Comment on bg-2022-69

Anonymous Referee #2

Referee comment on "Meteorological responses of carbon dioxide and methane fluxes in the terrestrial and aquatic ecosystems of a subarctic landscape" by Lauri Heiskanen et al., Biogeosciences Discuss., https://doi.org/10.5194/bg-2022-69-RC2, 2022

In this submission, the authors present an interesting assessment of the carbon fluxes (CO_2 and CH_4) in a subarctic region. The study area located in northern Finland covers 7 km2 consisting of five different ecosystem types. The focus of the study was to evaluate the temporal variability of the ecosystem-atmosphere carbon exchange using two years of measurements (2017-2019). The authors found that the different ecosystems had significantly different responses to the weather conditions. Major differences were found in the behavior of the ecosystems during four particular periods: 1) a rainy growing season in 2017, 2) the warmer-than average early growing season in 2018, 3) a heatwave and drought in the summer of 2018, and 4) a cold spell in autumn 2018. Heiskanen et al. found the study area to be a net sink of CO_2 and a source of CH_4 during the study period. However, the uncertainties are large.

The manuscript can contribute to the understanding of the carbon cycle by evaluating the role of different ecosystem elements and their response to forcing factors. Increasing our understanding of the ecosystems' response to the weather conditions is particularly relevant in the high latitudes, as these regions are highly vulnerable to the changing climate.

I have two major concerns about this work:

The analysis presented here is based on a data set including up to 90% of data that has been gap-filled (ca 90% of the data from the pine forest and ca 60% of the fen CO_2 fluxes were gap-filled, as well as ca 70% of the CH_4 fluxes). These data was then used to describe the temporal variability of the carbon exchange and to extrapolate the fluxes to a landscape level. In my opinion, gap-filling procedures are useful when the gaps are small and the uncertainties can be accounted for, which is not the case here.
My second concern is regarding the extrapolation to a landscape level. The upscaling was made using the gap-filled data set from the terrestrial ecosystems and only a few days of measurements from the lake ecosystems. I doubt that these data can really capture the temporal variability and, most certainly I do not think it can accurately represent the fluxes at a landscape level.

Reply to Referee #2

We thank the reviewers for their constructive comments. Please see below our general response for the main concerns and specific responses to each of the comments.

Lauri Heiskanen, Juha-Pekka Tuovinen, Henriikka Vekuri, Aleksi Räsänen, Tarmo Virtanen, Sari Juutinen, Annalea Lohila, Juha Mikola and Mika Aurela

General response (to both Referees)

We agree that the EC data coverage at the upland pine forest site was low. This was mainly due to necessary wind sector exclusions and unavoidable equipment failures. The pine forests within the area are patchy and grow mostly on narrow eskers. Thus, the EC tower had to be installed on an edge of the forested area to guarantee sufficient (>80%) flux footprint coverage over the forest wind sector. This placement led to exclusion of 48% of the EC flux data, as the other wind sectors covered peatland and lake ecosystems. While our data coverage is admittedly low at this site, it should be noted that, in practice, EC data sets are generally far from being complete. For example, in the widely used global Fluxnet2015 database (Zhu et al., 2022), comprising 1532 site-years, 68% of the data are missing. Our fen data had a better coverage than this.

Furthermore, the annual balance is most affected by the flux uncertainties when the flux magnitude is largest, i.e. during the growing season (Richardson & Hollinger, 2007). The longest data gaps in the forest data took place in October 2017 – February 2018, May – June 2018 and April – May 2019, i.e. outside the peak growing season, and fortunately the data coverage during the growing seasons was better than the annual average (Fig. S1, to be included in the supplement of the revised version).

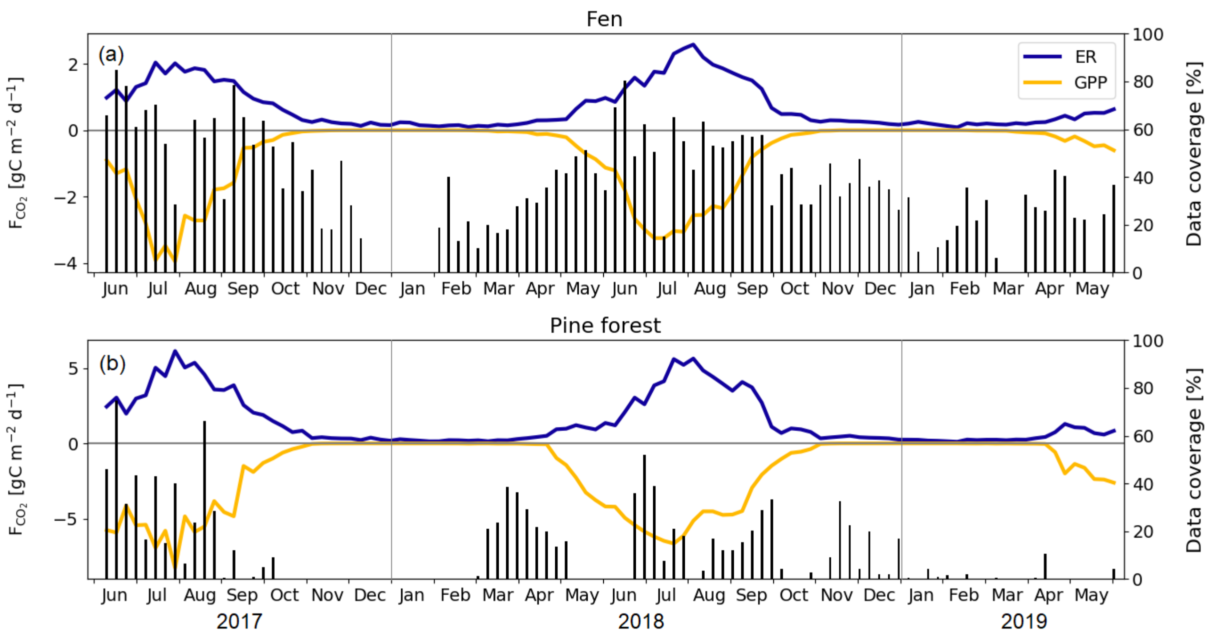

Figure S1. Fen (a) and pine forest (b) EC data coverage and weekly average ER and GPP fluxes.

Nevertheless, we concur that the implications of data gaps require further attention and, while addressing the issue, we reconsidered our data screening, gap-filling and uncertainty estimation procedures and made major improvements to them. As the winters had the lowest data coverage at the pine forest site and the CO_2 fluxes are then relatively stable and their environmental responses weak and obscure, we decided to change the winter gap-filling method to averaging of fluxes. For the growing season gap-filling, we studied how a machine learning method called extreme gradient boosting (XGBoost, Chen & Guestrin, 2016) could handle the large number of gaps in the pine forest EC flux data. This kind of decision tree-based machine learning methods have been shown to perform well even with long data gaps (Zhu et al., 2022; Irvin et al., 2021).

In the XGBoost method, the environmental variables that we used to predict NEE were PPFD, air temperature, relative humidity, vapour pressure deficit, soil temperature at -10 cm, soil temperature at -5 cm and soil moisture at -10 cm. First, we optimized the hyperparameters of the model using grid search. The determined hyperparameters were 0.8 for 'colsample_bytree', 0.05 for 'learning_rate', 20 for 'max_depth' and 9 for 'min_child_weight'. We then evaluated model performance using 10-fold cross validation and found that R^2 was 0.88 ± 0.02 and mean squared error was 0.003 ± 0.0006 mg CO_2 m^{-2} s^{-1} (Fig. R1).

