-1} in location 1-ControlB to be due to natural variation in site-years, as this is a more commonly observed C budget (Aben et al., 2024; Evans et al., 2021).

Year-to-year variation between C budgets is commonly observed (Aben et al., 2024; Weideveld et al., 2021). In contrast to our expectations, the colder, wetter year 2021, which had higher annual WTD and summer WTD, showed a trend towards having higher C budgets than 2022. It is not fully clear why C budgets were higher in 2021. In the current dataset, C budget seemed independent from annual WTD, summer WTD, and regulated DWL, which contrasts national datasets (Tiemeyer et al., 2020; Evans et al., 2021). In national studies, WTD is usually correlated to vegetation type, land-use intensity, and site-specific soil properties (Tiemeyer et al., 2016). Importantly, sites investigated here revealed a summer WTD between 50 cm to 80 cm, characteristic for the Friesland region (Provincie Fryslân, 2021), which could lead to high emissions in a short period of time (Regina et al., 2014). Furthermore, the difference in soil properties (e.g., pore size distribution, stability of soil organic matter, alternative electron acceptor loading) in most sites could obscure effects of WTD on soil respiration in the topsoil, as these variables are important for soil respiration (McCarter et al., 2020; Normand et al., 2021) but we did not measure them. Therefore, we cannot rule out a relationship between the water table and C budget, especially if more sites with near-surface summer WTD and with a wider range of soil properties had been included.

4.4. Relationship between R_{eco}^{night} and hydrological drivers of soil respiration in peatlands

To better understand the mechanisms driving variation in CO_2 emission, we studied how R_{eco}^{night} varied according to WTD and soil moisture. Interestingly, R_{eco}^{night} increased with lowering WTD on the scale of single nights, likely because a deeper WTD facilitates oxygen intrusion and hence aerobic oxidation of soil organic matter (Iiyama et al., 2012). However, R_{eco}^{night} only increased at WTD up to around 50 cm, while there was no apparent effect of WTD on R_{eco}^{night} at deeper WTD (> 50 cm). Since most sites had a managed DWL below 50 cm, which stimulated summer WTD below 50 cm, this means that most sites could emit high quantities of CO_2 during the growing season, when temperature is highest and most emissions occur (Updegraff et al., 2001). Therefore, it is possible that if more sites were included with a shallow managed DWL close to the surface (i.e. well-above 50 cm) or with drainage-irrigation management increasing WTD to well-above 50 cm, we may have observed contrasting groups of C budget - annual WTD relationships.

The apparent absence of a relationship between WTD and R_{eco}^{night} below WTDs around ~50 cm may be explained by the effect of soil moisture: deep WTDs occur during periods of drought, and we found an quadratic relationship between $WFPS_e$ and R_{eco}^{night}. During those conditions, the soil moisture content of the labile carbon-rich topsoil may become low enough to initiate drought stress on the microbial community, thereby constraining respiration and hence CO_2 production. Drought constraints on peat respiration were shown in a controlled lab study by Säurich et al., 2019 and field study by Makiranta et al., 2009, who found a similarly shaped relationship between $WFPS_e$ and CO_2 emission as in the current study. Peat layers below 50 cm (henceforth subsoil) are often characterized by lower respiration rates and, consequently, CO_2 flux potential compared to the topsoil (Quadra et al., 2023; Regina et al., 2014; Säurich et al., 2019). Since the (degraded) topsoil generally has the highest content and lability of carbon (Leifeld et al., 2012; Weideveld et al., 2021; Kuzyakov and Gavrichkova, 2010) and has the highest oxygen intrusion (Iiyama et al., 2012), reductions in emissions from these layers can strongly impact total emissions. Higher emission observed in 2021 may support the moisture-optimum aspect of the effects of WTD on CO_2 emission, as lower emission in 2022 may have been due to moisture limitation of microbial activity in the topsoil despite higher temperature. We expect that the soil moisture – R_{eco}^{night} relationship stems from the response of microbial respiration to various soil moisture levels.

