A spring burst of emissions account for most of the inter-annual and intra-lake difference in methane emissions in a small eutrophic reservoir: insights from two years of eddy covariance monitoring

Temporal patterns and biophysical controls on methane emissions from a small eutrophic reservoir: insights from two years of eddy covariance monitoring

Sarah Waldo1, Jake J. Beaulieu1, William Barnett2, D. Adam Balz3, Michael J. Vanni4, Tanner Williamson4, and John T. Walker5

1Center for Environmental Measurements and Modeling, United States Environmental Protection Agency, Office of Research and Development, Cincinnati, 45268, USA
2Neptune and Company, Inc., Lakewood, 80215, USA
3Pegasus Technical Services, Cincinnati, 45268, USA
4Miami University, Department of Biology, Oxford, 45056, USA
5Center for Environmental Measurements and Modeling, United States Environmental Protection Agency, Office of Research and Development, Durham, 27709, USA

Correspondence to: Sarah Waldo (sarahrwaldo@gmail.com)
*Currently at United States Environmental Protection Agency, Region 10, Seattle, 98101, USA

Abstract. Waters impounded behind dams (i.e. reservoirs) are important sources of greenhouses gases, especially methane (CH4), but emission estimates are their contribution is not well constrained due to high spatial and temporal variability, limitations in monitoring methods to characterize hot spot and hot moment emissions, and the limited number of studies that investigate diurnal, seasonal, and interannual patterns in emissions. In this study, we investigate the temporal patterns and biophysical drivers of CH4 emissions from Acton Lake, a small eutrophic reservoir, using a combination of methods: eddy covariance monitoring, continuous warm-season ebullition measurements, spatial emission surveys, and measurements of key drivers of CH4 production and emission. We used an artificial neural network to gap-fill the eddy covariance time series and to explore the relative importance of biophysical drivers on the inter-annual timescale. We combined the best available spatial and temporal monitoring information to estimate annual whole-reservoir emissions. Acton Lake had cumulative areal emission rates of 40.6 ± 5.9 and 71.4 ± 4.2, 45.6 ± 8.3 and 51.4 ± 4.3 g CH4 m-2 in 2017 and 2018, respectively, or 97.4 ± 14 and 30171 ± 10 Mg CH4 in 2017 and 2018 across the whole 2.4 km2 area of the lake. The main difference between years was a period of elevated emissions lasting less than two weeks in the spring of 2018, which contributed 17% of the total-annual emissions in the shallow region of the reservoir, and XX% of total annual emissions. The spring burst coincided with a phytoplankton bloom, which was likely driven by favourable precipitation and temperature conditions due to favourable sediment temperature and algal carbon substrate availability in 2018 compared to 2017. CH4 emissions only displayed diurnal patterns 18.5% of the monitoring period, suggesting that factors that do not follow a diurnal pattern (e.g. substrate availability) may be driving emissions. Combining spatially extensive measurements with temporally continuous monitoring enabled us to quantify aspects of the spatial and temporal variability in CH4 emission. We found that the
relationships between CH₄ emissions and sediment T depended on location within the reservoir and observed a clear spatio-temporal offset in maximum CH₄ emissions as a function of reservoir depth. These findings suggest a strong spatial pattern in CH₄ biogeochemistry within this relatively small (2.4 km²) reservoir. In addressing the need for a better understanding of GHG emissions from reservoirs, there is a trade-off in intensive measurement of one water body versus short-term and/or spatially limited measurements in many water bodies. The insights from multi-year, continuous, spatially extensive studies like this one can be used to inform both the study design and emission upscaling from spatially or temporally limited results, specifically the importance of trophic status and intra-lake reservoir variability in assumptions about upscaling CH₄ emissions.