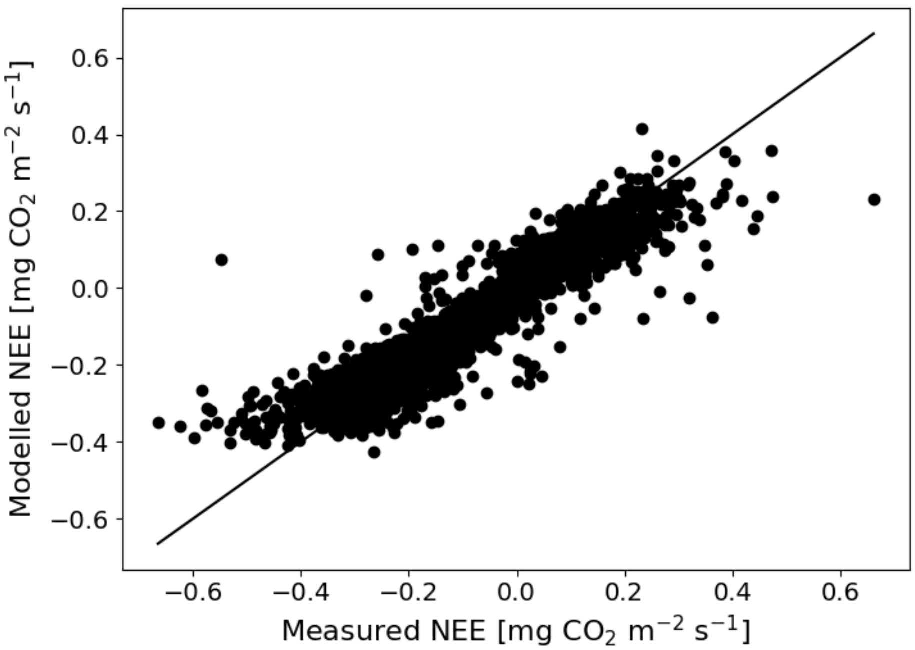

Figure R1. Measured eddy covariance NEE versus XGBoost modelled NEE (30-min fluxes) in the pine forest.

We inspected the effect of gap-filling on the pine forest CO_2 fluxes and annual balances against synthetic data sets that either had a complete temporal coverage or the same gaps as the measured data. We made a total of 50 continuous, synthetic time series of 30-min CO_2 fluxes that had statistical characteristics similar to the original measurement data (Fig. R2). The synthetic data sets were generated using an artificial neural network (ANN). We used a sequential model with four hidden layers and three different activation functions: linear, hyperbolic tangent and rectified linear activation. The mean squared error was used as the loss function. The ANN was implemented using the Keras library (Chollet, 2015). We utilized all the available measurement data to train the ANN, and after modelling for all 30-min periods we added noise to the modelled NEE. This was done by binning the residuals in 10 bins based on NEE and then selecting a residual for each 30-min modelled NEE randomly from the appropriate bin. Parallel, incomplete data sets were made by placing the original data gaps in the synthetic time series and gap-filled with the XGBoost method (Fig. R3).

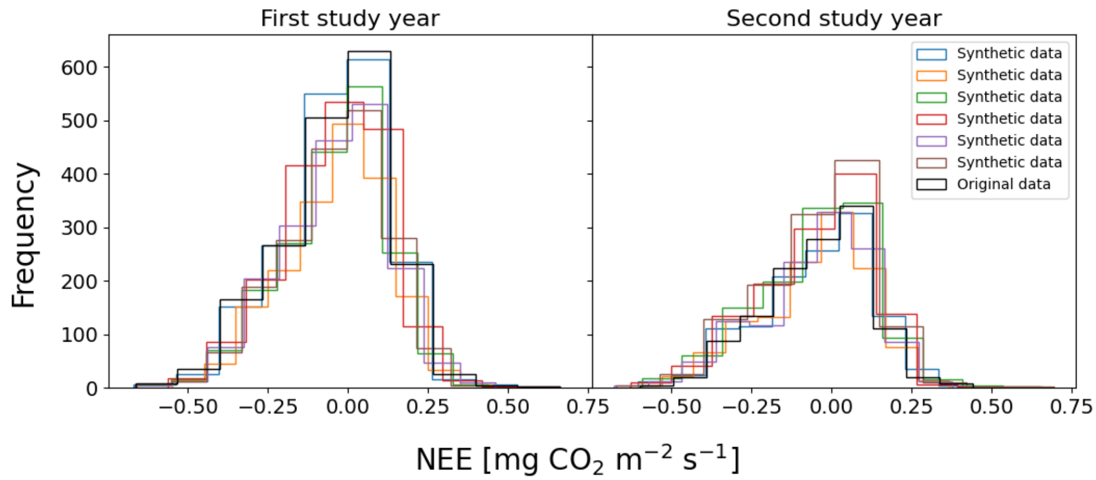

Figure R2. Distribution of the original, measured CO_2 flux data and representative examples of synthetic data sets used for testing the gradient boosting method.

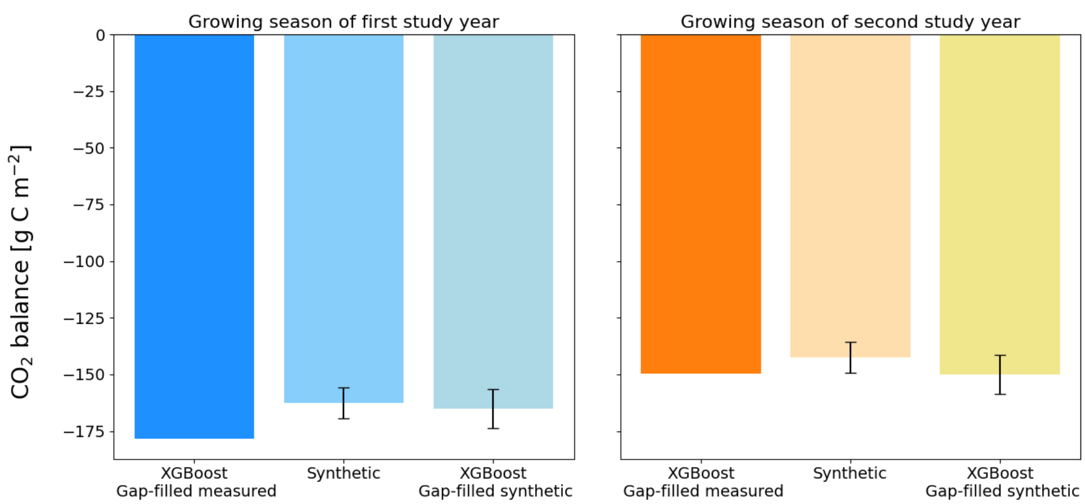

Figure R3. Growing season CO_2 balances estimated from measured data with the gradient boosting (XGBoost) gap-filling method, from synthetic data and from synthetic data with gaps filled with XGBoost. The balances of synthetic data represent the mean of 50 synthetic data sets and error bars their standard deviation.

We found that the XGBoost gap-filling method produces reliable, unbiased results for the pine forest EC data. Even though this data set is limited by a large number of gaps, the consistent results obtained for the full and gap-filled synthetic data lend support to this method. Thus, XGBoost was used for gap-filling the growing season CO_2 flux data measured at the pine forest site. For consistency, it was also used for the fen data.

For gap-filling the pine forest CO_2 fluxes during winters, we averaged the observed fluxes in two soil temperature categories, over and under -2 ºC at 10 cm depth. The mean fluxes were 0.0173 and 0.0103 mg CO_2 m^{-2} s^{-1} in the warmer and colder category, respectively. The winter period was determined based on the timing of frost at 10 cm depth, which occurred in 31 September 2017 – 24 April 2018 and 30 September 2018 – 20 April 2019.

