Comment on bg-2022-69
Anonymous Referee #1
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-RC1, 2022

General comments:
The manuscript bg-2022-69 by Heiskanen et al. estimated the ecosystem- and landscape-scale CO_2 and CH_4 fluxes and their responses to meteorological parameters in a heterogenous subarctic region, by measuring and upscaling the ecosystem-scale CO_2 and CH_4 fluxes of upland forest, pine bog, fen, and lake. The landscape-scale C balance and its regulating factors are very important topics, especially in the high-latitude regions where climate change is more rapid and severe than other regions of the globe. However, my major concern is the data coverage issue of this study. For their upland pine forest eddy covariance flux measurements, 86% and 91% of flux data are gaps over the two years respectively, which has extremely low temporal representativeness and inevitably introduced large uncertainty in the annual C estimate due to gap-filling. Moreover, only five-day flux measurements for each year (or only one year) over the lakes would also greatly challenge the accuracy of flux estimates for the lake ecosystems.

In my opinion, the bottom-up approach of upscaling C fluxes from the ecosystem scale to the landscape scale itself has error propagation issues. Therefore, the low data coverage that existed in most of the ecosystem-scale flux measurements in this study would lead to a tremendous flux estimate uncertainty in the landscape-scale C balance estimate (or even at the ecosystem-level already), questionable data reliability, and probably misleading result analysis and conclusions.

Reply to Rederee #1

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).

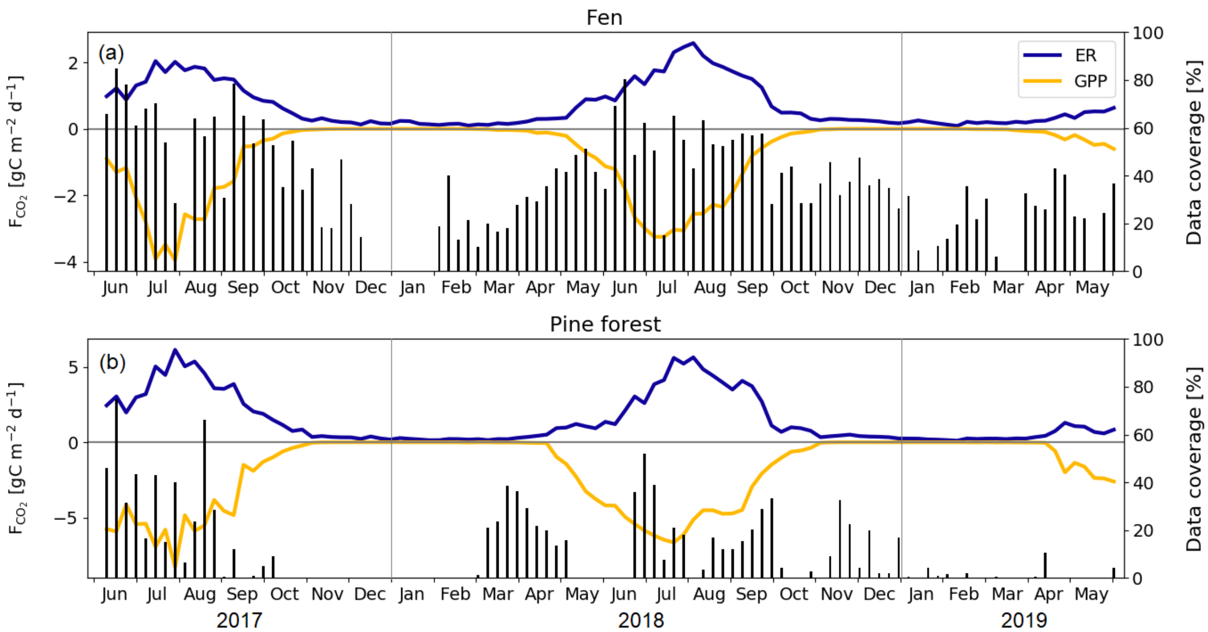

Figure S1. Fen (a) and pine forest (b) EC data coverage and weekly average ER and GPP fluxes.

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).