1 Introduction

Reservoirs are a globally important source of methane (CH₄) and other greenhouse gases (GHG) to the atmosphere, with recent estimates attributing 773 Tg carbon dioxide equivalents (CO₂-e) per year to reservoir surface emissions, nearly 80% as CH₄ (Deemer et al., 2016). The dominance of CH₄ in reservoir GHG budgets is due to the combination of gross CH₄ emissions and methane’s large warming potential relative to CO₂. Reservoir CH₄ emissions have been estimated to be equivalent to roughly half of the global CH₄ burden from rice cultivation (~1200 Tg CO₂-e yr⁻¹, Ciais et al., 2013). Inland waters (lakes, rivers, and reservoirs) can be hot spots for microbial decomposition of organic matter, and respiration from these waters globally may offset the terrestrial carbon sink by up to 60% (Cole et al., 2007; Ciais et al., 2013). The carbon dynamics of reservoirs are of special interest for several reasons. Reservoirs generally receive more sediment input (hence organic C) from their watershed than comparable lakes, as they tend to be located lower in the landscape and have a larger ratio of catchment area to surface area (Hayes et al., 2017). Reservoirs also tend to drain watersheds with more agricultural or urban land use than the natural lake watersheds (Thornton et al., 1990). The distribution of lakes and reservoirs across the United States is such that in many parts of the country total lentic surface area is dominated by reservoirs. Furthermore, emissions from reservoirs are considered anthropogenic and thus should be included in national greenhouse gas (GHG) emission inventories reported to the United Nations (Lovelock et al., 2019).

Emissions of GHGs from reservoirs are highly variable in space and time, making the reservoir GHG budgets difficult to constrain. This is especially true for CH₄, the production and emission pathways of which are highly dynamic. One key production pathway of CH₄ in water bodies is methanogenesis in anoxic sediment. Some of this CH₄ dissolves into the water column where it may be oxidized into carbon dioxide (CO₂) by methanotrophs or may diffuse to the atmosphere. Methane may also accumulate as bubbles in the sediment until the buoyant force of the gas bubble overcomes the overlying static pressure. The rate of this CH₄ bubbling, or ebullition, is affected by several biological and physical factors including carbon substrate availability, sediment temperature, oxygen availability, turbulence, and overlying pressure (Tuser et al., 2017). Thus, ebullition is highly variable in space and time (Wik et al., 2016). Another potentially important source of CH₄ is production by phytoplankton in oxic surface water, considered a “paradox” until recently (Schmidt and Conrad 1993; Grossart et al., 2011; Tang et al., 2014, 2016; DelSontro et al., 2018). The rate of diffusive efflux of this surface mixed layer CH₄ can be highly dynamic as it depends on the balance between production and emission (Hartmann et al., 2020), for which ebullition, or bubbling, is an important emission pathway. CH₄ is produced in reservoir sediments by methanogens. Some of this CH₄ dissolves into the water column where it may be oxidized into carbon dioxide by methanotrophs or may diffuse to the atmosphere.
Monitoring methods, mean that many sub-daily pulse events (Zhang et al., 2021), lake-zone spatial patterns (Juutinen et al., 2009; DelSontro et al., 2011; Maiace et al., 2013; McClare et al., 2020), and the relative contributions of hot-spots (Wik et al., 2016; Beaulieu et al. 2016), and hot-moments (Bastien et al., 2011; Demarty et al., 2011; Jammet et al., 2015; Beaulieu et al., 2018; Harrison et al., 2018), and food web dynamics (Barosewicz et al., 2021; Grasset et al., 2018) in accurately characterizing lake and reservoir CH4 emissions. Under-sampling in stochastic systems leads to underestimation (Wik et al., 2016). The synthesis by Deemer et al. (2016) showed that reservoir GHG emission studies using the spatially integrated methods reported higher FCH4 than studies using survey methods. Despite the need to better capture the spatiotemporal dynamics of reservoir CH4 fluxes (FCH4) and its drivers, most monitoring studies to date have used survey methods that are often short-term, intermittent, and/or spatially limited. Use of micrometeorological methods such as eddy covariance (EC) to monitor reservoir CH4 fluxes (FCH4) can address many of the monitoring challenges by providing pseudo-continuous, long-term, spatially integrated flux measurements. As described in the synthesis by Deemer et al. (2016), studies using the spatially integrated methods of EC or acoustic monitoring reported higher FCH4 than the median FCH4 from studies using methods with less spatial and temporal coverage (e.g. floating chambers, thin boundary layer, inverted funnels), consistent with the finding that low sampling coverage in stochastic systems leads to underestimation (Wik et al., 2016). A low-power open-path CH4 sensor capable of making measurements for EC has only been available since circa 2011 (McDermitt et al., 2011), and using micrometeorological techniques to measure fluxes over open water (vs. land) can be difficult due to site, footprint, and boundary layer turbulence considerations (Kenny et al., 2017, Higgins et al., 2013, Sahlée et al., 2014). Thus, relatively few studies have used EC to characterize FCH4 over inland waters (Jammet et al., 2015, Jammet et al. 2017, Desmukh et al., 2014, Eugster et al., 2011, Schubert et al., 2012, Podgrajske et al., 2014a, Podgrajsek et al., 2014b, Beaulieu et al., 2018). Further highlighting the scarcity of studies using this technique, the recent FLUXNET-CH4 synthesis (Knox et al., 2019) of long-term (>1 year) EC monitoring of FCH4 had only two open water sites among the 60 included. A low-power open-path CH4 sensor capable of making measurements for EC has only been available since circa 2011 (McDermitt et al., 2011), and using micrometeorological techniques to measure fluxes over open water (vs. land) can be difficult due to site, footprint, and boundary layer turbulence considerations (Kenny et al., 2017, Higgins et al., 2013, Sahlée et al., 2014). Thus, relatively few studies have used EC to characterize FCH4 over inland waters (Jammet et al., 2015, Jammet et al. 2017, Desmukh et al., 2014, Eugster et al., 2011, Schubert et al., 2012, Podgrajsek et al., 2014a, Podgrajsek et al., 2014b, Beaulieu et al., 2018). To our knowledge, this study is only the second to report pseudo-continuous, multi-year FCH4 results over open-water, and the first to report long-term FCH4 over open-water in a temperate region, for a eutrophic system, and for a reservoir.
In this study reports the results of two years of pseudo-continuous (via EC and active funnel traps for ebullition), spatially extensive (via spatially-balanced CH₄ emission surveys) measurements of F_C₄H and key drivers of CH₄ production and emission. We organize our findings around two questions that can inform both the design of future monitoring studies and emission upscaling from limited results: (1) How important can interannual and intra-lake variability be in a single reservoir, and what causes it? we investigate biophysical drivers of CH₄ emissions from a midlatitude reservoir at multiple temporal and spatial scales by combining two years of continuous F_C₄H measured over the shallower inlet region of the reservoir via EC, warm season continuous ebullition measurements at a shallow and deep site, spatially balanced CH₄ emission surveys, and measurements of key drivers of CH₄ production and emission. We expected to see elevated emissions in the shallower inlet area relative to the rest of the reservoir based on previous work (Beaulieu et al., 2016), and designed our investigation to leverage both spatial and temporal coverage in characterizing reservoir F_C₄H. We use an artificial neural network to gap-fill the EC timeseries and to provide insight into the most important biophysical drivers of F_C₄H, notably sediment temperature, overlying static pressure, and water column mixing. (2) What does this tell us about how limited monitoring resources can best be used to constrain reservoir methane emissions? Insights into temporal patterns and biophysical drivers of F_C₄H from individual water bodies will provide important constraints on the contribution of inland waters to the global GHG budget.