In the literature, contrasting results have been found for the effect of WTD on CO_2 emission. One study based on Eddy Covariance data from sixteen locations showed that different land uses along a management-related WTD gradient suggest a relationship between C budget and WTD (Evans et al., 2021). When looking only at sites with similar land use as in our study (grasslands), the study found increasing C budgets with deeper annual WTD between ~20 and 55 cm. However, this relationship was largely determined by two grasslands from Canada and Chile with low productivity. The study also found that an annual WTD deeper than 55 cm led to higher C budget, but sites with this annual WTD were croplands. Another study, based on campaign-wise measurements with manual closed chambers in 118 locations in Germany, showed a Gompertz-type relationship between annual WTD and C budget with a strong reduction of C budget at annual WTD higher than 50 cm and a much smaller effect at deeper annual WTD (Tiemeyer et al., 2020). These locations were also variable in land use but because this study included a high total number of sites, the patterns were less impacted by the small subset of sites with a different land use. We found a similar Gompertz-type relationship, although in our study this relationship was found between WTD and R_{eco}^{night}, rather than between C budget and annual WTD.

The studies (Evans et al., 2021; Tiemeyer et al., 2020; and our study) all agree that drainage up to 50 cm likely leads to increased CO_2 emission. It is interesting to note that these conclusions were reached with different methodologies (Eddy Covariance, campaign-wise with manual chambers, campaign-wise with automatic chambers). Thus, although a limitation of campaign-wise measurements is that gap-filling of long methodology-related data gaps comes with uncertainty (Gao et al., 2023; Liu et al., 2022), the agreement in results with other studies gives further confidence in our findings. However, the effect of WTD on CO_2 emission at depths deeper than 50 cm still needs to be investigated further to determine the main driving factors of CO_2 emission at this depth and their relationship with WTD.

4.5. Comparison chamber-based carbon budget with carbon budget estimated by Tier 1 and Tier 2 models

To analyze the representation of regional CO_2 emission by national inventory reporting (NIR), we compared the chamber-based C budgets with the C budgets estimated by Tier 1 (IPCC EFs) and Tier 2 (SOMERS and GLG) models. The Tier 1 IPCC EFs (Drösler et al., 2013) predict higher C budgets for deep-drained sites (22.35 t CO_2 ha^{-1} yr^{-1}) than shallow-drained sites (13.19 t CO_2 ha^{-1} yr^{-1}), but in our data, these had a similar average C budget (both average 14.7 t CO_2 ha^{-1} yr^{-1}) close to the IPCC emission factor for shallow-drained sites. Furthermore, because Tier 1 EFs only provide two possible values for CO_2 emission from shallow-drained nutrient-rich grasslands on organic soils, they did not reflect the variation in C budgets found in our dataset. One explanation why deep-drained sites had lower C budgets than IPCC predictions could be our methods, as we used a novel approach to estimate C budgets, and previous studies have suggested that the methods used are important for C budget estimates (Schrier-Uijl et al., 2014; Brouns et al., 2015; Kruijt et al., 2020; Weideveld et al., 2021; Liu et al., 2022). A second reason might be that differences in soil properties (e.g., pore size distribution, stability of soil organic matter, alternative electron acceptor loading) of Frisian peatlands could lead to lower soil respiration in the topsoil (McCarter et al., 2020; Normand et al., 2021) than in the sites used for determining IPCC EFs.

The between-site and between-year variation in chamber-based C budgets mismatched the variation in NECBs estimated by Tier 2 models (GLG and SOMERS), as the differently estimated C budgets showed little correlation (Fig. 6C/D). The average C budget estimated by the GLG model (7.6 t CO_2 ha^{-1} yr^{-1}, van den Akker et al., 2008) was also much lower than the average chamber-based C budget (14.7 t CO_2 ha^{-1} yr^{-1}). Possibly, the relationship between land subsidence and WTD that is assumed in this model did not apply to our data. Also, the alternative version of this model, which uses the lowest annual WTD of the past eight years, might give a different result which could be more similar to our data.

Interestingly, the average C budget of SOMERS (12.7 t CO_2 ha^{-1} yr^{-1}) deviated less from average chamber-based C budget (14.7 t CO_2 ha^{-1} yr^{-1}) than other TIER 1 and TIER 2 approaches. One explanation for this small deviation is that the SOMERS TIER 2 approach has been calibrated against C budgets estimates from similar automated chambers as those used in the current study. It is important to note that SOMERS is intended to be applied at a grid-scale and that it is based on coarse soil types, which might not accurately reflect the carbon content of the soil. Furthermore, the assumptions of the underlying models of SOMERS could expect stronger effects of variables such as WTD, soil moisture, and temperature than were present in the Frisian locations, especially because SOMERS only included one Frisian site for its validation. Finally, SOMERS estimates carbon cycling of the whole parcel rather than of a representative measuring plot, although it seems unlikely that field scale emission differs from plot scale emission to such an extent that could explain the large deviations observed in 11 comparisons replicated in 2 years. Therefore, further development of the SOMERS models may be needed to improve site-specific estimates of C budget related to management choices in drained peatlands.