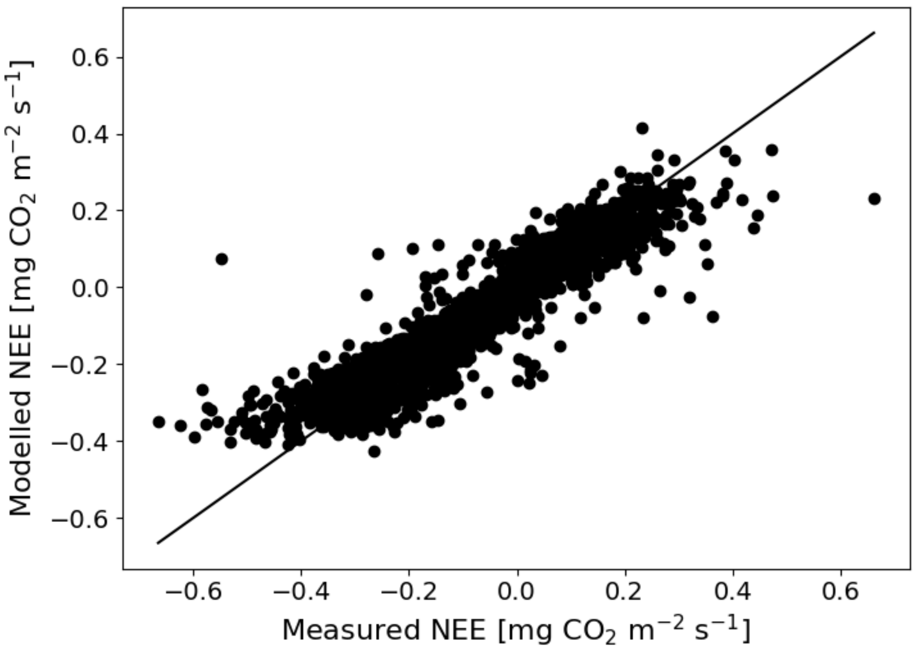

Figure R1. Measured eddy covariance NEE versus XGBoost modelled NEE (30-min fluxes) in the pine forest.

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).

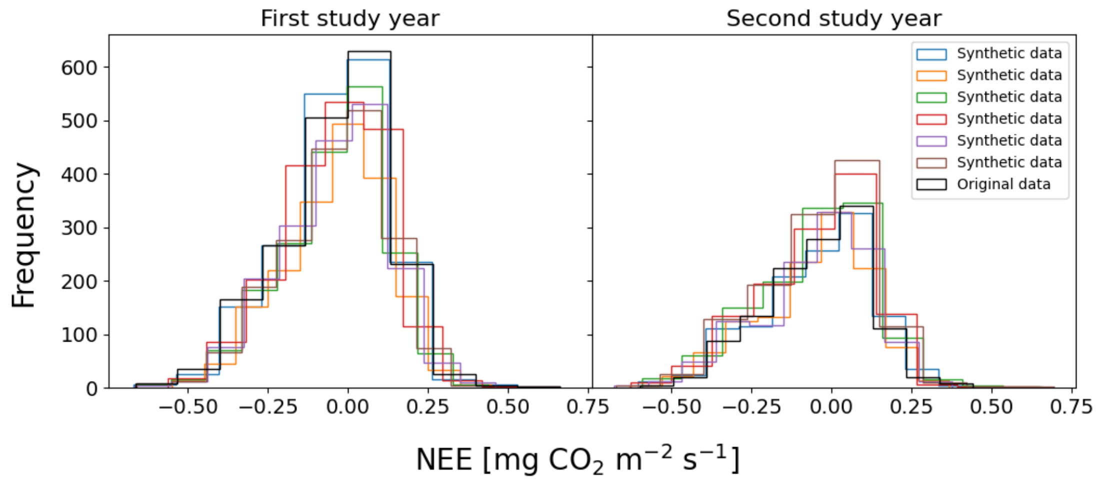

Figure R2. Distribution of the original, measured CO_2 flux data and representative examples of synthetic data sets used for testing the gradient boosting method.