2. Methods

2.1 Site description

Acton Lake is a small hypereutrophic reservoir located in southwestern Ohio (39.57 N, 84.74 W, 262 masl, Fig. 1a). The dam was constructed in 1956 and the lake reservoir and surrounding state park have been managed by the Ohio Department of Natural Resources since 1957. The lake's reservoir's surface area is 2.4 km², it has a maximum depth of ~8 m, and the area near the dam undergoes thermal stratification in the summer. Although Acton Lake is immediately surrounded by a forested state park, land use in its watershed is >80% agricultural, with the majority used for intensive row cropping (Renwick et al., 2018). We used four main methods to monitor CH₄ fluxes (F_C₄H) from Acton Lake during 2017 and 2018 the period between 1 February 2017 thru 1 December 2018: (1) the EC technique, (2) continuous ebullition monitoring with active funnel traps, (3) bi-weekly chamber measurements of diffusive emissions, and (4) spatially extensive surveys. The locations of the EC tower sites, active funnel trap/bi-weekly chamber measurement sites, and spatially extensive survey sites are depicted in Fig. 1a; the cumulative footprint probability distribution of the two flux tower sites is shown in Fig. 1b. The EC instrumentation was sited in the shallow region of Acton Lake due to logistical constraints related to both tower installation and boat traffic in the reservoir. How the methods were used in this study is summarized in Table 1. We used auxiliary meteorological and limnological measurements from stream gauging stations, a weather station, and thermistor string maintained by the Miami University (Renwick et al. 2018; Andersen et al. 2020), the locations of which are also shown in Fig. 1a.
2.2 Eddy covariance flux measurements