Importantly, however, accounting for year-to-year variation in Tier 1 and 2 models is challenging. This variation is largely caused by variables such as WTD, air and soil temperature, root and litter carbon storage, and soil moisture, while data on these variables is often not available. Therefore, when establishing emission factors, simplification is needed, while striving to minimize uncertainty through measurements over a sufficient spatiotemporal scale, especially taking care not to limit data to one year, which may have unusually high or low C budgets. Using a method such as the one applied in our study can help provide these data.

4.6. Limitations and uncertainties

Accurate estimation of C budgets is essential for gaining insights into carbon dynamics within ecosystems. One notable concern in current C budget estimations is the potential underestimation of GPP due to the chamber warming effect (on average increasing T_{air} + 0.82 °C) that may stimulate photosynthesis during chamber closure and presence across most of the year when leaf temperature is below its temperature optimum (Li et al., 2020; McPherson, 1983; Wagner and Reicosky, 1992; Woledge and Dennis, 1982). On the other hand, the simultaneous small increase in soil temperature (average increase T_{soil} + 0.38 °C at 5 cm depth could partly counter this increase in GPP by increasing soil respiration. Furthermore, since the effect of the chambers on T_{air} and T_{soil} was similar for different drainage-irrigation measures, this likely does not affect interpretations of treatment effects. We expect a net underestimation of NEE as T_{air} increased more than T_{soil}, and photosynthesis is more sensitive to temperature than soil respiration (Urban et al., 2007). More research is needed to quantify the effect of increased

T_{air} and T_{soil} on NEE, e.g. by comparing NEE between cooled and non-cooled chambers. Furthermore, regression times to estimate NEE can have a large influence on C budget estimations (Shi et al., 2022), which deserves more attention in future research. Although the absolute size of NEE is likely affected by methodological choices, we assume that NEE differences between sites, between years and between drainage-irrigation measures are less prone to a biased analysis (Liu et al., 2022). Furthermore, we acknowledge that land-use intensity, drainage-irrigation management, and annual groundwater table are often correlated (Couwenberg, 2011; Tiemeyer et al., 2016; Evans et al., 2021). Therefore, the nature of the relationship between C budgets and WTD, as well as the size of C budgets, is partly determined by these factors.

In summary, while there is confidence in the relative differences and spatial patterns of C budget estimations, there is recognition that absolute CO_2 emission values may be subject to uncertainties. Addressing the identified challenges, such as (transparent) chamber effects, will contribute to refining the accuracy of C budget estimations. Future research should further explore the correlation between drainage-irrigation methods and land-use intensity, providing a more nuanced understanding of the factors influencing carbon dynamics in drained peatlands.

4.7. Implication for management

Our study suggests that drainage-irrigation management can potentially reduce carbon emission from peatlands. The current analysis emphasises the importance of rewetting the uppermost 50 cm of the soil throughout the year. Increased WTD in the range between 0 and 50 cm stimulates CO_2 emission as confirmed by the saturation-curve relationship between daily WTD and R_{eco}^{night}.

Lowering land-use intensity (e.g. lower nitrogen fertilizers, less grass cuts, no tillage, lower grazing density) may further reduce CO_2 emission as suggested by case studies (Beetz et al., 2013), national inventories (Tiemeyer et al., 2016; Tiemeyer et al., 2020; Evans et al., 2021) and meta-analyses (Wilson et al., 2016). Reducing evapotranspiration rates by adapted grassland management may increase soil moisture levels to levels high enough reduce CO_2 emission (Fig. 5; Säurich et al., 2019).

5. Conclusion

The data presented here gave an overview of emission spatial heterogeneity and of the drivers of between-site and between-year carbon budget from drained peatlands the Friesland province. Also, we presented a novel method to determine CO_2 emission, combining periodic measurements by automated chambers with gap-filling using a Random Forest model, which was shown to give a good trade-off between site disturbance, cost, labor intensity and accuracy. Water table depth (WTD) positively correlated to nightly ecosystem respiration up to 50 cm, but this was not reflected in the relationship between annual and summer WTD and carbon budgets. The deep WTD during the growing season likely led to suboptimal soil moisture conditions in the topsoil, which became too dry for high CO_2 emission. Furthermore, we could not detect an effect of drainage-irrigation management on carbon budgets, which may be related to the large between-site and between-year variation combined with a small sample size. Finally, the mismatch in carbon budget estimations by chambers and prediction by Tier 1 and Tier 2 models calls for an improved representation of CO_2 emission drivers in Tier 2 and Tier 3 approaches to better include between-site and between-year variation. Methodological short-comings of automated lid-closed chambers need improvement before embedding their carbon budget estimates in National Inventory Reporting schemes. To conclude, our study showed that 1) shallow WTDs greatly determine CO_2 emission, 2) regional measurements of CO_2 emission are instrumental for model validation, and 3) periodic automatic chamber measurements can be an effective and efficient method to determine these emissions.