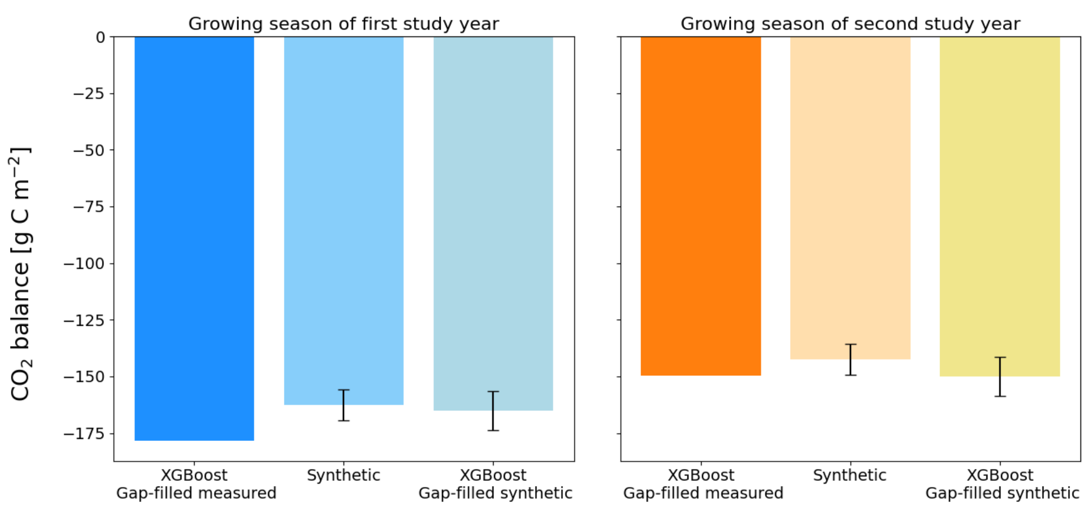

Figure R3. Growing season CO_2 balances estimated from measured data with the gradient boosting (XGBoost) gap-filling method, from synthetic data and from synthetic data with gaps filled with XGBoost. The balances of synthetic data represent the mean of 50 synthetic data sets and error bars their standard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

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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.

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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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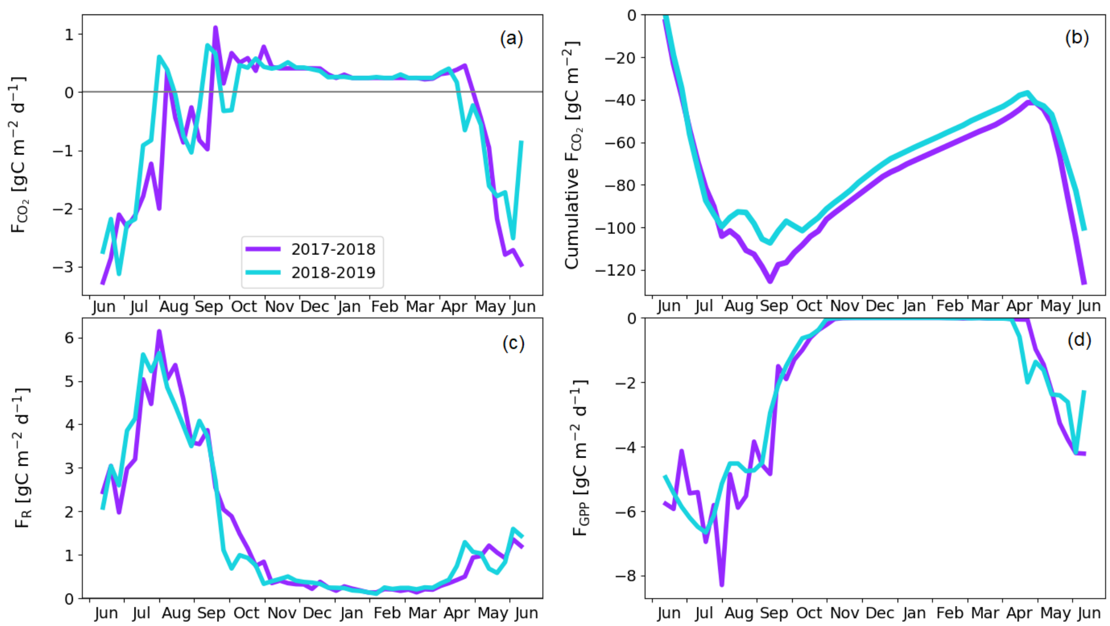

Figure 8. Pine forest fluxes. Weekly averaged (a) and cumulative (b) CO_2 flux, and weekly averaged ecosystem respiration (c) and gross primary productivity (d).