This site is registered as AmeriFlux site US-Act; information about the site as well as the flux data presented in this study are available online (https://ameriflux.lbl.gov/sites/siteinfo/US-Act). The EC instrumentation consisted of an ultrasonic anemometer to measure 3-D wind speed and direction (Model 81000, R.M. Young Company, Traverse City, MI, USA) and open path infrared gas analyzers (IRGAs) for measuring the number density of CH$_4$ (LI-7700), and CO$_2$ and water vapor (LI-7500A, LiCor Biosciences, Lincoln, NE, USA). The EC data streams were recorded at 10-Hz by a data logger (LI-7550, LiCor Biosciences, Lincoln, NE, USA), which was also equipped with a temperature sensor and a pressure transducer. The EC system was deployed from a dock piling 20 m from the northwestern shore of Acton Lake from 1 February 2017 thru 14 April 2018 (“EC S-1” in Fig. 1). The instruments were brought to the lab for calibration and maintenance on 15 April 2018, then redeployed on a tower installed into the lake reservoir sediment in the northeast corner of the lake reservoir on 5 May 2018 (“EC S-2” in Fig. 1). The system was shut down on 1 December 2018. Images of the EC system at each deployment location are included in the SI (Fig. S1). In addition to the EC setup, the flux tower was equipped with a net radiometer (NRLite2, Kipp and Zonen, Delft, The Netherlands), a cellular modem for remote communication (AirLink, Campbell Scientific, Logan, UT, USA), and a time-lapse camera (WCT-00125 TimelapseCam, WingScapes, Calera, AL, USA). The time-lapse camera was used to determine periods of ice cover. The system was powered by solar panels and a battery bank regulated via a solar charge controller (SunSaver, Morningstar Corporation, Newtown, PA, USA). All components of the EC system were run on a 12V system until relocation to the aquatic tower, when the EC setup (LI-7700, LI-7500A, RMYoung, and LI-7500) was retrofitted to run on 24V. The raw 10-Hz EC data was processed into 30-minute fluxes using the software EddyPro v. 6.2 (LiCor Biosciences, Lincoln, NE, USA). We used measurements of water depth from the Miami University weather station to determine instrument height above water surface on an hourly timestep, integrated into the flux processing as a dynamic metadata file. Additional processing steps followed community standards and included filtering the 10 Hz CO$_2$ measurements when CO$_2$ signal strength was <70, double coordinate rotation, block averaging, time lag compensation using covariance maximization, WPL density correction (Webb et al., 1980), and correction for high-pass and low-pass filtering effects (Moncrieff et al., 2004; Moncrieff et al., 1997).

The area contributing to the measured flux was characterized for both sites using the online two-dimensional flux-footprint prediction tool (Kljun et al., 2015). We used R for postprocessing, and the code is available on GitHub (https://github.com/USEPA/actonEC). The 30-minute fluxes were rejected when the period did not pass the tests for stationarity and developed turbulent conditions (QC level 2 per the integrated scale of Foken et al., 2004). EC S-1 fluxes were further filtered for periods when winds were from the shore (between 195° and 330°); at EC S-2 we filtered for periods of low turbulence using a friction velocity ($u_{*}$) threshold of 0.07 m s$^{-1}$, based on the site-specific relationship between $u_{*}$ and fluxes of CH$_4$ and CO$_2$ (Aubinet et al., 2012). We did not use $u_{*}$ filtering at EC-S1 because the temporal coverage was insufficient to determine a $u_{*}$ threshold. We define “acceptable” data or “acceptance rate” as those data meeting the EC QA/QC requirements, while “data coverage” includes non-operability due to power or instrument failures.

The overall EC QA/QC data acceptance rate for the two-year monitoring period (26 January 2017 – 13 November 2018) was 31.3% (Fig. S2). In 2017, the data acceptance rate was lower, 23.4%, due to power issues and the need to filter for wind direction at the near shore EC S-1 site where the instrumentation was located for the whole year vs. 39.8% in 2018 when the instrumentation was relocated in the spring to the mid reservoir EC S-2 site. The data coverage for the period of monitoring...
from EC S-2 (May thru November) was 52.8%. Re-siting removed the need to filter periods based on wind direction and coincided with an improvement to the battery system that reduced incidences of power failure. At EC S-1, non-operability of the LI7700 due to power loss or other issues caused the majority of data rejection (40.4% of total monitoring periods), followed by filtering for wind direction (28.1%), and quality control filtering (7.8%). At EC S-2, power loss caused the majority of gaps (36.3%), followed by quality control filtering (16.6%).