CRediT authorship contribution statement

Thomas P.A. Nijman: Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis, Data curation. **Quint van Giersbergen:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation. **Tom S. Heuts:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation. **Reinder Nouta:** Writing – review & editing, Investigation, Data curation. **Coline C.F. Boonman:** Writing – review & editing, Data curation. **Mandy Velthuis:** Writing – review & editing, Methodology, Formal analysis. **Bart Kruijt:** Writing – review & editing, Funding acquisition, Conceptualization. **Ralf C.H. Aben:** Writing – review & editing, Software, Resources, Methodology. **Christian Fritz:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no competing interests.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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References

Aben, R.C., van de Craats, D., Boonman, J., Peeters, S.H., Vriend, B., Boonman, C.C., van der Velde, Y., Erkens, G., van den Berg, M., 2024. Using automated transparent chambers to quantify CO 2 emissions and potential emission reduction by water infiltration systems in drained coastal peatlands in the Netherlands. EGUsphere 2024, 1–31. https://doi.org/10.5194/egusphere-2024-403.

van den Akker, J.J.H., Kuikman, P.J., de Vries, F., Hoving, I., Pleijter, M., Hendriks, R.F. A., Wolleswinkel, R.J., Simões, R.T.L., Kwakernaak, C., 2008. Emission of CO2 from agricultural peat soils in the Netherlands and ways to limit this emission. International Peat Society, pp. 645–648.

Baty, F., Ritz, C., Charles, S., Brutsche, M., Flandrois, J.-P., Delignette-Muller, M.-L., 2015. A toolbox for nonlinear regression in R: the package nlstools. J. Stat. Softw. 66 (5 SE-Articles), 1–21. https://doi.org/10.18637/jss.v066.i05.

Beetz, S., Liebersbach, H., Glatzel, S., Jurasinski, G., Buczko, U., Höper, H., 2013. Effects of land use intensity on the full greenhouse gas balance in an Atlantic peat bog. Biogeosciences 10, 1067–1082. https://doi.org/10.5194/bg-10-1067-2013.

Boonman, J., Hefting, M.M., Van Huissteden, C.J.A., Van Den Berg, M., Van Huissteden, J., Erkens, G., Melman, R., Van Der Velde, Y., 2022. Cutting peatland CO2 emissions with water management practices. Biogeosciences 19 (24), 5707–5727. https://doi.org/10.5194/bg-19-5707-2022.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32. https://doi.org/10.1023/A:1010933404324.

Brouns, K., Eikelboom, T., Jansen, P.C., Janssen, R., Kwakernaak, C., van den Akker, J.J., Verhoeven, J.T., 2015. Spatial analysis of soil subsidence in peat meadow areas in Friesland in relation to land and water management, climate change, and adaptation. Environ. Manag. 55 (2), 360–372. https://doi.org/10.1007/s00267-014-0392-x.

Byun, E., Rezanezhad, F., Fairbairn, L., et al., 2021. Temperature, moisture and freeze–thaw controls on CO2 production in soil incubations from northern peatlands. Sci. Rep. 11, 23219 https://doi.org/10.1038/s41598-021-02606-3.

Campbell, D.I., Glover-Clark, G.L., Goodrich, J.P., Morcom, C.P., Schipper, L.A., Wall, A. M., 2021. Large differences in CO2 emissions from two dairy farms on a drained peatland driven by contrasting respiration rates during seasonal dry conditions. Sci. Total Environ. 760 https://doi.org/10.1016/j.scitotenv.2020.143410.

Christiansen, J.R., Korhonen, J., Juszczak, R., Giebels, M., Pihlatie, M., 2011. Assessing the effects of chamber placement, manual sampling and headspace mixing on CH4 fluxes in a laboratory experiment. Plant and Soil 343 (1–2), 171–185. https://doi.org/10.1007/s11104-010-0701-y.

Couwenberg, J., 2011. Greenhouse gas emissions from managed peat soils: is the IPCC reporting guidance realistic?, 8 http://www.mires-and-peat.net/.