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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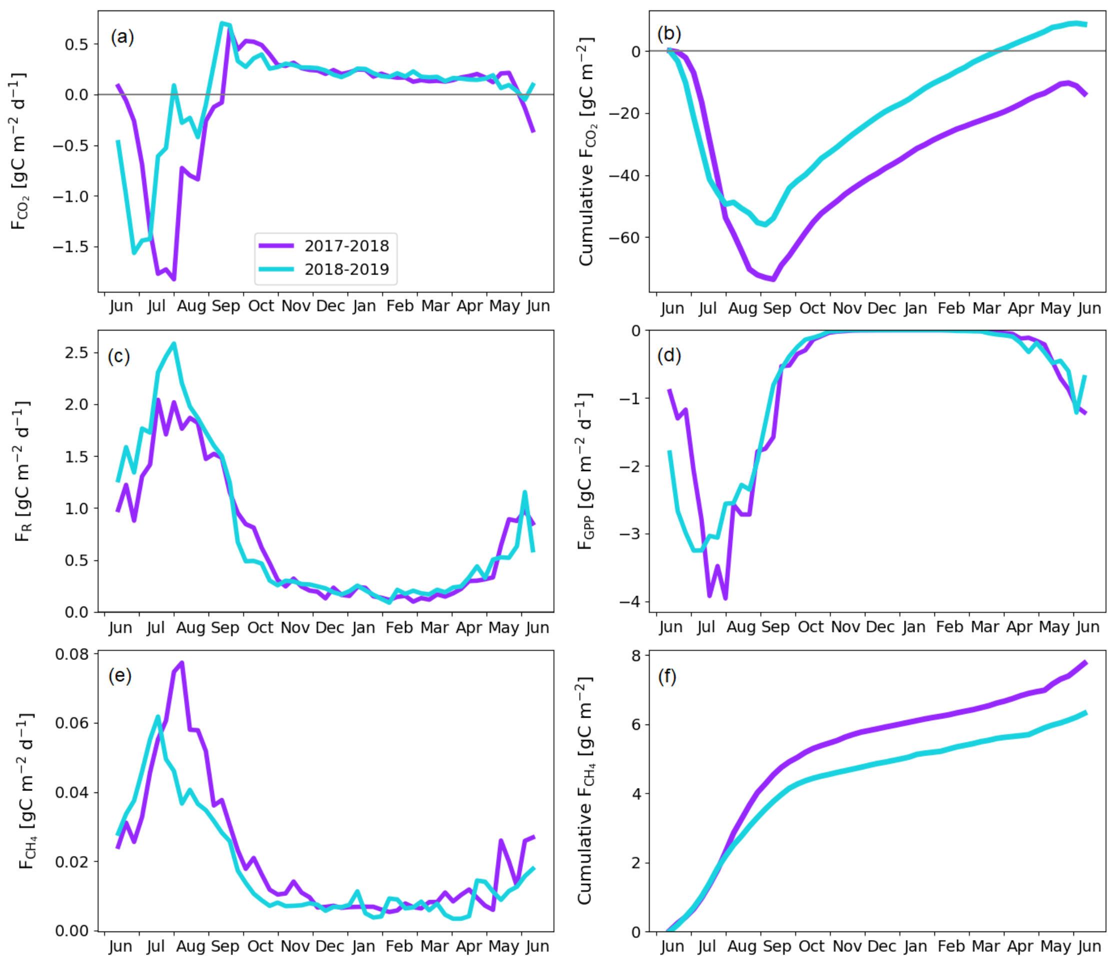

Figure 9. Fen fluxes. Weekly averaged CO_2 (a), ER (c), GPP (d) and CH_4 (e) flux, and cumulative CO_2 (b) and CH_4 (f) flux.

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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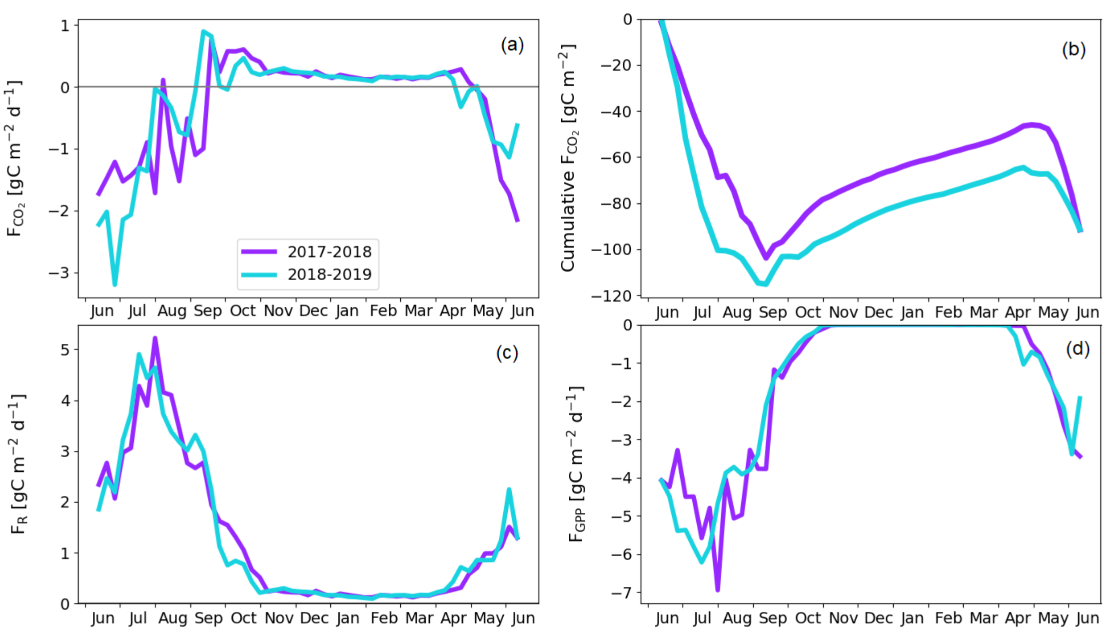