The ER and GPP fluxes were partitioned based on environmental response functions that were fitted to the gap-filled NEE data. The partitioning was done similarly to the method described in the original manuscript, with the exception of the moving window size that did not change as there were enough data for fitting with the default time windows (three or seven days).

The NEE flux uncertainty was estimated including measurement uncertainty, modelling uncertainty and u* filtering uncertainty. For the ER and GPP fluxes resulting from the partitioning procedure, the total uncertainty estimate consisted of the regression fit uncertainty and u* filtering uncertainty.

The uncertainty related to the selection of u* threshold was estimated for the 30-min fluxes by filtering the data with 100 bootstrapped u* thresholds and gap-filling each of the resulting time series. The u* uncertainty was defined as the standard deviation of the 100 gap-filled NEE values. To estimate the random measurement uncertainty, we sorted the measured data into 0.2 (forest) or 0.1 mg CO_2 m^{-2} s^{-1} (fen) wide bins and calculated the standard deviation of model residuals for each bin. The relationship between the measurement uncertainty and the magnitude of the flux was then used to estimate the uncertainty of measured data (Richardson et al., 2008). Modelling uncertainty was estimated from an ensemble of 10 models following the procedures detailed by Irvin et al. (2021). These include post-processing calibration (Platt scaling) of the uncertainty intervals, required for machine learning regression models.

To estimate the uncertainty of the annual balances, the uncertainty related to u* filtering was determined as the standard deviation of the 100 bootstrapped balances. Also, the gap-filling uncertainties were determined using a similar bootstrapping approach. For winter, we resampled the wintertime data 100 times with replacement and calculated alternative balances from these samples. For the growing season, we used the 10 models from the model ensemble to calculate alternative balances. In both cases, the gap-filling uncertainty was determined as the standard deviation of the balances.

In addition to developing the gap-filling procedures, we improved the carbon balance estimates of lakes. Instead of directly using the rather scarce measurement data, we employed the continuous data obtained from the Arctic Lake Biochemistry Model (ALBM), which was calibrated with our flux measurement data (for details, see Kou et al., 2022). ALBM is a one-dimensional process-based model, which takes into account the varying environmental conditions on a daily basis. Local meteorological data were used as input, and the annual balances were calculated from the modelled daily fluxes.

The improved methods introduced above will be described in detail in the revised manuscript. The methodological changes affected modestly the numerical results reported in the manuscript; however, our conclusions remained basically the same. The manuscript will be updated accordingly. The main changes are presented below.

Abstract

…

The landscape area was an annual CO_2 sink of -45 ± 22 and -33 ± 23 g C m^{-2} and a CH_4 source of 3.0 ±

0.2 and 2.7 ± 0.2 g C m^{-2} during the first and second study year, respectively. The pine forest had the largest contribution to the landscape-level CO_2 sink, -126 ± 21 and -101 ± 19 g C m^{-2}, and the fen to the CH_4 emissions, 7.8 ± 0.2 and 6.3 ± 0.3 g C m^{-2}, during the first and second study year, respectively.

…

The annual C balances were affected most by the rainy peak growing season in 2017, the warm summer in 2018 and the heatwave and drought event in July 2018. The rainy period increased ecosystem respiration (ER) in the pine forest due to continuously high soil moisture content, and ER was on a level similar to the following, notably warmer summer. A similar flux response to abundant precipitation was not observed for the fen ecosystem, which is adapted to high water table levels, and thus a higher ER sum was observed during the warm summer 2018.

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3.2.1 Pine forest fluxes

The pine forest acted as a net CO_2 sink during both study years. The annual CO_2 balances during the first and second study year were -126 ± 21 and -101 ± 19 g C m^{-2}, respectively (Fig. 8b, Table A6). For other evergreen needleleaf forests in northern Fennoscandia, the observed balances have been smaller in magnitude: the Scots pine forest at Värriö in northern Finland was a CO_2 sink in 2012–2014 (-48 to -7 g C m^{-2}) and a small source in 2015 (14 g C m^{-2}) (Kulmala et al., 2019), while the Norway spruce forest at Kenttärova in northern Finland had a close-to-neutral balance (on average -2 g C m^{-2}) (Aurela et al., 2015).

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There were two periods when the CO_2 fluxes behaved differently between the two study years due to differing meteorological conditions. First, even though the summer was warmer in 2018 than in 2017, and thus one could expect enhanced respiration, the ER flux of the pine forest ecosystem was on average similar during the growing seasons. This was due to the rainy period in June–August 2017 (Fig. 3), as a result of which forest soil remained saturated or nearly saturated in water during the growing season (Fig. 6d). As the forest soil moisture content was continuously close to the maximum water holding capacity, the effect of abundant precipitation emerged as increasing lake water table levels (Fig. 6c). We suspect that the stronger ER temperature response observed in June–August 2017 was caused by enhanced heterotrophic soil respiration (Fig. A1), which is known to increase with soil moisture until near water saturation (Orchard and Cook, 1983; Moyano et al., 2012; McElligott et al., 2017; Du et al., 2020).

The second period of dissimilar behaviour in CO_2 fluxes was observed when the drought and heatwave discussed above limited GPP fluxes; compared to the previous year, the GPP sum in 22 July – 17 August was 35 g C m^{-2} lower in 2018 (Z test, $p = 0.003$) (Fig. 8d). The daily maximum VPD surpassed the 20 hPa limit, indicating meteorological drought, for the first time on 2 July and the last time on 1 August 2018 (Fig. 6a), during which period the average air temperature was 5 °C higher than in the previous year (Fig. 3). In July 2018, the forest soil moisture at 10 cm depth also dropped by 50 % from the normal growing season level, decreasing to 0.1 m^3 m^{-3} on 22 July (Fig. 6d). Soil moisture recovered to a normal level three weeks later on 13 August.

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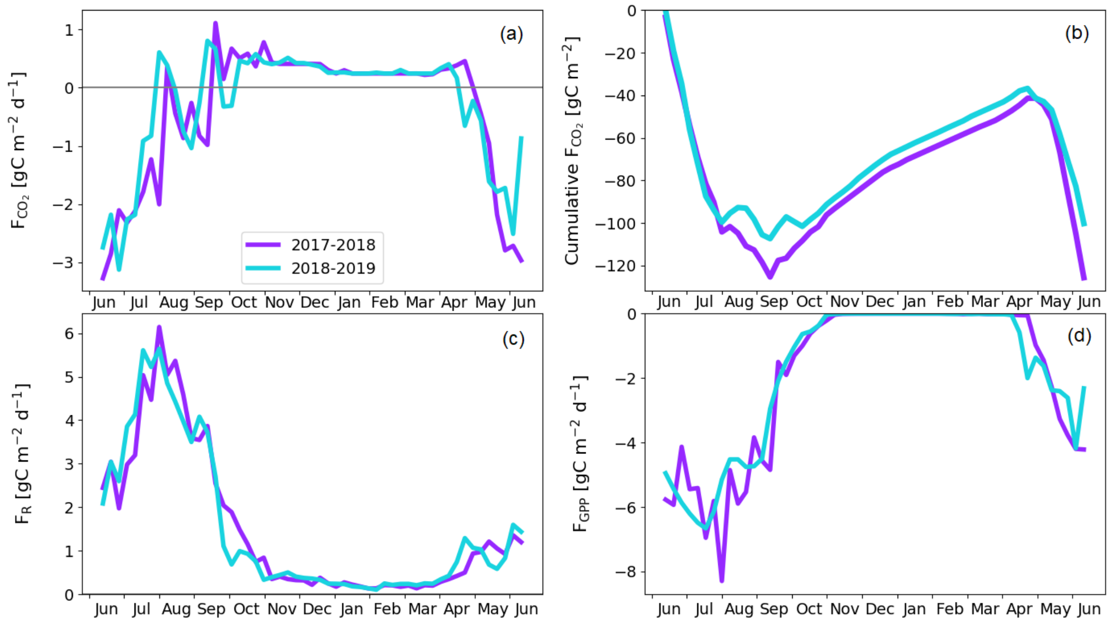

Figure 8. Pine forest fluxes. Weekly averaged (a) and cumulative (b) CO_2 flux, and weekly averaged ecosystem respiration (c) and gross primary productivity (d).