Drösler, M., Verchot, L.V., Freibauer, A., Pan, G., 2013. Drained inland organic soils. 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands, pp. 1–79.

Elzhov, T.V., Mullen, K.M., Spiess, A., Bolker, B., 2023. _minpack.lm: R Interface to the Levenberg-Marquardt nonlinear least-squares algorithm found in MINPACK, plus support for Bounds_. R package version 1, 2–4. https://CRAN.R-project.org/package=minpack.lm.

Erkens, G., Melman, R., Jansen, S., Boonman, J., Hefting, M., Keuskamp, J., Bootsma, H., Nougues, L., van den Berg, M., van der Velde, Y., 2022. Subsurface Organic Matter Emission Registration System (SOMERS), december.

Evans, C.D., Peacock, M., Baird, A.J., Artz, R.R.E., Burden, A., Callaghan, N., Chapman, P.J., Cooper, H.M., Coyle, M., Craig, E., Cumming, A., Dixon, S., Gauci, V., Grayson, R.P., Helfter, C., Heppell, C.M., Holden, J., Jones, D.L., Kaduk, J., Morrison, R., 2021. Overriding water table control on managed peatland greenhouse gas emissions. Nature 593 (7860), 548–552. https://doi.org/10.1038/s41586-021-03523-1.

Fan, Y., Tcherkez, G., Scafaro, A.P., Taylor, N.L., Furbank, R.T., von Caemmerer, S., Atkin, O.K., 2024. Variation in leaf dark respiration among C3 and C4 grasses is associated with use of different substrates. Plant Physiol. https://doi.org/10.1093/plphys/kiae064.

Fenner, N., Freeman, C., 2011. Drought-induced carbon loss in peatlands. Nat. Geosci. 4 (12), 895–900. https://doi.org/10.1038/ngeo1323.

Fritz, C., Geurts, J., Weideveld, S., Temmink, R., Bosma, N., Wichern, F., Smolders, A., Lamers, L., 2017. Meten is weten bij bodemdaling-mitigatie. Effect van peilbeheer en teeltkeuze op CO2-emissies en veenoxidatie. Bodem 20.

Gao, D., Yao, J., Yu, S., Ma, Y., Li, L., Gao, Z., 2023. Eddy covariance CO2 flux gap filling for Long data gaps: A novel framework based on machine learning and time series decomposition. Remote Sens. (Basel) 15 (10). https://doi.org/10.3390/rs15102695.

Haahti, K., Koivusalo, H., Hökkä, H., Nieminen, M., Sarkkola, S., 2012. Factors affecting the spatial variability of water table depth within a drained peatland forest stand in northern Finland Kersti. Suo 63 (3–4), 107–121. http://suo.fi/article/9883.

Han, L., Yu, G., Chen, Z., Zhu, X., Zhang, W., 2022. Spatiotemporal pattern of ecosystem respiration in China estimated by integration of machine learning with ecological understanding global biogeochemical cycles. Global Biogeochemical Cycles 36 (e2022GB007439), 1–15. https://doi.org/10.1029/2022GB007439.

Iiyama, I., Osawa, K., Nagata, O., 2012. Soil O2 profile affected by gas diffusivity and water retention in a drained peat layer. Soils Found. 52 (1), 49–58. https://doi.org/10.1016/j.sandf.2012.01.005.

IPCC, 2023. Summary for Policymakers: Synthesis Report. Climate Change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change 1–34.

Järveoja, J., Nilsson, M.B., Crill, P.M., Peichl, M., 2020. Bimodal diel pattern in peatland ecosystem respiration rebuts uniform temperature response. Nat. Commun. 11 (1), 4255. https://doi.org/10.1038/s41467-020-18027-1.

Joosten, H., 2010. The global peatland CO2 picture: peatland status and drainage related emissions in all countries of the world. Wetlands International, Ede, The Netherlands, pp. 1–36. https://seors.unfccc.int/applications/seors/attachments/get_attachment?code=KQCOAC7O06NRP20DN3D428EH3HHU4E3V.

Joosten, H., Clarke, D., 2002. Wise use of mires and peatlands -background and principles including a framework for decision-making. In: International Mire Conservation Group and International Peat Society, pp. 13–35. http://www.gret-perg.ulaval.ca/fileadmin/fichiers/fichiersGRET/pdf/Doc_generale/WUMP_Wise_Use_of_Mires_and_Peatlands_book.pdf.

