

LETTER

Diel variation in CO₂ flux is substantial in many lakes

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Scientific Significance Statement

Lakes act as both sources and sinks of carbon dioxide (CO₂), with the magnitude and direction of this flux determined by characteristics of the waterbody and its surrounding catchment, as well as weather and sunlight. Despite an increasing awareness of diel (over 24 h) variation in the flux of CO₂ from aquatic ecosystems, comparable in situ data from lakes around the

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Associate editor: Jill S. Baron

world are limited. Here we present, for the first time, an international assessment of diel CO₂ fluxes, and show that diel variation can be grouped into three recognizable patterns linked to the productivity of lakes. Our findings suggest that the time of day greatly influences CO₂ fluxes in lakes, with resulting implications for scaling up single daytime measurements to values relevant to global carbon budgets.

Abstract

Lakes play a significant role in the global carbon cycle, acting as sources and sinks of carbon dioxide (CO₂). In situ measurements of CO₂ flux (FCO₂) from lakes have generally been collected during daylight, despite indications of significant diel variability. This introduces bias when scaling up to whole-lake annual aquatic carbon budgets. We conducted an international sampling program to ascertain the extent of diel variation in FCO₂ across lakes. We sampled 21 lakes over 41 campaigns and measured FCO₂ at 4-h intervals over a full diel cycle. Rates of FCO₂ ranged from -3.16 to 4.39 mmol m⁻² h⁻¹. Integrated over a day, FCO₂ ranged from -381.68 to 878.49 mg C m⁻² d⁻¹ (mean = 76.54) across campaigns. We identified three characteristic diel patterns in FCO₂ related to trophic status and show that for half of the campaigns, daily flux estimates were biased by > 50% if based on a single (daytime) measurement.

Lakes play an important yet uncertain role in the global carbon cycle (Cole et al. 2007) by transporting and processing terrestrial carbon along the land–ocean aquatic continuum (Engel et al. 2018), storing large amounts in sediment (Henry et al. 2024), and exchanging carbon dioxide (CO₂) and methane (CH₄) with the atmosphere (Holgerson and Raymond 2016). Gas flux across the air–water interface is a function of the transfer velocity (k), and the difference in partial pressure (pCO₂) between the surface water and the atmosphere (Cole et al. 2010). The combination of these two variables determines the direction (in or out of the lake, i.e., influx and efflux) and magnitude of the gas flux. Both k and pCO₂ are controlled by biophysical drivers which vary spatially and temporally, resulting in potentially large variations in CO₂ flux (FCO₂) (Vachon et al. 2017; Rudberg et al. 2024). While considerable work has been done on FCO₂ spatial variation across and within lakes (e.g., Rocher-Ros et al. 2017) and temporal variation at annual and seasonal time scales (Denfeld et al. 2018; Reed et al. 2018; Ngochera and Bootsma 2020), less is known about variation in FCO₂ over diel timescales. This variation has been recognized as a large source of uncertainty when upscaling CO₂ fluxes from inland waters into global budgets (Xu et al. 2019; Ran et al. 2022; Lauerwald et al. 2023).

There is a strong theoretical basis for expecting FCO₂ diel variability to be substantial, as the primary drivers of pCO₂ and k have diel patterns (e.g., sunlight, temperature, wind speed). For example, lakes with high primary production from photosynthesizing algae or macrophytes will uptake large amounts of CO₂ in the day, resulting in lower (even negative) daytime FCO₂ (Wang et al. 2024). The transfer velocity (k) is determined by wind speed, convection, and other drivers of turbulent mixing (Crusius and Wanninkhof 2003; Podgrajsek et al. 2015; Czikowsky et al. 2018) that vary in relative

importance over diel (Imberger 1985) and seasonal cycles (Read et al. 2012). Hence, the interaction of k and pCO₂ is likely to produce complex patterns in FCO₂ that will be moderated by the characteristics of individual waterbodies.

Several methods are used to collect measurements of FCO₂ from lakes (Lauerwald et al. 2023). Eddy covariance (EC) systems capture data at fine temporal resolution (Eugster et al. 2003; Liu et al. 2016; Golub et al. 2023) but they measure flux over a relatively large spatial footprint (> 1 ha) and may be too coarse for smaller lakes or large ones with significant spatial heterogeneity. There is also a clear unresolved issue between lake-surface and atmosphere FCO₂ measurements (Baldocchi et al. 2020). Modeling of flux using a gas transfer velocity (k) and the concentration gradient of the gas in the air and surface water is also common (e.g., Yang et al. 2019), but determining k is often challenging (Dugan et al. 2016). Chamber measurements provide direct estimates at a local scale (m²) and are suitable for understanding the mechanisms driving fluxes from smaller lakes (Bastviken et al. 2022). However, carrying out chamber measurements on lakes is logistically difficult, particularly in the nighttime, resulting in a large bias towards daytime measurements. Where chambers have been used to measure FCO₂ from aquatic ecosystems, it has tended to be for detailed studies at a small number of sites (e.g., Ojala et al. 2011; Natchimuthu et al. 2017).

Several studies have documented significant diel variability in FCO₂ in streams and rivers (Attermeyer et al. 2021; Gómez-Gener et al. 2021; Woodrow et al. 2024), and in lakes where EC data are available (Shao et al. 2015; Spank et al. 2020; Golub et al. 2023; Hounshell et al. 2023) but it is surprisingly hard to find direct measurements of FCO₂ from lakes overnight. A recent review of data availability describing FCO₂ over diel cycles found 29 published estimates from lakes, ponds, and one reservoir (Rudberg et al. 2021), with an almost

equal split between higher daytime or higher nighttime FCO₂. Higher nighttime FCO₂ has been recorded in several eutrophic waterbodies (Ran et al. 2022; Zhang et al. 2022; Rulík et al. 2023; Zhao et al. 2024), with some researchers advocating the use of a night/day ratio to correct the bias introduced by daytime sampling alone (Wang et al. 2024).