3.2.2 Fen fluxes

The fen ecosystem was a small net CO_2 sink of -14 ± 17 g C m^{-2} and a small net CO_2 source of 9 ± 11 g C m^{-2} during the first and second year, respectively (Fig. 9b, Table A6). There were three periods during which either CO_2 or CH_4 fluxes diverged between the years: the start of the growing season, the warmer-than-average growing season of 2018 and the drought and heatwave event in 2018.

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The warm growing season increased the ER flux sum by 32 g C m^{-2} (Z test, $p = 0.124$) during 11 June – 23 September 2018 (mean air temperature 13.2 ºC) compared to 2017 (10.5 ºC). Half of this difference, 16 g C m^{-2} (Z test, $p = 0.043$), accumulated in just 26 days, 17 July – 12 August, when the temperature difference between the years was largest (13.4 ºC and 17.9 ºC in 2017 and 2018, respectively).

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The earlier start of the growing season in 2018 resulted in a higher CO_2 uptake in 11–30 June compared to the previous year (Fig. 9, Table A6); the balances of this period were -5 ± 13 and -20 ± 17 g C m^{-2} in 2017 and 2018, respectively. This was due to the nearly doubled GPP (Z test, $p < 0.001$), which was 27 ± 3 and 49 ± 4 g C m^{-2} in 2017 and 2018, respectively.

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The higher CO_2 uptake during the early growing season of 2018 was offset by the decreased uptake due to the drought and heatwave event in 8 July – 4 August 2018. The GPP sum was 17 g C m^{-2} smaller (Z test, $p = 0.229$) during this period in 2018 than in 2017 (Fig. 9d).

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The drought decreased the annual CH_4 emissions, mostly during 21 July – 28 August 2018, when the emissions were 0.8 g C m^{-2} lower (Z test, $p < 0.001$) than during the same period in the previous year (Fig. 9e).

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The total carbon balance, i.e. the sum of the CO_2 and CH_4 fluxes, showed that the fen was an annual carbon sink of -7 ± 17 g C m^{-2} and a carbon source to the atmosphere, 15 ± 11 g C m^{-2}, in the first and second study year, respectively (Table A6). The lower net CO_2 uptake during the drought period contributed most of the difference between the years.

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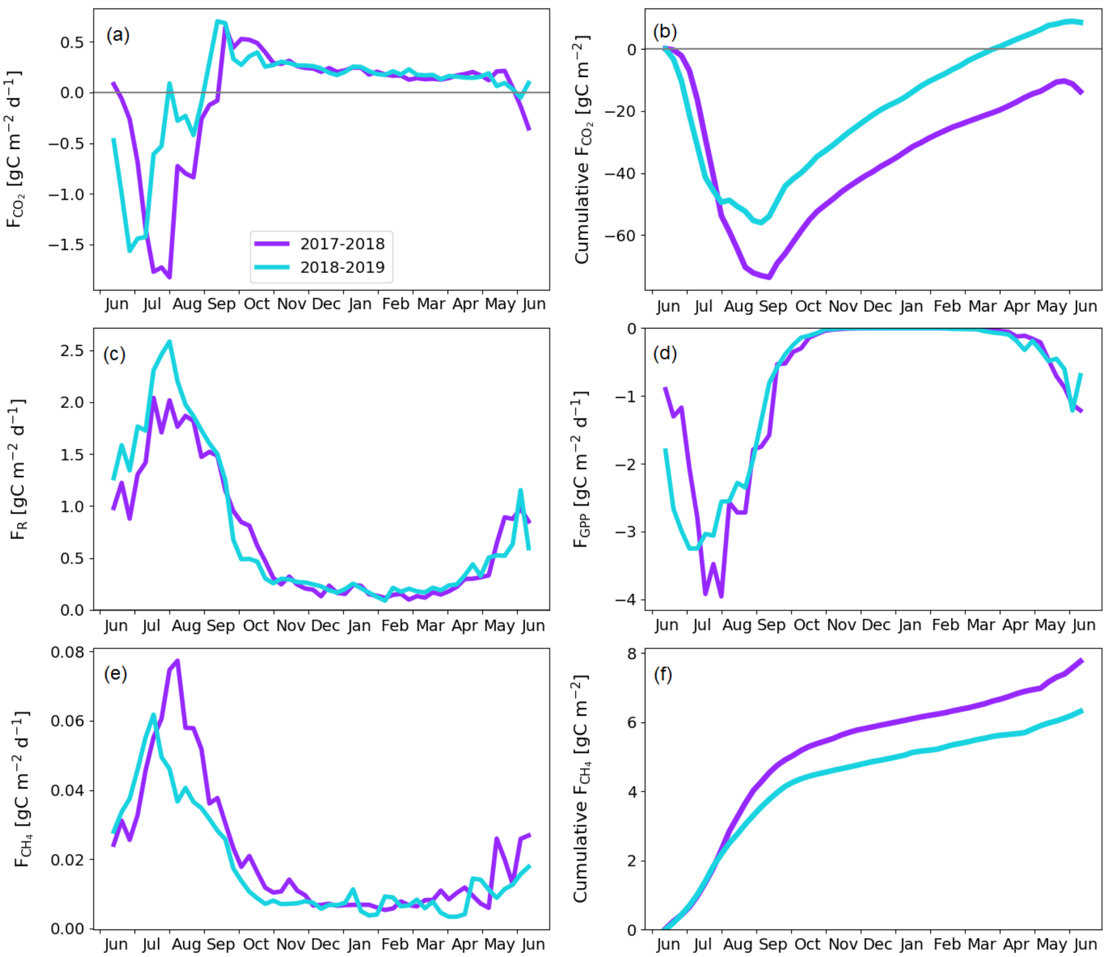

Figure 9. Fen fluxes. Weekly averaged CO_2 (a), ER (c), GPP (d) and CH_4 (e) flux, and cumulative CO_2 (b) and CH_4 (f) flux.

3.2.3 Lake fluxes

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Based on the model calculations with ALBM (Kou et al., 2022), which was calibrated with the flux measurements at the MS and OS lakes (Sect. 2.5), the annual CO_2 emissions were on average 28 g C m^{-2} from the MS lake and 97 g C m^{-2} from the OS lake (Table 6). The modelled CH_4 emissions were 1 g C m^{-2} from the MS lake and 4 g C m^{-2} from the OS lake.

The modelled CO_2 emissions were higher than those observed for a nearby small (9.6 ha) Lake Kipojärvi, which is surrounded by an esker and a peatland and had an annual CO_2 balance of 11.5 g C m^{-2} (Juutinen et al., 2013). However, the annual CH_4 emissions from Lake Kipojärvi, 3.4 g C m^{-2}, were similar to the modelled emissions.

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Table 6. Modelled annual CO_2 and CH_4 balances [g C m^{-2}] of the MS and OS lakes during the two study years (Kou et al., 2022).