Figure 11. Treed pine bog fluxes. Weekly averaged CO_2 flux (a), and cumulative CO_2 flux (b), and weekly averaged ER (c) and GPP (d) flux.

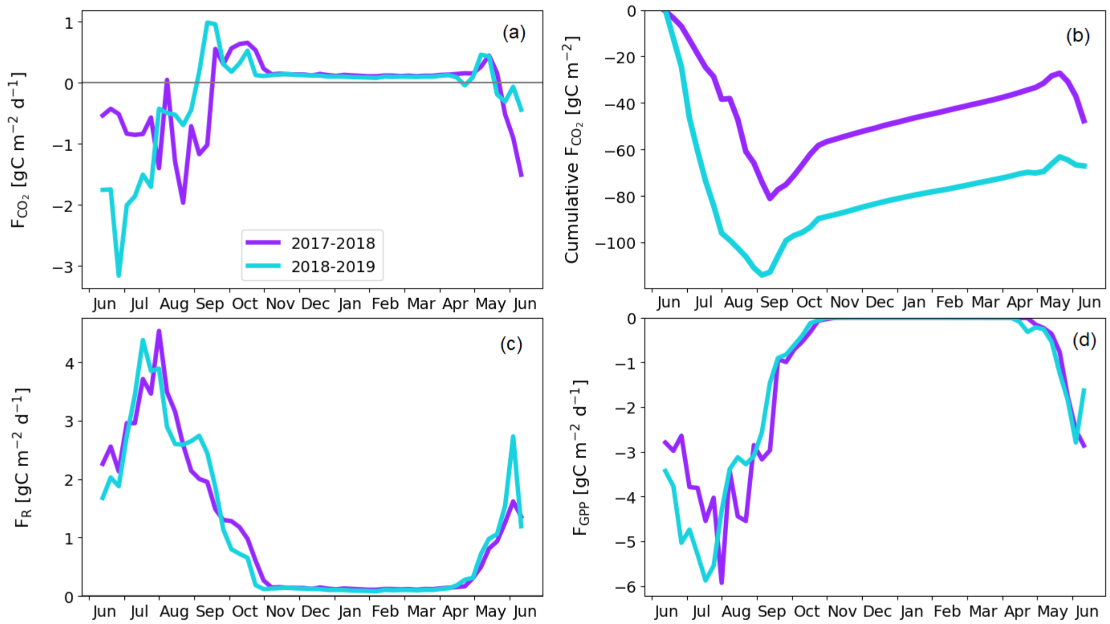

Figure 12. Sparsely treed pine bog fluxes. Weekly averaged CO_2 flux (a), and cumulative CO_2 flux (b), and weekly averaged ER (c) and GPP (d) flux.

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.

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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.