The aim of this work was to characterize diel FCO₂ variability across a broad range of lakes, using a standardized approach. We measured FCO₂ over a diel cycle in 21 lakes, using low-cost CO₂ sensors and floating chambers. We hypothesized that FCO₂ would have high diel variability in lakes with high productivity and diel variability in turbulence drivers, particularly nocturnal heat loss and afternoon wind peaks. We used our data to calculate an integrated daily carbon flux for each study lake, and we compared these integrated fluxes to daily fluxes extrapolated from a single midday FCO₂ to estimate temporal up-scaling bias.

Methods

Study sites

We recruited researchers through the Global Lake Ecological Observatory Network to conduct a field campaign comprising in-situ flux measurements every 4 h over one diel cycle (~ 28 h) using floating chambers and directly measured pCO₂ over several minutes. We encouraged the use of inexpensive in-situ sensors (i.e., SensAir, see Bastviken et al. 2015), which enabled research groups with limited funding to participate.

In some cases, participants used sensors that they already had, for example, a Gasetm Dx-4030 spectrometer (Rööm et al. 2022) or Los Gatos GHG analyzer (McClure et al. 2020).

We measured FCO₂ in 21 lakes between November 2016 and October 2018 (Fig. 1). Lakes varied in terms of surface area, depth, trophic status, seasonality of ice-cover and mixing regime, among other characteristics (Table 1). Diel sampling was done once in 12 lakes and was repeated on non-consecutive days twice in 5 lakes, 3 times in 5 lakes, and 4 times in 1 lake, resulting in 41 campaigns. Over half ($n = 23$) of the campaigns were conducted in summer, eight were in spring and autumn, and two were in winter. Two sampling locations were used at two lakes (Pallasjärvi and Mendota) which were spatially different enough to warrant separate consideration, leading to 23 flux measurement sites in total.

Flux measurement

Campaigns lasted between 17 and 28 h and consisted of six or seven sampling periods spaced approximately every 4 h. Chambers were fitted with foam collars and had an average volume of 12 L (range 7–31 L). The surface area of the water enclosed averaged 0.11 m² (range 0.06–0.28). We vented the chambers, placed them on the water surface and allowed them to drift for at least 5 min. The FCO₂ measurement was replicated in most cases, either using multiple chambers at the same time, or consecutive deployments of the same chamber. In most cases, sensors were calibrated using N₂ gas and the

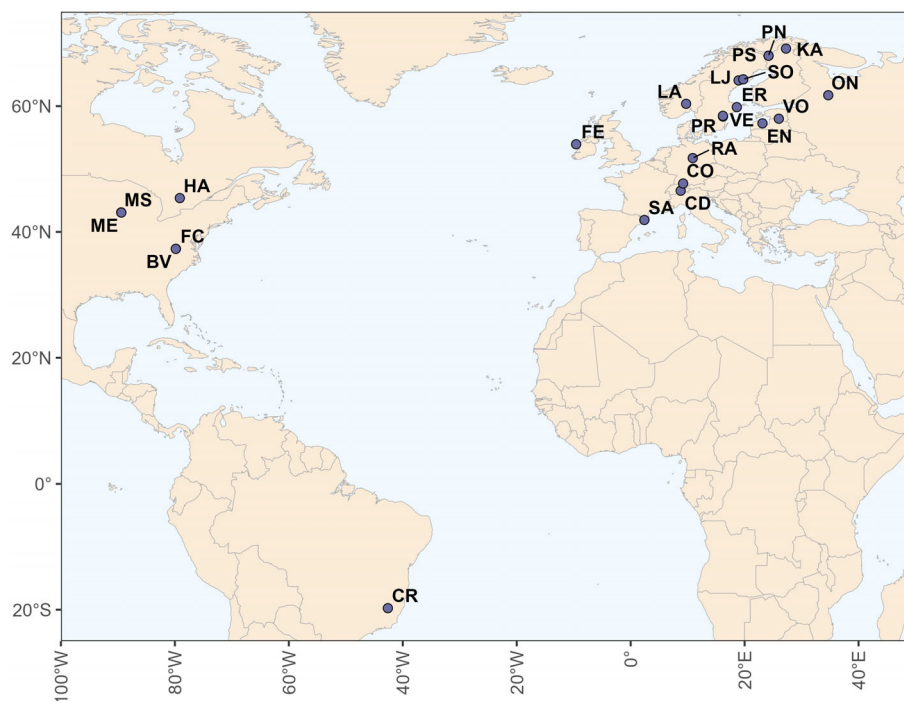


Fig. 1. Location of our study sites. Lake name abbreviations can be found in Table 1.

Table 1. Characteristics of lakes included in this study.