	11 June 2017 – 10 June 2018	11 June 2018 – 10 June 2019
Mineral sediment lake		
CO_2 flux	24.4	32.0
CH_4 diffusive flux	1.0	1.1
CH_4 ebullition flux	0.3	0.3
Total C flux	25.6	33.4
Organic sediment lake		
CO_2 flux	99.4	94.2
CH_4 diffusive flux	2.9	3.3
CH_4 ebullition flux	0.8	0.9
Total C flux	103.1	98.4

3.2.4 Pine bog fluxes

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The annual CO_2 balance of the treed pine bog ecosystem was similar in the first and second study year, -92 ± 102 and -92 ± 110 g C m^{-2}, respectively (Fig. 11b, Table A6). The corresponding estimates for the sparsely treed pine bog ecosystem were lower and more uncertain: -48 ± 134 and -68 ± 145 g C m^{-2} (Fig. 12b, Table A6).

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For both pine bog ecosystems, the GPP rates were higher during the latter year from mid-June to mid-July (Figs. 11d, 12d).

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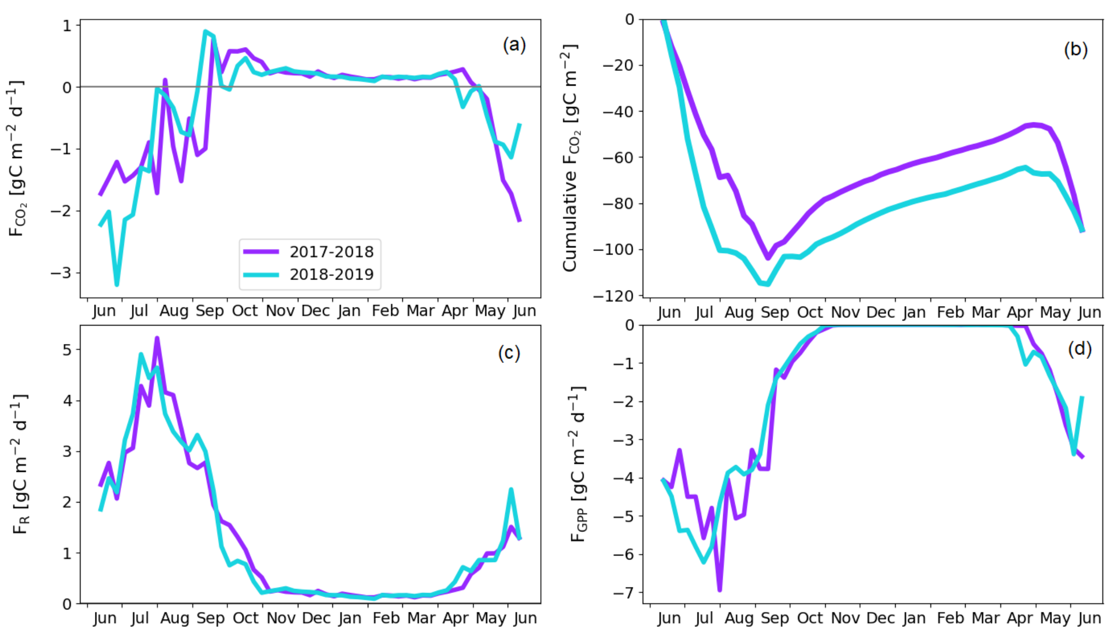

Figure 11. Treed pine bog fluxes. Weekly averaged CO_2 flux (a), and cumulative CO_2 flux (b), and weekly averaged ER (c) and GPP (d) flux.

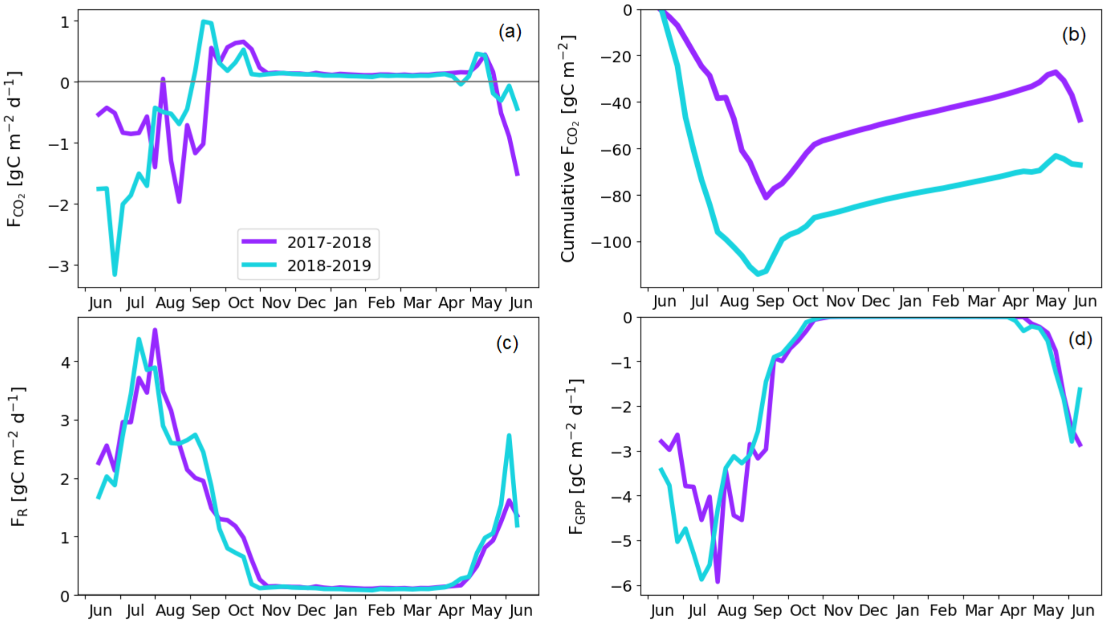

Figure 12. Sparsely treed pine bog fluxes. Weekly averaged CO_2 flux (a), and cumulative CO_2 flux (b), and weekly averaged ER (c) and GPP (d) flux.

3.3 Upscaled landscape-level fluxes

By upscaling the ecosystem balances to our study area of 7 km^2, we obtained an annual landscape CO_2 balance of -45 ± 22 and -33 ± 23 g C m^{-2} for the two study years. The corresponding CH_4 balances were 3.0 ± 0.2 and 2.7 ± 0.2 g C m^{-2}, and the total C balances were -42 ± 22 and -31 ± 23 g C m^{-2}, respectively (Fig. 13 b,f, Table A6).

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The average annual terrestrial C uptake of the landscape was -338 ± 156 t C of which 24 % (82 t C) was released back to the atmosphere by the lakes, resulting in a net C uptake of 256 ± 156 t C within the landscape (Fig. 14).

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However, different ecosystems showed different environmental responses, and during the two study years there were three periods when the ecosystem-specific fluxes clearly deviated from each other, which differences were reflected in the landscape-level C balance.

…

Second, the rainy peak growing season in 2017 increased the ER rates of the pine forest ecosystem compared to the same period the next year, which was much warmer, and thus the ER fluxes were similar (Figs. 8, A1). Conversely, at the fen the warm summer of 2018 increased the ER sum, compared to the cool, rainy summer in 2017. This was due to the inherently different water balance between uplands and peatlands.

…

However, as the modelled lake CH_4 emissions were slightly higher during the second year (Table 6), there was only a minor difference in the annual landscape-level CH_4 balance (Fig. 13f, Table A6). During the two study years, the meteorological conditions were not optimal for C sequestration as the fen on average acted as a weaker CO_2 sink, and even a source in the second year, than in some previous years (Aurela et al., 2007).