Jurasinski, G., Glatzel, S., Hahn, J., Koch, S., Koch, M., Koebsch, F., 2016. Turn on, fade out-methane exchange in a coastal fen over a period of six years after rewetting. In EGU general assembly conference abstracts (pp. EPSC2016-14899), April.

Karki, S., Kandel, T.P., Elsgaard, L., Labouriau, R., Lærke, P.E., 2019. Annual CO 2 fluxes from a cultivated fen with perennial grasses during two initial years of rewetting. Mires and Peat 25. https://doi.org/10.19189/MaP.2017.DW.322.

Kassambara, A., 2020. Package "rstatix": pipe-friendly framework for basic statistical tests. In R package version 0.6.0. https://cran.r-project.org/web/packages/rstatix/rstatix.pdf.

Keenan, T.F., Migliavacca, M., Papale, D., Baldocchi, D., Reichstein, M., Torn, M., Wutzler, T., 2019. Widespread inhibition of daytime ecosystem respiration. Nat. Ecol. Evol. 3 (3), 407–415. https://doi.org/10.1038/s41559-019-0809-2.

Kruijt, B., Nouta, R., Jacobs, C., van den Berg, M., Fritz, C., Klumpp, K., Osborne, B., 2020. Towards operational quantification of GHG exchange in heterogeneous agricultural landscapes and experimental plots. In: EGU General Assembly Conference Abstracts, May, p. 6122. https://doi.org/10.5194/egusphere-egu2020-6122.

Kruijt, B., Berghuis, H., Bataille, L., Biermann, J., Buzacott, A., Van Giersbergen, Q., Heuts, T., Jans, W., Nouta, R., Bosma, N., Lootens, R., Franssen, W., Van den Berg, M., Van der Velde, Y., Fritz, C., 2023. CO2 Emissions from Peatlands in the Netherlands: Drivers of Variability in Eddy Covariance Fluxes, Dutch National Research Programme on Greenhouse Gases in Peatlands (NOBV).

Kuzyakov, Y., Gavrichkova, O., 2010. Time lag between photosynthesis and carbon dioxide efflux from soil: a review of mechanisms and controls. Glob. Chang. Biol. 16 (12), 3386–3406. https://doi.org/10.1111/j.1365-2486.2010.02179.x.

Leifeld, J., Menichetti, L., 2018. The underappreciated potential of peatlands in global climate change mitigation strategies. Nature Communications 9 (1). https://doi.org/10.1038/s41467-018-03406-6.

Leifeld, J., Steffens, M., Galego-Sala, A., 2012. Sensitivity of peatland carbon loss to organic matter quality. Geophys. Res. Lett. 39 (14), 1–6. https://doi.org/10.1029/2012GL051856.

Li, C., Han, W., Peng, M., Zhang, M., 2020. Developing an automated gas sampling chamber for measuring variations in CO_2 exchange in a maize ecosystem at night. Sensors 20 (21), 6117. https://doi.org/10.3390/s20216117.

Liu, W., Fritz, C., Weideveld, S.T.J., Aben, R.C.H., van den Berg, M., Velthuis, M., 2022. Annual CO2 budget estimation from chamber-based flux measurements on intensively drained peat meadows: effect of gap-filling strategies. Front. Environ. Sci. 10 (May), 1–14. https://doi.org/10.3389/fenvs.2022.803746.

Mahabbati, A., Beringer, J., Leopold, M., Mchugh, I., Cleverly, J., Isaac, P., 2021. A comparison of gap-filling algorithms for eddy covariance fluxes and their drivers. Geosci. Instrum. Methods Data Syst. 10, 123–140. https://doi.org/10.5194/gi-10-123-2021.

Mäkiranta, P., Laiho, R., Fritze, H., Hytönen, J., Laine, J., Minkkinen, K., 2009. Indirect regulation of heterotrophic peat soil respiration by water level via microbial community structure and temperature sensitivity. Soil Biol. Biochem. 41 (4), 695–703. https://doi.org/10.1016/j.soilbio.2009.01.004.

McCarter, C.P.R., Rezanezhad, F., Quinton, W.L., Gharedaghloo, B., Lennartz, B., Price, J., Connon, R., Van Cappellen, P., 2020. Pore-scale controls on hydrological and geochemical processes in peat: implications on interacting processes. Earth Sci. Rev. 207, 103227 https://doi.org/10.1016/j.earscirev.2020.103227.

McPherson, H., 1983. The measurement, within seconds, of apparent photosynthetic rates using a portable instrument. Photosynthetica 17, 395–406.