Lake	Code	Lat	Long	Mean depth (m)	Max depth (m)	Surface area (km ²)	Altitude (m)	Fetch (m)	Catchment area (km ²)	Mixing regime	Humic	Trophic status
Beaverdam reservoir	BV	37.31	-79.81	6	13.4	0.39	509	28	4.11	Di	No	Meso
Cadagno	CD	46.55	8.77	9.7	21	0.26	1920	120	2.51	Mero	No	Meso
Carioca	CR	-19.75	-42.61	4.76	11.8	0.14	268	110	0.72	Mono	No	Eu
Constance	CO	47.69	9.20	90	253	536	395	NA	11,500	Mono	No	Oligo
Engure	EN	57.25	23.12	0.4	2.1	41.3	3	200	644	Poly	No	Eu
Erken	ER	59.83	18.62	9	20.65	24.2	11.1	25	141	Di	Yes	Meso
Falling Creek reservoir	FC	37.30	-79.84	4	9.3	0.12	591	30	3.68	Di	No	Meso
Feeagh	FE	53.93	-9.57	14.5	45	3.92	20	500	85	Mono	Yes	Oligo
Harp	HA	45.38	-79.13	10	35	0.7	350	500	4.71	Di	No	Oligo
Kaamanen	KA	69.13	27.26	0.7	0.7	0.019	153.3	30	0.24	Poly	Yes	Oligo
Langtjern	LA	60.36	9.73	2	12	0.23	516	50	4.8	Di	Yes	Oligo
Ljusvattentjärn	LJ	64.09	18.93	5.2	9.7	0.02	252	129	0.24	Di	Yes	Oligo
Mendota	ME	43.10	-89.42	12.7	25.3	39.9	259	3000	562	Di	No	Eu
Mendota shore	MS	43.08	-89.40	3	3	39.9	259	10	562	Di	No	Eu
Onego	ON	61.73	34.67	30	127	9720	33	700	51,540	Di	Yes	Meso
Pallasjärvi North	PN	68.01	24.21	4	5	0.48	267	145	105.2	Di	No	Oligo
Pallasjärvi South	PS	68.00	24.20	1.5	2	0.18	267	82	105.2	Di	No	Oligo
Parsen	PR	58.34	16.20	3.4	8	0.13	72	345	1.82	Di	No	Meso
Rappbode	RA	51.74	10.89	28.6	89	3.95	423	200	274	Di	No	Meso
Sau Reservoir	SA	41.98	2.38	29	65	5.8	425	3065	1680	Mono	No	Eu
Stortjärn	SO	64.26	19.76	2.7	6.7	0.04	299	60	0.65	Di	Yes	Meso
Venasjön	VE	58.45	16.19	5.4	10.5	0.68	47	95	1.70	Di	No	Eu
Vörtsjärn	VO	58.28	26.03	2.8	6	270	34	230	3374	Poly	Yes	Eu

“zero calibration” method per Bastviken et al. (2015) although this was not possible at some remote locations. At sites where relative humidity was high, an appropriate correction was made. Flux rates were calculated following eq. 1 in Rudberg et al. (2021).

In addition to FCO₂, we collated lake (Table 1) and campaign (Supporting Information Table S1) metadata to use as explanatory variables for our analyses. We measured water temperatures and pCO₂ of the surface water and gathered meteorological data from the nearest weather station to calculate the mixing depth (Z_{mix}) and turbulent velocity scales for wind shear (u^*), and convection (w^*) following Imberger (1985). Photosynthetically active radiation was converted to total shortwave radiation following Read et al. (2011). Campaign-specific partial pressure of CO₂ in the atmosphere was downloaded from the Copernicus Atmosphere Monitoring Service (2021).

Statistical methods

All results were based on the mean flux from replicates within each sampling time period of every diel campaign (de Eyto et al. 2025). We removed outliers within each sampling period before averaging, based on the interquartile range criterion. We binned measurements across 11 time periods to allow for comparison of diel cycles across campaigns with varying start times (Supporting Information Table S2). Day and night sampling periods were determined using the R package “geosphere” (Hijmans et al. 2016). For lakes at northern latitudes, we also used shortwave radiation ($< 50 \text{ W m}^{-2}$) to determine nighttime.

We used longitudinal k -means clustering to determine common diel flux patterns across campaigns. In brief, this analysis tests for different temporal trajectories or “shapes” from repeated measurements, and optimal clusters of similar shapes are selected based on variance ratio criteria (Genolini and Falissard 2010). Importantly, this algorithm does not have linearity or distribution assumptions, so trajectories or “shapes” of repeated measurements can take many forms. Within each campaign, flux data were scaled as z -scores to have equal mean and variation. This reduced bias in the cluster analysis that might be skewed by very high or low flux values and allowed the cluster analysis to identify common patterns in diel fluxes, irrespective of measurement differences between campaigns that might have impacted the flux magnitude. We tested for 2–9 possible clusters with 20 redraws using the “kml” package (Genolini et al. 2015) in R. The optimal number of clusters was selected as that with the highest average Calinski–Harabatz quality value across redraws. Each campaign was assigned a cluster based on the results of the optimal clustering algorithm.

We then used a classification tree analysis to assess the characteristics and conditions associated with each cluster, using the “rpart” package (Therneau and Atkinson 2013). We included 18 predictor variables of cluster in the classification

tree (Supporting Information Table S3), selected by reducing cross-correlation with analogous variables (i.e., selecting for $|\text{Pearson } r| < 0.75$). The resulting classification tree was pruned by selecting the model with the fewest nodes and a cross-validated error rate within ± 1 standard error of the model with the overall lowest cross-validated error.

Finally, we calculated the area under each diel flux curve using trapezoidal integration in the R package “pracma” (Borchers 2023). This allowed us to calculate daily flux ($\text{mg C m}^{-2} \text{ d}^{-1}$) for each campaign, based on FCO₂ integrated across 4-h time periods ($\text{dFCO}_{2\text{int}}$). We compared this to extrapolations based on multiplying the midday flux rate by 24 ($\text{dFCO}_{2\text{mid}}$) as is often used in upscaling, to examine potential bias introduced by using a single daytime FCO₂.