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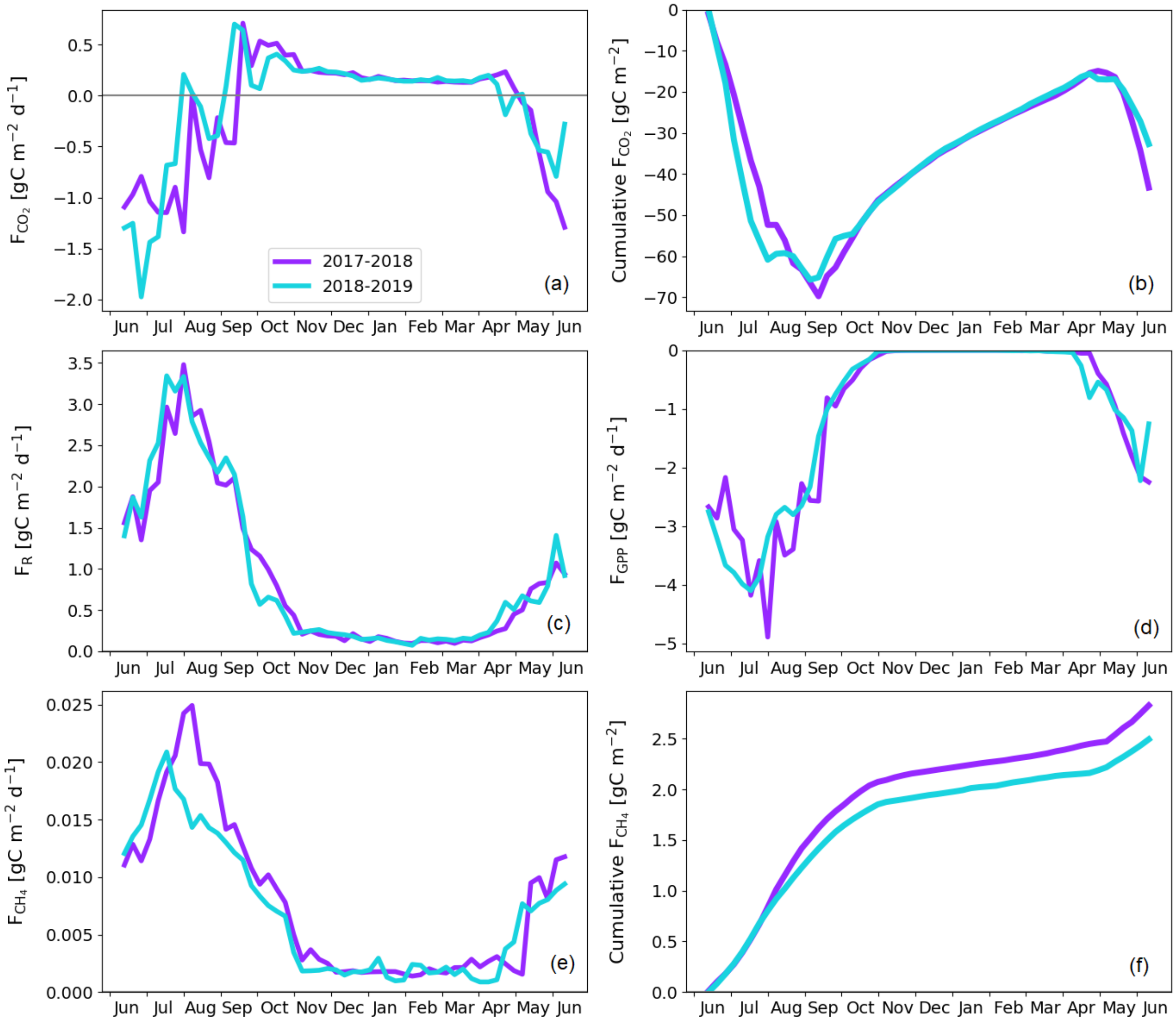

Figure 13. Landscape-level fluxes. Weekly averaged CO_2 (a), ER (c), GPP (d) and CH_4 (e) flux, and cumulative CO_2 (b) and CH_4 (f) flux.

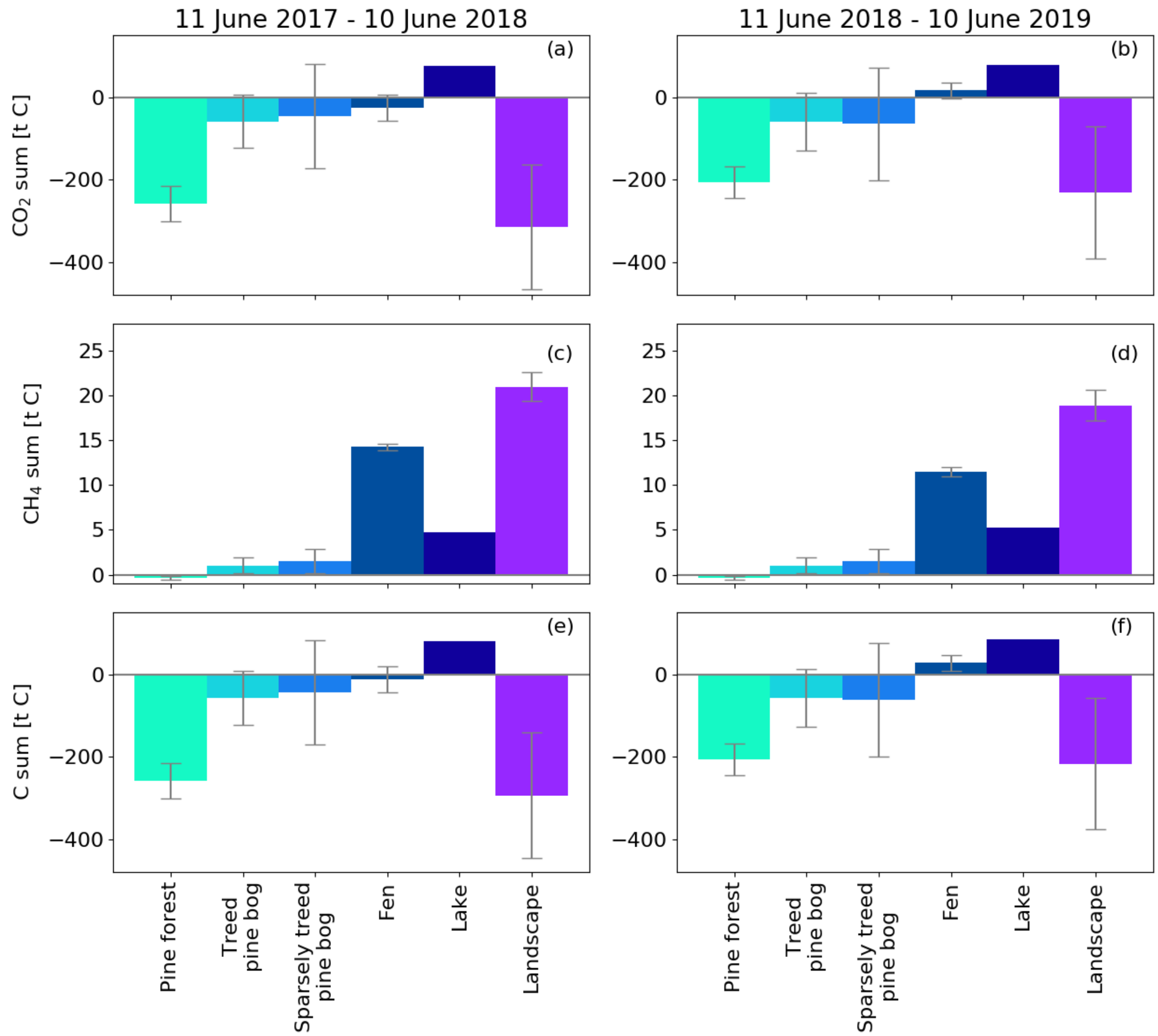

Figure 14. Annual CO_2, CH_4 and C flux sums for different ecosystems and the landscape (Fig. 1) scaled with the corresponding area. The CH_4 flux estimate for forest is from Dinsmore et al. (2017) and for pine bog from Bubier et al. (2005). The error bars denote the 95 % confidence interval. Uncertainty estimates were not available for the modelled lake balances (Kou et al., 2022).