2.3 Active funnel trap ebullition measurements

The active funnel traps (AFT) were based on the design of Varadharajan et al. (2010) and have been previously described by Beaulieu et al. (2018). Briefly, they consisted of a 0.3 m² funnel attached to a rigid tubing gas collection chamber equipped with a differential pressure sensor to monitor accumulated gas volume on a 5-minute timestep. We modified the Varadharajan design by incorporating siphons that auto-purge the collected bubble gas and refill the tubing volume with water. This modification keeps the AFTs from becoming filled with gas, allowing them to make useful measurements for longer periods of time. Trap gas samples were collected bi-weekly and analysed via a gas chromatograph equipped with a flame ionization detector (Bruker 450 GC, USA) to determine the composition of the bubble gas. The active trap data reduction followed the method described in Varadharajan et al. (2010) and Varadharajan and Hemond (2012). Circuit calibration to determine the relationship between voltage and height was performed pre- and post-trap deployment in the 2017 field season, and post-deployment in the 2018 field season. The volume of gas in the trap is calculated as:

\[ \text{AFT}_{vol} = (\text{Circ}_{vol} \times m + b) \times \pi \frac{\text{AFT}_d^2}{2} \]  

where \( \text{AFT}_{vol} \) is the volume of gas in the funnel trap, \( \text{Circ}_{vol} \) is the voltage output from the differential pressure sensor, \( m \) and \( b \) are the sensor-specific laboratory calibration multiplier and offset coefficients, and \( \text{AFT}_d \) is the diameter of the funnel tubing. Figure S2 shows a time series of the active trap volume measurements. We used a 12-point moving average (60 min) to smooth the gas volumes and minimize noise. Periods with known issues were filtered out of the dataset (e.g. power issues, trap drift from target location, etc.), as were large negative fluxes that reflected siphon purges. Following Varadharajan and Hemond (2012), we calculated fluxes on multiple time-bin widths (30-min, 1, 2, 6, 12, 24, 48 hr) but used the 2-hr rolling timestep for calculating the flux used in our final analysis:

\[ F_{\text{CH}_4} = \frac{\text{AFT}_{vol}[\text{CH}_4]}{T_f - T_i} A_f \]  

where \( \text{AFT}_{vol} \) is the volume of gas in the trap (l), \( [\text{CH}_4] \) is the \( \text{CH}_4 \) concentration in the bubble gas (mg \( \text{CH}_4 \) l⁻¹), \( T_f - T_i \) is the elapsed time (s), and \( A_f \) is the cross-sectional area of the funnel (m²). The AFT data reduction was performed in R and the scripts are available online (https://github.com/USEPA/actonEC). The AFTs were deployed in late spring and retrieved in the fall each year. The shallow AFT (U-14) monitored ebullition from May 9 – October 3 in 2017, and from June 6 – December 11 in 2018. The deep AFT (U-12) monitored ebullition from May 10 – October 30 in 2017, and from May 24 – November 9 2018.

2.4 Chamber diffusion measurements
Diffusive $F_{CH_4}$ was measured with a floating chamber biweekly at two sites during the field season. We used a rectangular, round-ended aluminum chamber with external polyvinyl chloride floats and a headspace fan, based on the CSIRO chamber described in Zhao et al. (2015). An ultra-portable greenhouse gas analyzer (UGGA, PN: 915-0011, ABB, Los Gatos, CA) monitored the change in CH$_4$ mixing ratio in the chamber headspace over the duration of the chamber deployment (> 1 - 5 min), measuring at 1Hz and recording an averaged measurement every 5 s. We monitored the real-time UGGA time series to prevent ebullitive emissions from overwhelming the diffusive emission measurements. If a spike in CH$_4$ concentration was detected, we re-set the chamber. The floating chamber data reduction method has been described in detail in Beaulieu et al. (2016). Briefly, we used the following equation to calculate diffusive fluxes (moles m$^{-2}$ s$^{-1}$):

$$F_{gas,D} = \frac{\Delta gas}{\Delta t} \left( \frac{1}{V} \right) \left( \frac{PRT}{1000} \right)$$