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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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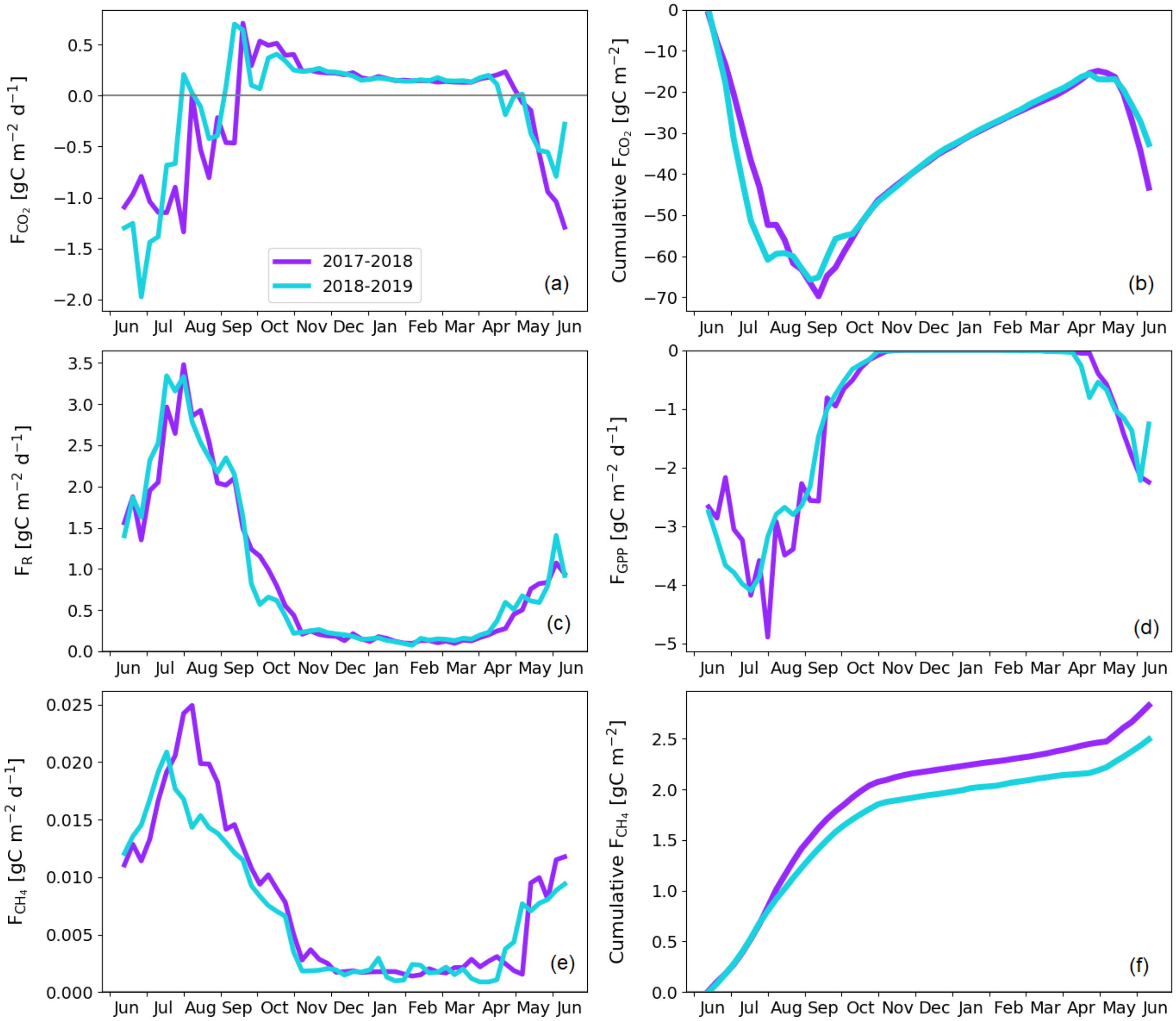

Figure 13. Landscape-level fluxes. Weekly averaged CO_2 (a), ER (c), GPP (d) and CH_4 (e) flux, and cumulative CO_2 (b) and CH_4 (f) flux.