Results

Our complete dataset comprised 41 diel campaigns and 992 individual flux chamber measurements across 23 sites. After averaging across replicates within sampling periods, the final dataset comprised 277 FCO₂ rates ranging from -3.16 to $4.39 \text{ mmol m}^{-2} \text{ h}^{-1}$ (mean = 0.29, median = 0.14) (Fig. 2A). We measured negative (influx) FCO₂ 103 times and positive (efflux) 174 times. Mean FCO₂ per campaign ranged from -1.31 and $3.13 \text{ mmol m}^{-2} \text{ h}^{-1}$ and the standard deviation per campaign varied from 0.02 to $1.30 \text{ mmol m}^{-2} \text{ h}^{-1}$. In other words, FCO₂ was very stable in some lakes over the diel cycle, while in others, there were large differences depending on the time of day the sample was taken. We recorded wholly negative FCO₂ in 11 campaigns, wholly positive FCO₂ in 19 campaigns with the remaining 11 campaigns switching between influx and efflux over the diel cycle. Humic lakes tended to have positive and larger FCO₂ compared to non-humic lakes which centered on neutral (Fig. 2B). Oligotrophic lakes displayed small, slightly positive effluxes while mesotrophic to eutrophic were highly variable (Fig. 2C). Autumn campaigns skewed towards efflux, while influxes, indicating demand for CO₂, were more likely in campaigns carried out during the growing season in mesotrophic to eutrophic lakes. The biggest seasonal difference was found in Lake Mendota where fluxes were entirely negative in the spring and positive in the autumn. We found that campaigns where the surface water pCO₂ was close to equilibrium with the atmosphere ($398\text{--}410 \text{ ppm CO}_2$ at the time of sampling) corresponded with FCO₂ close to zero, low standard deviations in FCO₂ and switches between influx and efflux during the campaign (Supporting Information Fig. S1). Across all campaigns, there was no significant difference in FCO₂ measured between day and nighttime (Supporting Information Figs. S2, S3; Table S4) or between sampling periods (Supporting Information Fig. S4; Table S5).

We found that the optimal clustering algorithm for the patterns of diel flux resulted in three clusters (Fig. 3A). Campaigns in Cluster A ($n = 17$) had the highest fluxes in the late

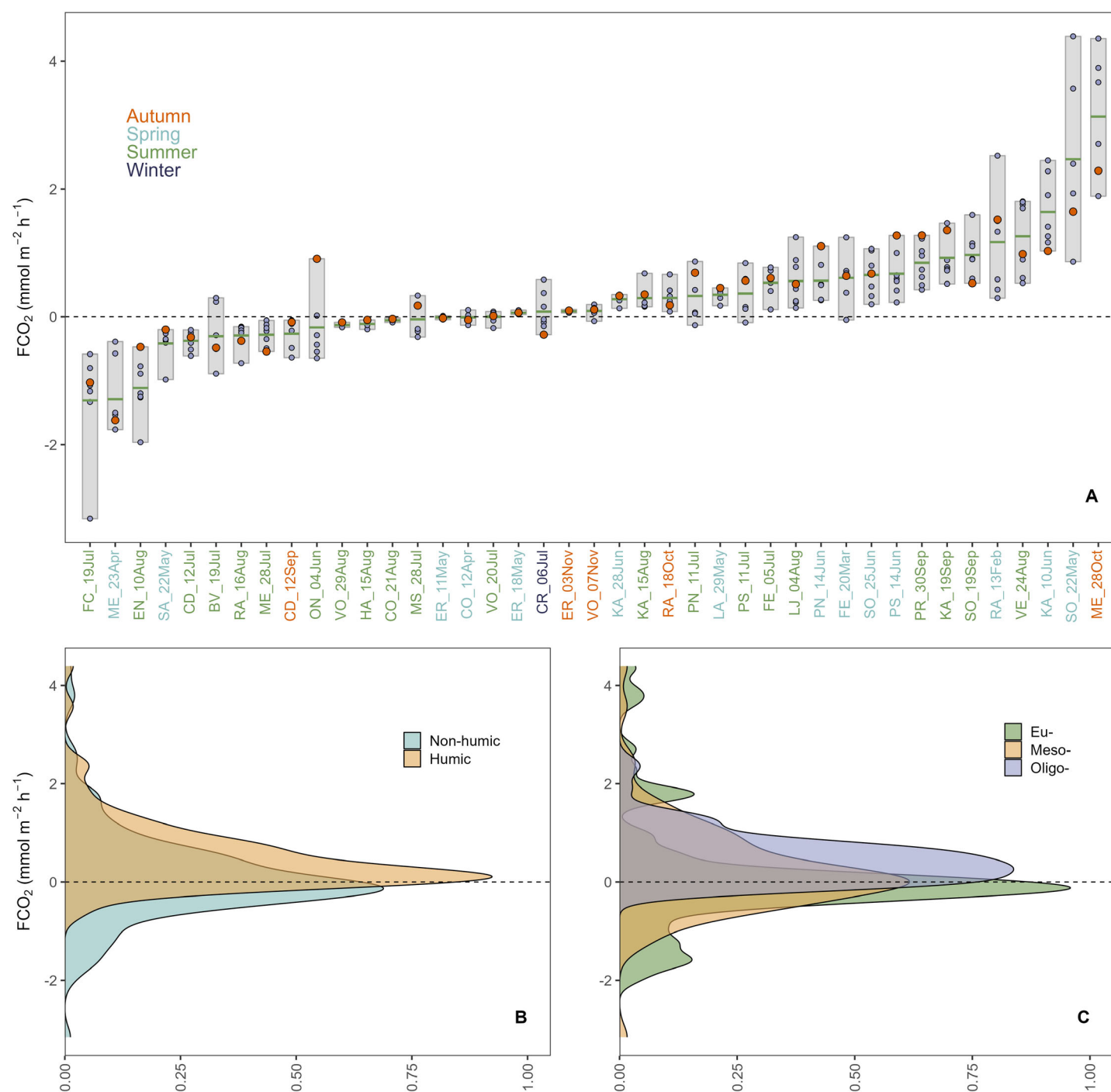


Fig. 2. CO₂ flux between water and air measured during 41 sampling campaigns (A). Each gray box represents the range of FCO₂ measured over a diel campaign. The horizontal line within each box indicates the mean FCO₂ per campaign, and green dots are FCO₂ measured at ~4 h intervals over a diel cycle. The orange dot is the midday value. Data below the dashed line are influxes (CO₂ into the lake), while those above the line are effluxes (CO₂ out of the lake) to the atmosphere. Campaigns are ordered left to right according to the mean FCO₂ per campaign. Density plots of 277 measurements of FCO₂, with study sites split according to non-humic/humic water (> 30 mg L⁻¹ PtCO) (B), and by trophic status (C).