Moyano, F.E., Manzoni, S., Chenu, C., 2013. Responses of soil heterotrophic respiration to moisture availability: an exploration of processes and models. Soil Biol. Biochem. 59, 72–85. https://doi.org/10.1016/j.soilbio.2013.01.002.

Normand, A.E., Turner, B.L., Lamit, L.J., Smith, A.N., Baiser, B., Clark, M.W., Hazlett, C., Kane, E.S., Lilleskov, E., Long, J.R., Grover, S.P., Reddy, K.R., 2021. Organic matter chemistry drives carbon dioxide production of peatlands. Geophys. Res. Lett. 48 (18), e2021GL093392 https://doi.org/10.1029/2021GL093392.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., R Core Team, 2021. nlme: Linear and Nonlinear Mixed Effects Models. https://CRAN.R-project.org/package=nlme.

Poyda, A., Reinsch, T., Struck, I.J., Skinner, R.H., Kluß, C., Taube, F., 2021. Low assimilate partitioning to root biomass is associated with carbon losses at an intensively managed temperate grassland. Plant and Soil 460 (1–2), 31–50. https://doi.org/10.1007/s11104-020-04771-2.

Provincie Fryslân, 2021. Veenweideprogramma 2021–2030.

Pumpanen, J., Longdoz, B., Kutsch, W.L., 2010. Field measurements of soil respiration: principles and constraints, potentials and limitations of different methods. Soil Carbon Dynamics: An Integrated Methodology 16–33. https://doi.org/10.1017/CBO9780511711794.003.

Quadra, G.R., Boonman, C.C.F., Vroom, R.J.E., Temmink, R.J.M., Smolders, A.J.P., Geurts, J.J.M., Aben, R.C.H., Weideveld, S.T.J., Fritz, C., 2023. Removing 10 cm of degraded peat mitigates unwanted effects of peatland rewetting: a mesocosm study. Biogeochemistry 163 (1), 65–84. https://doi.org/10.1007/s10533-022-01007-6.

R Core Team, 2019. R: A Language and Environment for Statistical Computing. In: R Foundation for Statistical Computing. http://www.r-project.org.

Regina, K., Sheehy, J., Myllys, M., 2014. Mitigating greenhouse gas fluxes from cultivated organic soils with raised water table. Mitig. Adapt. Strat. Glob. Chang. 20 (8), 1529–1544. https://doi.org/10.1007/s11027-014-9559-2.

Rochette, P., Hutchinson, G.L., 2005. Measurement of soil respiration in situ: chamber techniques. Micrometeorology in Agricultural Systems 47, 247–286. https://doi.org/10.2134/agronmonogr47.c12.

Säurich, A., Tiemeyer, B., Dettmann, U., Don, A., 2019. How do sand addition, soil moisture and nutrient status influence greenhouse gas fluxes from drained organic soils? Soil Biol. Biochem. 135 (November 2018), 71–84. https://doi.org/10.1016/j.soilbio.2019.04.013.

Schrier-Uijl, A.P., Kroon, P.S., Hendriks, D.M.D., Hensen, A., Van Huissteden, J., Berendse, F., Veenendaal, E.M., 2014. Agricultural peatlands: towards a greenhouse gas sink - A synthesis of a Dutch landscape study. Biogeosciences 11 (16), 4559–4576. https://doi.org/10.5194/bg-11-4559-2014.

Shi, R., Su, P., Zhou, Z., Yang, J., Ding, X., 2022. Comparison of eddy covariance and automatic chamber-based methods for measuring carbon flux. Agron. J. 114, 2081–2094. https://doi.org/10.1002/agj2.21031.

Tiemeyer, B., Albiac Borraz, E., Augustin, J., Bechtold, M., Beetz, S., Beyer, C., Drösler, M., Ebli, M., Eickenscheidt, T., Fiedler, S., Förster, C., Freibauer, A., Giebels, M., Glatzel, S., Heinichen, J., Hoffmann, M., Höper, H., Jurasinski, G., Leiber-Sauheitl, K., Zeitz, J., 2016. High emissions of greenhouse gases from grasslands on peat and other organic soils. Glob. Chang. Biol. 22 (12), 4134–4149. https://doi.org/10.1111/gcb.13303.