4 Conclusions

The lakes in the study area released 24 % of the C that was sequestered by the landscape during the two-year study period.

…

There were three periods when the C fluxes of the terrestrial ecosystems were clearly different between the two study years due to meteorological conditions. In the pine forest, the CO_2 fluxes were affected by the rainy weather in summer 2017 increasing the ER rate to the level observed during the warmer growing season the following year. At the fen, however, the warm growing season in 2018 resulted in a higher ER sum than in the previous growing season, highlighting the differing water balance of the fen and upland forest ecosystems. The warmer-than-average early growing season in 2018 advanced the plant growth at the fen, thus increasing the CO_2 uptake of the ecosystem. All terrestrial ecosystems were affected by a short but severe drought event in July 2018, which decreased the GPP rates and thus CO_2

uptake. However, both the onset of and recovery from drought effects occurred more rapidly at the fen than in the pine forest. Additionally, during the drought the CH_4 emissions from the fen decreased due to water level drawdown and possibly also due to decreased plant root carbon input.

Appendix

Table A6. Annual CO_2, CH_4 and C flux balances of the five ecosystems and landscape. Uncertainty estimates were not available for the lake balances (Kou et al., 2022) and thus they are not taken into account in the landscape-scale uncertainty estimates.

	11 June 2017 – 10 June 2018	11 June 2018 – 10 June 2019
CO_2 balance [g C m^{-2}]		
Pine forest	-126 ± 21	-101 ± 19
Treed pine bog	-92 ± 102	-92 ± 110
Sparsely treed pine bog	-48 ± 134	-68 ± 145
Fen	-14 ± 17	9 ± 11
Lakes	53	56
Landscape	-45 ± 22	-33 ± 23
CH_4 balance [g C m^{-2}]		
Pine forest	-0.2 ± <0.1 [a]	-0.2 ± <0.1 [a]
Pine bog	1.6 ± 1.4 [b]	1.6 ± 1.4 [b]
Fen	7.8 ± 0.2	6.3 ± 0.3
Lakes	3.3	3.7
Landscape	3.0 ± 0.2	2.7 ± 0.2
C balance [g C m^{-2}]		
Pine forest	-126 ± 21	-101 ± 19
Treed pine bog	-90 ± 102	-90 ± 110
Sparsely treed pine bog	-46 ± 134	-66 ± 145
Fen	-7 ± 17	15 ± 11
Lakes	56	60
Landscape	-42 ± 22	-31 ± 23

[a] From Dinsmore et al. (2017).

[b] From Bubier et al. (2005).

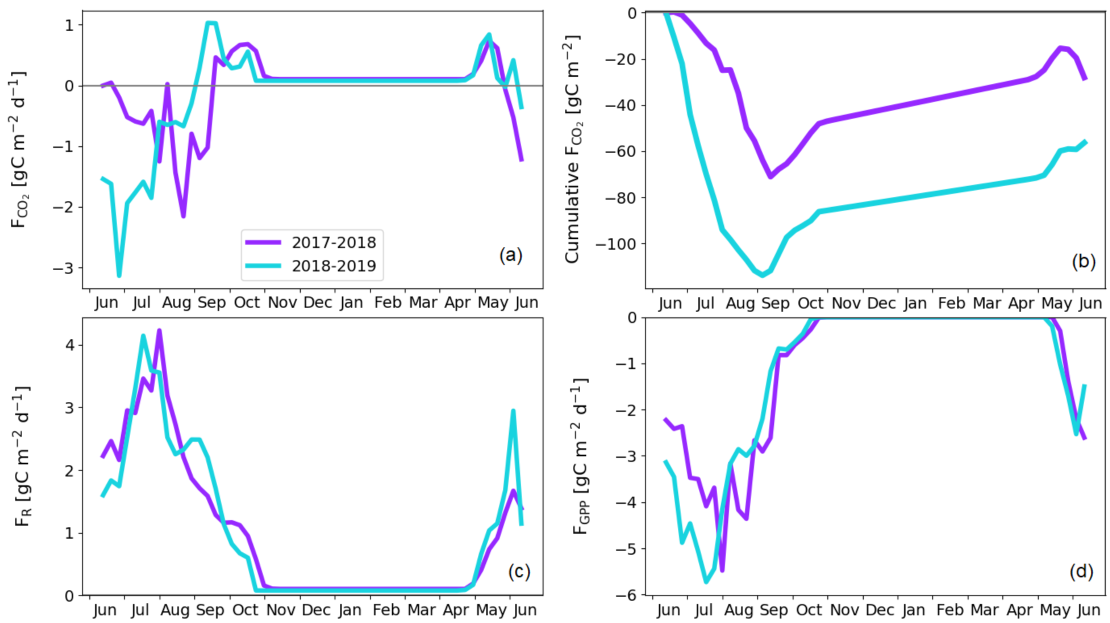

Figure A2. String top fluxes. Weekly averaged (a) and cumulative CO_2 flux (b), and weekly averaged ER (c) and GPP (d) flux, used for estimating pine bog ecosystem fluxes.

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Other comments:

L85: "we address questions how" --> "we address questions on (or questions about, or similar) how…" (In any case, is this sentence really necessary? The main questions addressed are stated as 1) and 2) in the following lines).

We changed this sentence to:
"Here, we address questions on how sensitive the C fluxes of different ecosystems are to changes in environmental conditions and how this is reflected on the landscape-level C exchange."

L103-L104: For clarity, I would recommend using the same terminology in the text and in the Table. Consider throughout the manuscript.

The ecosystem terminology is now uniform throughout the manuscript.

L107: "high string formations can remain" --> "high string formations that can remain"

Thank you, corrected.

L124: maybe I am missing it, but I cannot find the data that leads to this 10% contribution of the mosses and lichens to the total above ground biomass in table A1. Please check the numbers and clarify.

The total aboveground biomass can be calculated from Tables A1 (ground layer) and A4 (tree biomass). The missing reference to Table A4 is now added to the text.

L162-L164: Please give information about the impact of each screening criterion, i.e. percentage of rejection of each criterion, and the implications of rejecting these data in the final analysis.

A table showing the contribution of each filtering step was added to the supplement:

Table S1. Eddy covariance data coverage after each quality control filtering step.

	Gaps after each step		
Filtering criterion	Pine forest CO_2	Fen CO_2	Fen CH_4
1 Equipment failure	39 %	13 %	14 %
2 Wind direction	73 %	30 %	31 %
3 No. of recorded data and spikes	74 %	30 %	31 %
4 Covariance limit	74 %	31 %	32 %
5 Flux stationarity	82 %	51 %	54 %
6 u* threshold	85 %	57 %	58 %
7 Gas mixing ratio	89 %	64 %	69 %

L181: what was the measurement frequency of the Los Gatos gas analyzer? In general, details about CH_4 flux calculations are missing. Please clarify.