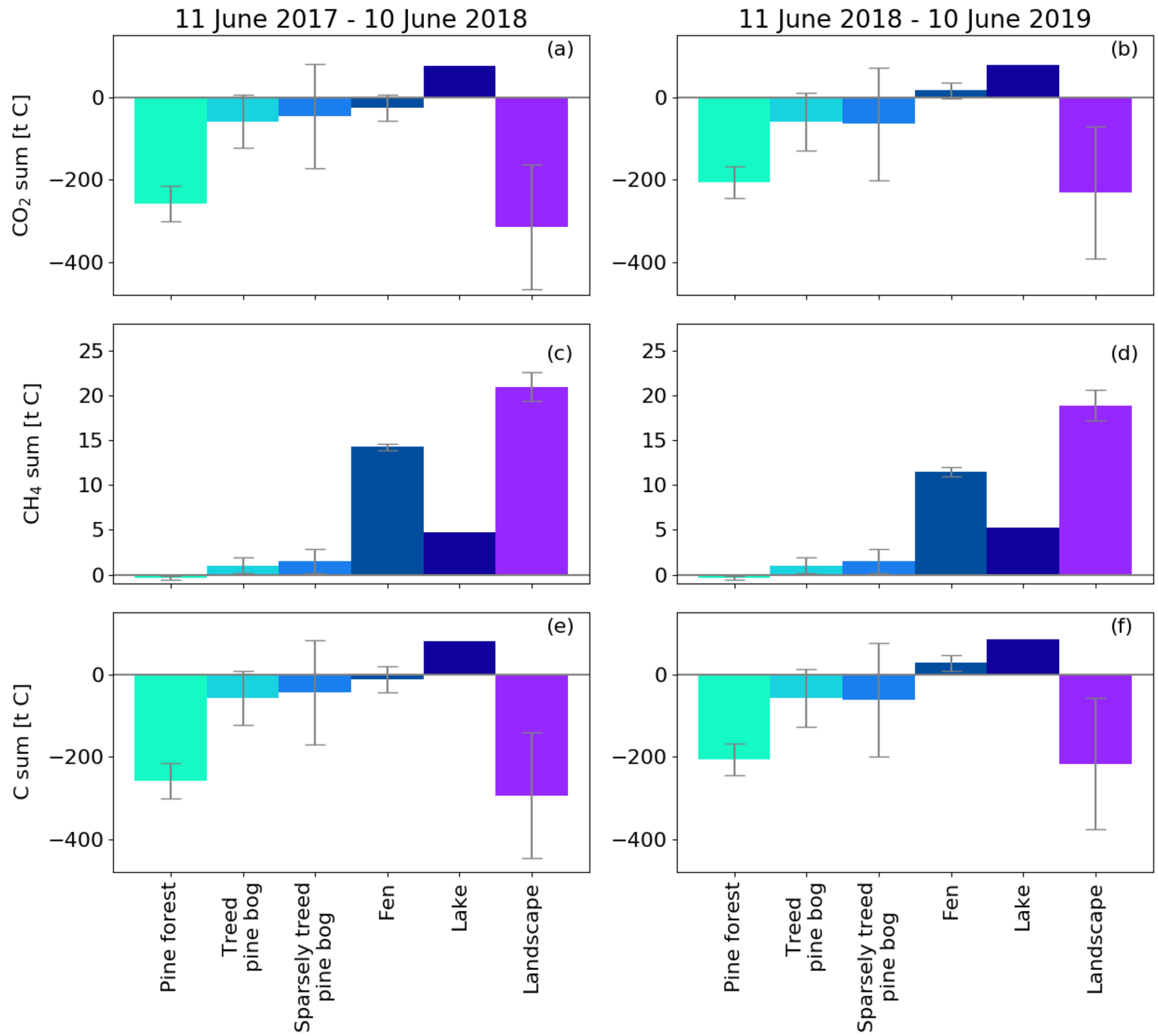

Figure 14. Annual CO_2, CH_4 and C flux sums for different ecosystems and the landscape (Fig. 1) scaled with the corresponding area. The CH_4 flux estimate for forest is from Dinsmore et al. (2017) and for pine bog from Bubier et al. (2005). The error bars denote the 95 % confidence interval. Uncertainty 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.

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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).

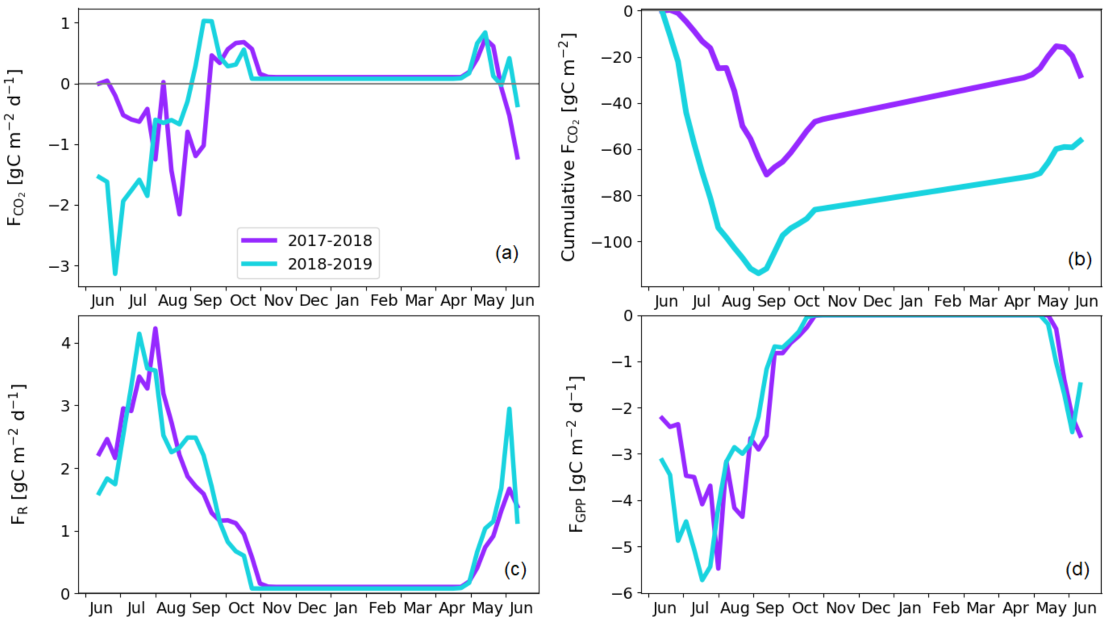

Figure A2. String top fluxes. Weekly averaged (a) and cumulative CO_2 flux (b), and weekly averaged ER (c) and GPP (d) flux, used for estimating pine bog ecosystem fluxes.