afternoon to evening, which decreased around midnight, and remained comparatively low during night into early morning, a pattern consistent with diurnal wind-driven efflux. Those in

Cluster B ($n = 11$) had relatively low fluxes in the afternoon that increased in the evening until midnight, followed by relatively high flux rates during night and into early morning, a

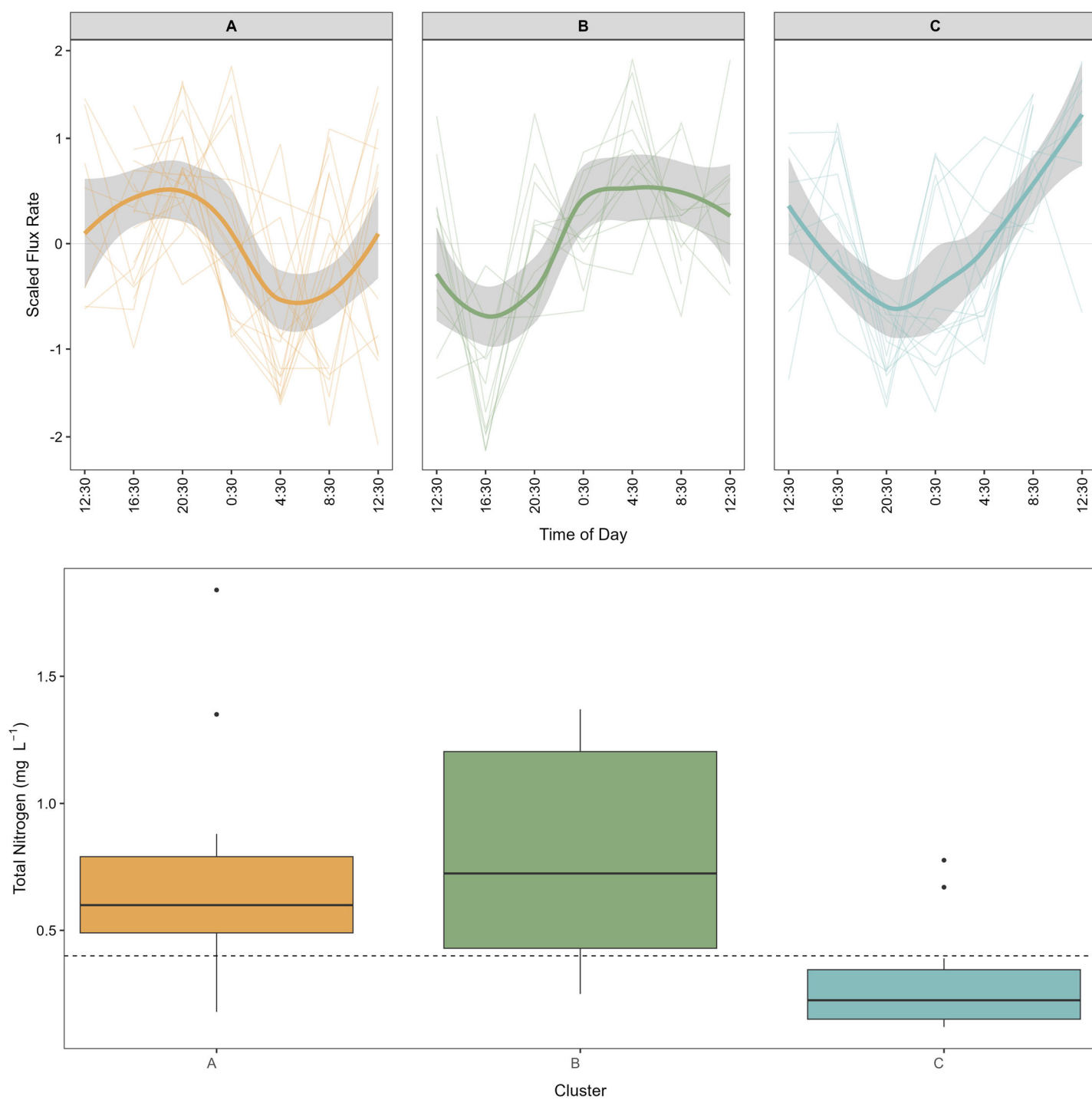


Fig. 3. Line plots (*top*) of the average diel flux pattern for each cluster identified from the scaled observed data using longitudinal *k*-means clustering. The heavy line is the average smoothed pattern within each cluster, with the gray area indicating the 95% confidence interval. Thin lines are the individual patterns for each campaign. Total nitrogen as a function of observed cluster results (*bottom*), driven by pruned regression tree results predicting clusters based on split on total nitrogen at 0.4 mg L⁻¹ (horizontal dashed line). Lakes with total nitrogen (TN) < 0.4 mg L⁻¹ were classified as Cluster C (blue; *n* = 11 campaigns, 82% correct classification). Lakes with TN ≥ 0.4 mg L⁻¹ were classified as Cluster A (gold; *n* = 30 campaigns, 53% correct classification), though lakes in Cluster B (green) had a similar mean and range of TN values.

pattern consistent with high productivity and respiration. Finally, we found that campaigns in Cluster C ($n = 13$) had moderate but decreasing fluxes during the afternoon that were lowest around midnight, and increased in early morning and into afternoon (i.e., “U-shaped” from midday to midday).