where $\Delta gas/\Delta t$ is the rate of change of the mixing ratio of CH$_4$ in the chamber headspace (ppm s$^{-1}$), $V$ is the chamber volume (m$^3$), $A$ is the chamber surface area (m$^2$), $P$ is the pressure in the chamber headspace, $R$ is the universal gas constant, and $T$ is the temperature in the chamber headspace. The rate of change $\Delta gas/\Delta t$ for each chamber deployment was determined via fitting linear and non-linear models to the dataset and using Akaike information criterion (AIC) to choose the more appropriate model. Only models with an $r^2$>0.9 were retained. Data analysis and reduction was performed using R, and the scripts are available online (https://github.com/USEPA/actonEC).

Biweekly chamber monitoring was conducted from May 10 to December 11 in 2017, and from May 18 to October to December 13 in 2018. Note that the chamber monitoring began earlier and ended later than the AFT monitoring each year, due to technical issues with the AFTs.

2.5 Water measurements

Water temperature depth profiles were recorded continuously at two sites close to U-14 and U-12 (Fig. 1) using thermistors. At the shallow site (U-14) a string of seven thermistors (RBRsoloT, RBR Ltd., Ottowa, ON, Canada) were deployed at 0.1, 0.25, 0.5, 0.75, 1, 1.5 m below the air-water interface and at the sediment-water interface. We used this temperature profile to characterize water column stability in the footprint of the EC flux measurements based on the Brunt-Vaisala buoyancy frequency using the R package rLakeAnalyzer (Winslow et al., 2019). The Brunt-Vaisala buoyancy frequency was used as to indicate water column stability. It represents the frequency at which a parcel of fluid will oscillate when displaced vertically, a measure of resistance to mixing. A high oscillation frequency indicates strong resistance to mixing, whereas a low frequency indicates little resistance to mixing. At the deep site (U-12), sondes measuring temperature (Pro ODO, YSI Incorporated, Yellow Springs, OH, USA) were deployed at 0.1, 0.5, 1, 1.5, 2, 3, 4, 5, 6, 7, and 8 m below the air-water interface. Water temperature, specific conductivity, dissolved oxygen, pH, and chlorophyll a were measured biweekly with a YSI Multiparameter sonde at 0.1 and 1.5 m below surface at the shallow site (U-14), and 0.1, 1, 2, 3, 4, 5, 6, 7, and 8 m below surface at the deep site (U-12). Water samples for chlorophyll analysis were collected by Miami University near the reservoir inlet. Water samples were collected with an integrated tube sampler from the water surface to the euphotic zone depth. Chlorophyll samples were collected on 1.0 mm glass fibre filters and frozen at -20°C in opaque containers until processed. They were extracted in 95% ethanol for 24 h and analysed with a TD-700 (Turner Designs, San Jose, CA, USA).

Dissolved gas surface and profile samples were collected biweekly from both U-12 and U-14 using the headspace equilibration method. We collected water samples at depths of 0.1, 2, 4, 6, and 7 m at U-12 and at 0.1, 0.75, and 1.3 m at U-14. Using a 140-
ml plastic syringe with a 2-way stopcock, we added 25 ml of ultra-high-purity helium to a syringe, then added 115 ml of sample water and agitated all samples for 5 minutes. We then transferred the headspace gas to pre-evacuated 12-ml glass vials topped with a silicone-coated Teflon septum stacked on top of a chlorobutyl septum (Labco Ltd., UK). The headspace gas samples were analysed using gas chromatography (see section 2.3) to determine the CH₄ composition, and the dissolved CH₄ concentrations were calculated using measured headspace composition and the temperature-specific Bunsen solubility coefficients (Yamamoto et al., 1976). Full documentation of the calculations is available at the National Ecological Observatory Network’s GitHub repository (https://github.com/NEONScience/NEON-dissolved-gas).