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Specific comments:

How was the upland forest CH_4 flux estimated as only eddy covariance CO_2 fluxes were measured there?

It was adopted from literature (Dinsmore et al., 2017). This was indicated in the manuscript (lines 298-299, 632, 656 and 700).

As the authors mentioned five major ecosystem types were investigated in this study and the fifth category is lake and stream, I wonder how to estimate the contribution from the connecting stream to the landscape-scale fluxes?

The stream emissions can be high per unit area (Juutinen et al., 2013; Wallin et al., 2018). However, the area coverage of streams within the studied landscape was so small (approximately 0.0026 km^2 or 0.04 % of the total area) that even assuming a high flux density the total stream emission does not affect the landscape-scale balances significantly. For instance, an annual flux estimate of 480 g C m^{-2} (Juutinen et al., 2013) would add only 1.25 t C to the 7 km^2 landscape-level balance, which is around 1.5% of the total lake emissions.

Juutinen, S., Väliranta, M., Kuutti, V., Laine, A. M., Virtanen, T., Seppä, H., Weckström, J. and Tuittila, E-S.: Short-term and long-term carbon dynamics in a northern peatland-stream-lake continuum: A catchment approach, J. Geophys. Res. Biogeosci., 118, 171-183, doi:10.1002/jgrg.20028, 2013.

Wallin, M. B., Campeau, A., Audet, J., Bastviken, D., Bishop, K., Kokic, J., … Grabs, T. (2018). Carbon dioxide and methane emissions of Swedish low-order streams-a national estimate and lessons learnt from more than a decade of observations. Limnology and Oceanography Letters, 3(3), 156–167. doi:10.1002/lol2.10061

Could you please also provide the basal area, stand density, and LAI of the upland pine-dominated forest stands within the landscape?

These data were added to the revised manuscript:

Table A5. Pine forest basal area, stand density and diameter at breast height (DBH) (mean ± standard deviation) derived from field measurements.

Tree species	Basal area	No. of trees per ha	DBH [cm]
Scots pine	13.2 ± 6.4	545 ± 827	15 ± 6
Downy birch	0.3 ± 0.7	103 ± 243	7 ± 6

How was the friction velocity threshold determined for each EC site? Or a citation from a previous study at this site if any?

The u* threshold and its uncertainty were determined as in Reichstein et al. (2005) and Papale et al. (2006). For the pine forest, due to the low temporal data coverage, we split the data into two seasons, summer (months 5-10) and winter (months 11-12 and 1-4), instead of four.

Please make sure that the ustar correction should be done after the flux storage correction to avoid that the ustar correction might have been applied during the storage period (counted twice).

The storage flux correction at the forest site is now done before the u* correction.

Section 2.2.2 is a bit confusing. So, for the fen ecosystem, both EC and chamber data are available? EC measurements have both CO_2 and CH_4 fluxes, but chambers measure CO_2 flux only? For the treed pine bog and sparsely treed pine bog ecosystems, only chamber-based CO_2 flux data are available? Please clarify.

We added a table to clarify the origin of different data sets:

Table A8. Origin of the data adopted for different 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).

Gaps account for 86% and 91% of flux data over the two years. That's a lot! I wonder how the authors could justify the data quality and accuracy of the forest fluxes and thus the robustness of the landscape-scale carbon balance estimated in this study.

Please see the general response above.

Only 30% of CH_4 flux data were left as the good-quality EC data. Please generally describe the CH_4 flux gap attributions as well.

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 %

Would the five-day flux measurements for each year represent the annual CO_2 and CH_4 fluxes of the lakes?

We agree that the lake data were limited. For the revised manuscript, we replaced the flux measurements with continuous data obtained from the Arctic Lake Biochemistry Model (ALBM), which was calibrated with our 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.

Kou, D., Virtanen, T., Treat, C. C., Tuovinen, J.-P., Räsänen, A., Juutinen, S., et al. Peatland heterogeneity impacts on regional carbon flux and its radiative effect within a boreal landscape. Journal of Geophysical Research: Biogeosciences, 127, https://doi.org/10.1029/2021JG006774, 2022.