The classification tree suggested total nitrogen was the key driver differentiating two of these three clusters. We note that total phosphorus was highly correlated with total nitrogen (TN) (Pearson $r = 0.84$) and using it in the classification analysis gives the same predicted cluster splits. Campaigns with total nitrogen $< 0.4 \text{ mg L}^{-1}$ were classified at Cluster C, representing generally oligotrophic systems with low primary productivity. Campaigns with total nitrogen $\geq 0.4 \text{ mg L}^{-1}$ were classified as Cluster A or B, representing more productive systems (Fig. 3B). However, some campaigns with lower TN

did cluster into A or B, resulting in a relatively high misclassification result of 47% (Supporting Information Fig. S5).

When integrated across sampling periods, $d\text{FCO}_{2\text{int}}$ for each campaign ranged from -381.68 to $878.49 \text{ mg C m}^{-2} \text{ d}^{-1}$ (mean = 76.54). In comparison, we found that extrapolated $d\text{FCO}_{2\text{mid}}$ ranged from -466.88 to $659.12 \text{ mg C m}^{-2} \text{ d}^{-1}$ (mean = 100.23). The absolute difference per campaign between these two calculations ($d\text{FCO}_{2\text{int}} - d\text{FCO}_{2\text{mid}}$) ranged from 0.21 to $314.89 \text{ mg C m}^{-2} \text{ d}^{-1}$, with some differences being positive and some being negative (Fig. 4A) because midday fluxes were above and below the observation mean in lakes with diel variation (red dots in Fig. 2A). When the difference is expressed as a proportion of $d\text{FCO}_{2\text{int}}$, we found that using $d\text{FCO}_{2\text{mid}}$ to estimate daily flux resulted in a potential error of $> 50\%$ in 19 out of 41 campaigns (Fig. 4B). This bias

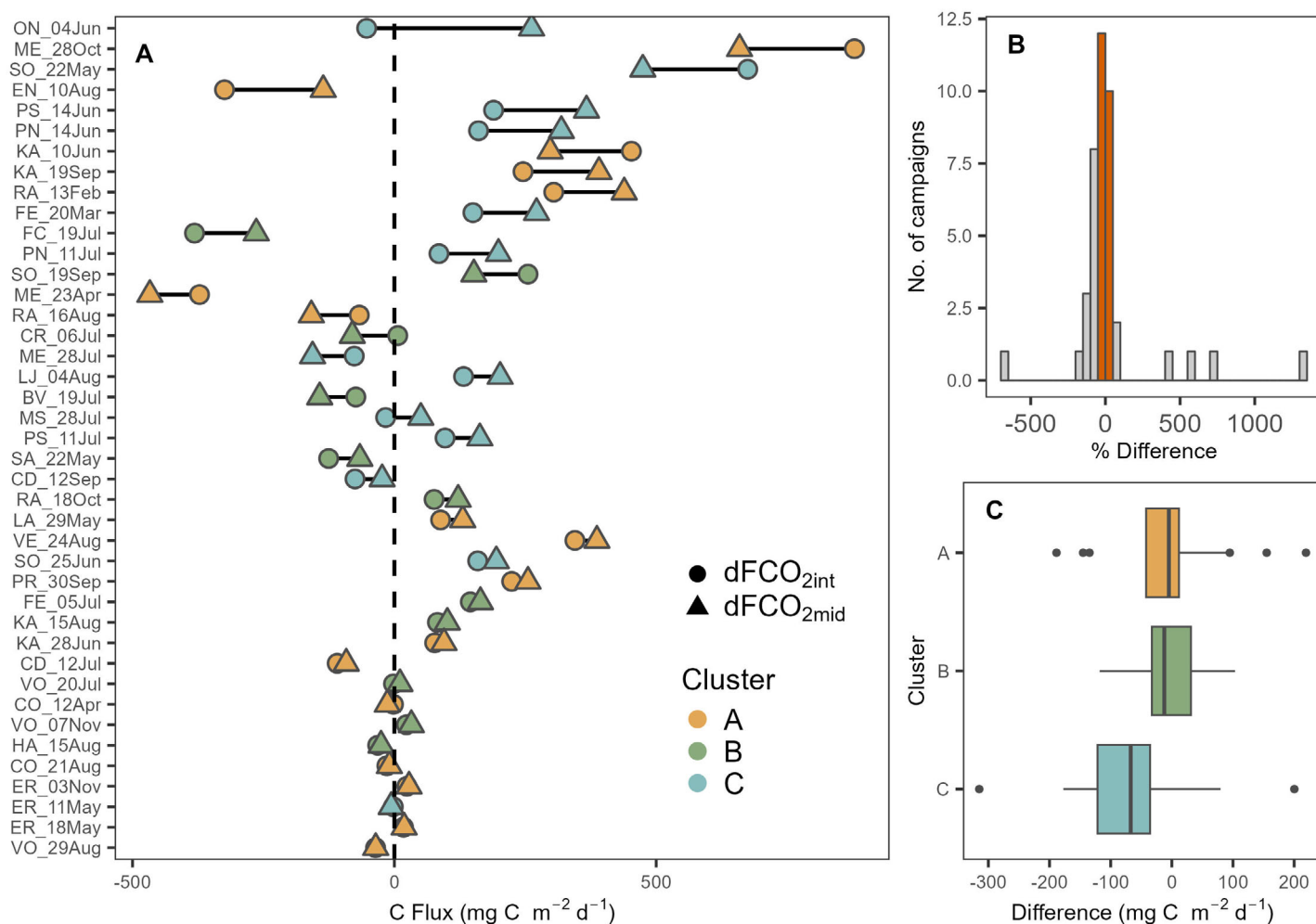


Fig. 4. Difference between CO₂ flux per day (mg C d^{-1}) for each campaign calculated by integrating across 6 measurements taken over 24 h ($d\text{FCO}_{2\text{int}}$) and by extrapolating from midday measurements ($d\text{FCO}_{2\text{mid}}$) (A). Data to the left of the dashed line are inflows, while those to the right are effluxes. Campaigns are ordered top to bottom by the difference ($d\text{FCO}_{2\text{int}} - d\text{FCO}_{2\text{mid}}$). Histogram of the differences expressed as the percentage of $d\text{FCO}_{2\text{int}}$, with campaigns where the difference was less than 50% indicated in orange (B). Difference in daily flux calculations within each cluster of campaigns shown in Fig. 3 (C).