The description of the fen EC flux measurements was revised:

"The measurements were conducted on a 5 m tall tower with a three-axis sonic anemometer (USA-1, METEK Meteorologische Messtechnik GmbH, Germany), a closed-path infrared gas analyser for CO_2 and H_2O mixing ratios (LI-7000, LI-COR Biosciences, USA) and a laser-based gas analyser for CH_4 mixing ratio (RMT-200, Los Gatos Research, USA). The heated inlet tubes (inner diameter 3.1 mm and 8 mm for LI-7000 and RMT-200, respectively) were 6 m long and had a flow rate of 6 l min^{-1} and 15 l min^{-1} for the LI-7000 and RMT-200, respectively. The sampling frequency was 10 Hz for both analysers. The same flux calculation and data processing methods were used as with the pine forest EC data, except for the discarded wind direction sector (260°–315°), the friction velocity limit (0.1 m s^{-1}), the relative stationarity limit (< 30 %) (Foken and Wichura, 1996) and mean CH_4 mixing ratio within 1.8–2.8 ppm."

L184: Please provide a more detailed explanation of what the chamber measurements are and how were they performed, for the non-expert readers.

The following explanation of chamber flux measurements was added to the revised manuscript:

"The manual chamber measurements of the four main plant communities were conducted bi-weekly in 12 June–11 October 2017 and 31 May–4 September 2018. A total of 17 chamber plots were used with four or five replicates on each PCT. For determining the ER flux and the light response of CO_2 flux, a transparent chamber was used with one to three shading elements over the chamber. The chamber was closed for 2 min during each measurement, and the CO_2 and CH_4 fluxes were calculated from the mixing ratio change measured inside the chamber

…

The EC and chamber measurements at the fen and the PCT-specific fluxes are presented in more detail by Heiskanen et al. (2021)."

L221: "glasses" --> "gases"

Corrected.

L235: please define the acronyms EC, TC, and FI.

The abbreviations are now explained:

"Samples were analysed within a month using a gas chromatograph equipped with electron capture, thermal conductivity and flame ionization detectors (Agilent 7890B, with Gilson GX271 autosampler)."

Sect. 2.2: Might be worth adding a table summarizing all the flux measurements, including location, gas, technique, period/dates of measurement, etc. As it is now, it is hard to keep track of which measurements were made, where and for how long.

We added the following table to the appendix.

Table A8. Measurement and modelled flux methods of ecosystems

Ecosystem	Eddy covariance measurements	Flux chamber measurements	Pine bog flux model (Sect. 2.4)	Arctic Lake Biogeochemistry Model (Kou et al., 2022)	Estimate from literature
Pine forest	CO_2				CH_4 [a]
Fen	CO_2, CH_4	CO_2, CH_4			
Lakes		CO_2, CH_4		CO_2, CH_4	
Pine bog			CO_2		CH_4 [b]

[a] From Dinsmore et al. (2017).

[b] From Bubier et al. (2005).

L300: The authors show throughout the manuscript that the years 2017 and 2018 were significantly different. These differences were mainly caused by the meteorological conditions affecting the different ecosystems, including the lakes. I think a good explanation is needed about why the annual balances at the OS lake can be extrapolated from year 2017 to 2018, regardless of the differences observed in all the other ecosystems.

Please see the general response above.

L324: Please define F_R, F_{GPP}, etc. in their first appearance in the text.

Thank you for noticing this. The abbreviations are now defined when they are used for the first time.

L410: Are these results really statistically different? This might be clear from the tables and figures in the appendix but, in my opinion, Figure 8 (and later on Fig. 9, 11-13) need to show some measure of uncertainty.

The significance levels (Z test) are now shown for each of the periods when the fluxes diverged between the years due to differing meteorological conditions.

L511-514: I understand that the convective processes (turnover mixing) can be the driver enhancing CO_2 fluxes. However, this physical mechanism has a limited effect in such shallow water bodies. Additionally, I would expect the vertical mixing to be strongest right after the ice melt (i.e. May according to Table 4). As the time passes, stronger stratification typical of the summer months would be expected again. The reason why the authors see an enhancement of the CO_2 fluxes but not on CH_4 fluxes has to do, in my opinion, with the different production mechanisms and accumulation of the gases (which might then vertically transported by the turnover mixing). Further discussion is needed in this regard.

We revised Section 3.2.3 dealing with lake fluxes and added the following discussion about the processes affecting seasonal variation in CO_2 and CH_4 fluxes:

"Both lakes showed largest CO_2 emissions in early June (Fig. 10a). However, similar development was not observed with the CH_4 fluxes (Fig. 10b). The dissimilarity between the gases is likely due to the differing production and accumulation processes. CO_2 emissions are driven by the amount of incoming dissolved and particulate carbon and the rate of decomposition of that organic carbon (Kortelainen et al., 2006), while CH_4 production is controlled by the CO_2 available for the methanogens to reduce it to CH_4 in anoxic conditions in sediments (Chapin et al., 2011). CH_4 concentration has been observed to be roughly constant with depth during the early summer, while CO_2 is strongly stratified, with a larger concentration towards the bottom of the lake (Denfeld et al., 2020). The turnover mixing caused by the breakdown of thermal stratification occurs around the start and end of the ice-free period, which increases especially the CO_2 emissions (López Bellido et al., 2009). At the MS lake, the flux measurements covered also the autumn turnover mixing in September, when CO_2 emissions increased compared to the previous month."

L520: Was it possible to detect any diurnal variability with the measurements presented in this study? If yes, it might be relevant to discuss.

We conducted lake flux measurements both during day- and nighttime on three occasions during the measurement campaign: 9-11 June 2017, 19-20 September 2017 and 17-18 August 2018. We did not find any diurnal variation during those periods.

Sect. 3.3. Please discuss the role of the lakes in the CO_2 fluxes at a landscape scale (i.e. in L631)

We added further discussion of the impact of lake CO_2 fluxes to landscape fluxes to Sect 3.3:

"The lakes in the landscape acted as CO_2 sources to the atmosphere throughout the growing seasons, with peak emissions linked with the spring thaw. However, the temporal variation in CO_2 emissions had only a minor effect on the temporal variation in landscape fluxes as the lake flux magnitude did not vary as much as the CO_2 fluxes of the terrestrial ecosystems during the growing seasons (Figs. 8, 9, 10). Integrated over the study area, the total lake emissions had a considerable effect on the landscape-scale annual balances (Fig. 14)."

L662: I agree on the statement "C exchange…on the lake it depended on the amount of available carbon in the sediment and the length of the ice-free period". However, I do not think this is really discussed in Sect. 3.2.3. Please revise.

We added the following discussion to Sect. 3.2.3:

"Based on the model calculations with ALBM (Kou et al., 2022), which was calibrated with the flux measurements at the MS and OS lakes (Sect. 2.5), the annual CO_2 emissions were on average 28 g C m^{-2} from the MS lake and 97 g C m^{-2} from the OS lake (Table 6). The modelled CH_4 emissions were 1 g C m^{-2} from the MS lake and 4 g C m^{-2} from the OS lake. The flux magnitude difference between the two lake types reflected the amount of labile C in water column and sediments. The modelled CO_2 emissions were higher than those observed for a nearby small (9.6 ha) Lake Kipojärvi, which is surrounded by an esker and a peatland and had an annual CO_2 balance of 11.5 g C m^{-2} (Juutinen et al., 2013). However, the annual CH_4 emissions from Lake Kipojärvi, 3.4 g C m^{-2}, were similar to the modelled emissions. Additionally, the length of the ice-free period can considerably affect the annual emission of different boreal lakes as ice cover prevents gas exchange with the atmosphere."

L682: "contribute positively the landscape resilience" --> "contribute positively to the landscape resilience"

Thank you, corrected.