Tiemeyer, B., Freibauer, A., Borraz, E.A., Augustin, J., Bechtold, M., Beetz, S., Beyer, C., Ebli, M., Eickenscheidt, T., Fiedler, S., Förster, C., Gensior, A., Giebels, M., Glatzel, S., Heinichen, J., Hoffmann, M., Höper, H., Jurasinski, G., Laggner, A., Drösler, M., 2020. A new methodology for organic soils in national greenhouse gas inventories: data synthesis, derivation and application. Ecol. Indic. 109 https://doi.org/10.1016/j.ecolind.2019.105838.

Tiemeyer, B., Heller, S., Oehmke, W., Dettmann, U., 2021. Auswirkungen von Wassermanagement und Grünlanderneuerung auf die THG-Emissionen von intensiv genutztem Moorgrünland, 20. https://doi.org/10.3220/PB1625728774000.

Tiemeyer, B., Heller, S., Oehmke, W., Gatersleben, P., Bräuer, M., Dettmann, U., 2024. Effects of water management and grassland renewal on the greenhouse gas emissions from intensively used grassland on bog peat. Agric. For. Meteorol. 345, 109858 https://doi.org/10.1016/j.agrformet.2023.109858.

Updegraff, K., Bridgham, S.D., Pastor, J., Weishampel, P., Harth, C., 2001. Response of CO2 and CH4 emissions from peatlands to warming and water table manipulation. Ecol. Appl. 11 (2), 311–326. https://doi.org/10.1890/1051-0761(2001)011[0311:ROCACE]2.0.CO;2.

Urban, O., Ač, A., Kalina, J., Priwitzer, T., Šprtová, M., Špunda, V., Marek, M.V., 2007. Temperature dependences of carbon assimilation processes in four dominant species from mountain grassland ecosystem. Photosynthetica 45, 392–399. https://doi.org/10.1007/s11099-007-0066-5.

Vaidya, S., Schmidt, M., Rakowski, P., Bonk, N., Verch, G., Augustin, J., Sommer, M., Hoffmann, M., 2021. A novel robotic chamber system allowing to accurately and precisely determining spatio-temporal CO2 flux dynamics of heterogeneous croplands. Agric. For. Meteorol. 296, 108206 https://doi.org/10.1016/j.agrformet.2020.108206.

Van den Akker, J.J.H., Hendriks, R.F.A., Pleijter, M., 2012. CO_2 emissions of peat soils in agricultural use: calculation and prevention. Agrociencia Uruguay 16 (3), 43–50. https://doi.org/10.31285/AGRO.16.563.

Vitale, D., Fratini, G., Bilancia, M., Nicolini, G., Sabbatini, S., Papale, D., 2020. A robust data cleaning procedure for eddy covariance flux measurements. Biogeosciences 17 (6), 1367–1391. https://doi.org/10.5194/bg-17-1367-2020.

Wagner, S.W., Reicosky, D.C., 1992. Closed-chamber effects on leaf temperature, canopy photosynthesis, and evapotranspiration. Agron. J. 84 (4), 731–738. https://doi.org/10.2134/agronj1992.00021962008400040035x.

Weideveld, S.T.J., Liu, W., Van Den Berg, M., Lamers, L.P.M., Fritz, C., 2021. Conventional subsoil irrigation techniques do not lower carbon emissions from drained peat meadows. Biogeosciences 18 (12), 3881–3902. https://doi.org/10.5194/bg-18-3881-2021.

Wilson, D., Blain, D., Couwenber, J., Evans, C., Murdiyarso, D., Page, S., Renou-Wilson, F., Rieley, J., Strack, M., Tuittila, E.S., 2016. Greenhouse gas emission factors associated with rewetting of organic soils. Mires and Peat 17 (4), 1–28. https://doi.org/10.19189/MaP.2016.OMB.222.

Woledge, J., Dennis, W., 1982. The effect of temperature on photosynthesis of ryegrass and white clover leaves. Ann. Bot. 50 (1), 25–35. https://doi.org/10.1093/oxfordjournals.aob.a086343.

Yu, Z., Loisel, J., Brosseau, D.P., Beilman, D.W., Hunt, S.J., 2010. Global peatland dynamics since the last glacial maximum. Geophys. Res. Lett. 37 (13) https://doi.org/10.1029/2010GL043584.

Zhu, S., McCalmont, J., Cardenas, L.M., Cunliffe, A.M., Olde, L., Signori-Müller, C., Litvak, M.E., Hill, T., 2023. Gap-filling carbon dioxide, water, energy, and methane fluxes in challenging ecosystems: comparing between methods, drivers, and gap-lengths. Agric. For. Meteorol. 332 (February), 109365 https://doi.org/10.1016/j.agrformet.2023.109365.