was particularly obvious for campaigns which displayed the U-shaped curve exemplified by Cluster C (Fig. 3), where we typically measured more positive midday FCO₂ than in the nighttime. Thus, the use of dFCO_{2mid} leads to an overestimate of daily flux, and a negative bias (Fig. 4C).

Discussion

The large range of estimated carbon fluxes from lakes (e.g., 1.99–3.58 PgC yr⁻¹; Del Sontro et al. 2018) can be partly attributed to uncertainties arising from poor spatial and temporal coverage of direct observations (Lauerwald et al. 2023). This work is an important contribution to understanding one source of temporal uncertainty, that is, diel variation in flux rates from lakes. The range of FCO₂ rates that we report (–3.16 to 4.39 mmol m⁻² h⁻¹) is within previously reported ranges (Natchimuthu et al. 2017; Potter and Xu 2023). Many of our FCO₂ measurements were negative, indicating influx of CO₂, and for some campaigns, this occurred for a substantial part of the diel cycle. CO₂ flux in some lakes was highly variable over diel timescales, particularly in mesotrophic–eutrophic lakes during spring and summer, and in lakes which were supersaturated with CO₂. Supersaturation can happen during spring and autumn turnover in dimictic lakes (Brentrop et al. 2021) and shortly after ice-off (Denfeld et al. 2018) leading to high FCO₂ (López Bellido et al. 2009). This is apparent in two campaigns which occurred close to ice-off (SO_May22 and KA_Jun10) (Supporting Information Table S1). Although we initially planned to conduct sampling campaigns three times at each lake over a 12-month period to allow comparison across seasons, this proved difficult owing to weather and staffing constraints. As a result, we lacked statistical power to quantitatively examine diel FCO₂ variation across seasons.

Large diel variability in FCO₂ has been recorded at eutrophic lakes in temperate to subtropical climates, with higher effluxes at night and lower efflux (or even influx) during the day attributed to respiration and photosynthesis respectively (Ran et al. 2022; Potter and Xu 2023; Wang et al. 2024). The campaigns in our dataset that took place in productive lakes had more nuanced patterns, one with afternoon maxima and dawn minima (Cluster A), and the other with afternoon minima and dawn maxima (Cluster B). Theoretically, the pattern observed in Cluster A may be related to windier conditions in the afternoon leading to higher gas exchange and greater flux rates compared to calmer conditions at night. In contrast, the Cluster B pattern is similar to that described in Hounshell et al. (2023) and Liu et al. (2016), where daytime influxes were linked to higher primary productivity in the afternoon and nighttime effluxes to convective mixing distributing respired CO₂ to surface waters overnight. Cluster C, characterized by low nitrogen, had a pattern that aligned with solar radiation, with fluxes highest at midday and lowest around midnight. This pattern may reflect photomineralization of dissolved

carbon at the lake surface, which can be considerable in boreal and northern temperate lakes with high dissolved organic carbon (Vachon et al. 2016).

We expected that the calculations of turbulent velocity scales for wind shear (u^*), and convection (w^*) might have been informative in determining the drivers of the patterns, particularly in Clusters A and B, but this was not the case. This may have been owing to insufficient resolution of turbulence parameters to adequately assess the linkage with FCO₂, or masking of diel patterns by the interactions of multiple drivers changing on diel and longer timescale. Further work to combine u^* and w^* estimates into gas transfer models (Podgrajsek et al. 2015; Erkkilä et al. 2018) may help to understand the underlying dynamics, but were beyond the scope of this paper.

The use of a diel variability factor (night/day ratio) to calculate daily average flux has been proposed recently (Wang et al. 2024), along with the use of a standardized time period of sampling, in order to make data comparable across studies (Potter and Xu 2023). While both these suggestions may work within subsets of lake types, our results show that the night/day ratio varied widely across our campaigns from –4.78 to 9.52 (Supporting Information Table S1; Fig. S6). We found no single time period within the diel cycle that universally represented the average diel FCO₂ (Supporting Information Fig. S7) across diel pattern clusters. We therefore caution against oversimplification of FCO₂ without careful consideration of diel variability. We suggest that a priori knowledge of surface pCO₂, either gained from predictive modeling using landscape features (Kortelainen et al. 2006; Valiente et al. 2022), remote sensing of related variables (Kutser et al. 2015) or targeted spot sampling, may be informative in identifying under- or supersaturated surface waters, enabling the design of appropriate sampling programs.

Our use of chambers equipped with relatively inexpensive sensors allowed the inclusion of many lakes which have not previously been sampled for FCO₂, and this is an obvious advantage of these systems (Hunt et al. 2017). These sensors have been successfully used in recent years in a number of sampling campaigns (e.g., Serikova et al. 2019; Baldocchi et al. 2020), and modifications are being deployed to counteract some of the known issues (e.g., humidity, Bastviken et al. 2020). We recommend using a similar protocol as described here to target understudied lakes in poorly monitored biomes (Lauerwald et al. 2023) and growing season in mesotrophic to eutrophic lakes to improve understanding of the scope of lakes for which diel variability is important to consider. Our geographically dispersed observations across varied lakes demonstrated significant bias in dFCO₂ in approximately half of all sampling campaigns if we do not consider the diel variation in flux rates. This underlines the importance of accounting for measurement biases when upscaling data from highly variable systems to global estimates.

Author Contributions

Angela Baldocchi, Alo Laas, Annalea Lohila, Anna Lupon, Amir Reza Shahabinia, Blaize A. Denfeld, Brian C. Doyle, Biel Obrador, Cayelan C. Carey, David Reed, David Rudberg, Elvira de Eyto, Eva-Ingrid Rõõm, Hannah E. Chmiel, Ilga Kokorite, Jānis Bikše, Jorge Encinas Fernández, James A. Rusak, Jan-Erik Thrane, Ludmila S. Brighenti, Mika Aurela, Matthias Koschorreck, Philipp S. Keller, Rafael Marcé, Ryan P. McClure, and Samuel Haverinen carried out fieldwork. Gesa A. Weyhenmeyer, R. Iestyn Woolway, Robyn L. Smyth, Hans Peter Grossart, Alo Laas, Heleen A. de Wit, Ankur R. Desai, Annalea Lohila, Anna Lupon, Blaize A. Denfeld, Brian C. Doyle, Cayelan C. Carey, Elvira de Eyto, Francois Clayer, Ludmila S. Brighenti, Matthias Koschorreck, Philipp S. Keller, Rafael Marcé, Ryan P. McClure, Steve Sadro, and David Bastviken conceived the research and designed the sampling methodology. Nathan Barros, Sarian Kosten, José Fernandes Bezerra-Neto, Francois Clayer, and Sari Juutinen contributed expertise and advice on analysis and provided ancillary data. Elvira de Eyto, Robyn L. Smyth, and Rachel M. Pilla collated the data, carried out the analysis and wrote the first draft of the manuscript.

Acknowledgments

This work is the result of an international team science effort facilitated by the Global Lake Ecological Observatory Network. In addition to the listed co-authors, many of the GLEON Lake Ecological Observatory Network community contributed to earlier stages of the DC-FLUX project, and we thank them for their input. Daniel Mercado provided the CO₂ atmospheric data and Seán Kelly provided analysis assistance to Elvira de Eyto. Robyn L. Smyth, Ankur R. Desai, Angela Baldocchi, Cayelan C. Carey, and David Reed acknowledge support from U.S. National Science Foundation from DEB-1754271, DEB-2025982, DEB-1440297, DEB-2327030, and the AGS Postdoctoral Fellowship award to David Reed. Robyn L. Smyth completed this work while serving at U.S. National Science Foundation. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the U.S. National Science Foundation or U.S. Federal government. Long-term funding from the Norwegian Environment Agency supported climate monitoring at Langtjern (Contract No. 22047069) and Eivind Ekholm Andersen assisted with this sampling. Data collection from Estonian lakes was supported by the Estonian Research Council grants (PSG32, PRG1167, PRG709, PUT1598, and IUT21-2). Anna Lupon was supported by the project FLUPRINT (EUR2023-143456), MICIU/AEI/FEDER UE, and Next Generation funding. Biel Obrador and Rafael Marcé acknowledge funding for the data collection at Sau reservoir from Project PID2020-114024GB-C31 and PID2020-114024GB-C32, funded by MCIN/AEI/10.13039/501100011033/. Work by David Bastviken and David

Rudberg were funded by the Knut and Alice Wallenberg Foundation (Grant 2016.0083), the European Research Council H2020 (Grant 725546), the Swedish Research Council (Grant 2016-04829), and FORMAS (Grant 2018-01794). The teams associated with these projects are acknowledged for valuable assistance. Gesa A. Weyhenmeyer received financial support from the Swedish Research Council (VR Grant No. 2020-03222 and FORMAS Grant No. 2020-01091). R. Iestyn Woolway was supported by a UKRI Natural Environment Research Council Independent Research Fellowship (NE/T011246/1). José Fernandes Bezerra-Neto and Ludmila S. Brighenti acknowledge support from Long-Term Ecological Research Project (PELD—Rio Doce, Process No. 441481/2016-7—Conselho Nacional de Desenvolvimento Científico e Tecnológico). Sari Juutinen was funded by the Research Council of Finland (RCF) (Grant numbers 334509 and 347662). Lauri Heiskanen, Valterri Hyöky, Md Shamsuzzaman, Hanna Salomaa and Lauha Jämsä are acknowledged for their help with the field work at FMI lakes Kaamanen and Pallasjärvi. The work on Pallasjärvi was funded by the ICOS Finland and the ACCC Flagship funding by RCF (Grant No. 337552). James A. Rusak thanks Nevan Baus for assistance in the field and acknowledges support from a Natural Science and Engineering Council of Canada Discovery Grant (RGPIN/05199-2018) and the Ontario Ministry of the Environment. Sarian Kosten's contribution was supported by NWO-TTW Project No. 18661 and NWO-VIDI 203.098. Rachel M. Pilla was supported by the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, Water Power Technologies Office, and Environmental Sciences Division at Oak Ridge National Laboratory. Oak Ridge National Laboratory is managed by UT-Battelle, LLC, for the U.S. Department of Energy under contract DE-AC05-00OR22725. We used artificial intelligence (ChatGPT) to assist with debugging code and generation of figs. Artificial intelligence was not used for any text generation or editing. We thank the associate editor and two anonymous reviewers for their helpful comments on an earlier draft.

Data Availability Statement

Data are available in the Irish Marine Institute's data repository at <https://www.doi.org/10/pqcm>. The code used in the paper is available at <https://github.com/edeeyto/DCFlux/>.

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Supporting Information

Additional Supporting Information may be found in the online version of this article.

Submitted 14 June 2025

Revised 06 September 2025

Accepted 08 September 2025