2.6 Whole-lake reservoir surveys

We conducted six surveys of Acton Lake over the summers of 2017 and 2018 to estimate whole-lake reservoir FCH₄. The fifteen sample collection sites (Fig. 1, light blue circles), were determined using a generalized random tessellation survey (GRTS) design (Stevens and Olsen 2004; Olsen et al. 2012), a probability design that has been shown to reduce uncertainty relative to other designs (Beaulieu et al., 2016). At each site, we measured CH₄ diffusion, CH₄ ebullition, and surface water quality parameters. Survey measurements of diffusive FCH₄ were conducted with floating chambers in the same manner as described in section 2.4. Survey measurements of ebullitive FCH₄ were conducted with passive funnel traps (PFTs) deployed overnight (>15 hours). The PFTs are a simplified version of the AFTs described in section 2.3: they consist of a 0.3 m² funnel attached to a section of tubing for gas collection, but do not have a pressure sensor or siphon. Upon retrieval, the total time of deployment and total volume of gas in the tubing were recorded, and three 25 mL samples of the gas were collected for gas composition analysis via gas chromatograph (see section 2.3). Ebullitive FCH₄ from the PFTs was also calculated using Equation 2 (section 2.3), but the trap volume was determined by direct measurement of the collected gas, and Tᵣ – Tᵢ is defined as the deployment period. Dissolved gas sample collection and depth profiles of water quality parameters were taken at one deep site (U-12) and one shallow site (U-14) during each whole-lake reservoir survey. They surveys were initiated on 10 July 2017, 31 August 2017, 4 October 2017, 10 July 2018, 14 August 2018, and 20 September 2018, and concluded the following day.

2.7 Gap-filling and upscaling

We use the term “gap-filling” to refer to our method to determine values for missing observations in our measurement time series, while “upscaling” refers to the best estimate of whole-lake reservoir FCH₄. For this analysis, we separated the year into different seasons, categorizing November thru March as “winter”, or the cold season, and May thru September as “summer”, or the warm season. We refer to April and October as the “shoulder” season. The spring burst period is defined as 24 May thru 4 June.

For the EC timeseries, we developed an artificial neural network (ANN) to gap-fill 30-minute FCH₄ using predictor variables with biophysical links to CH₄ production and emission: overlying static pressure, change in static pressure, sediment temperature (sedT), air temperature, latent heat flux (LE), sensible heat (H), wind speed, u⁎ (friction velocity, a measure of turbulence), and photosynthetically active radiation, overlying static pressure, and change in static pressure, where static pressure is the sum of overlying atmospheric and hydrostatic pressure. We also included indicators for the tower location, hour of day, and day of year as drivers. Gaps in the sedT, air temperature, wind speed, wind direction, and static pressure time series
were filled using observations from a nearby weather station. Gaps in LE, H, and \( u_{*} \) were gap filled using the mean diurnal course function from the R package REddyProc (Wutzler et al., 2019) on the 30-minute timestep. We used k-means clustering to assign ten clusters before selecting the training, testing, and validation datasets. The cluster assignments allowed us to select subsets with probabilities proportional to the clusters, ensuring that the clusters were not over- or underrepresented as a result of the splits. We employed a selective ensemble approach to optimize the ANN model performance, using the R package mnet (Venables and Ripley, 2020). Each ANN ensemble included models with 5-20 layers and 50 different starting weights, for a total of 800 model results. The top 100 models were selected based on the testing R² results, then the median CH₄ value from the best 100 models was used as the predicted flux. To characterize both sampling and model uncertainty, we replicated this procedure with 20 resamplings of the data. For each half hourly \( F_{CH₄} \) we calculated the median predicted value of the best 100 models in each of the 20 ensembles of 800 models (c.f. Knox et al., 2016). Missing half hourly \( F_{CH₄} \) values were gap filled using the median of the medians from the 20 ensembles. ANN modelling and gap-filling was performed in R and the scripts are available online (Barnett et al., 2021).

We gap-filled short gaps in the AFT continuous datasets using linear interpolation and calculated annual emissions via summing the daily observations. We gap-filled the biweekly chamber measurements of diffusive \( F_{CH₄} \) via linear interpolation. For periods at the start and end of the monitoring seasons with chamber measurements but no AFT measurements, we used the typical ratio between diffusive and ebullitive \( F_{CH₄} \) to estimate total \( F_{CH₄} \) for the site. We gap-filled the spatial survey measurements by interpolating between each of the three annual surveys. To estimate annual emission, we applied the \( F_{CH₄} \) value determined by the first survey of the year to every day between 1 May and the first survey, and the \( F_{CH₄} \) value determined by the last survey of the year out through 15 October. We assumed an \( F_{CH₄} \) of zero between 15 October and 1 May for both the spatial survey dataset and the AFT plus chamber datasets.

We squared the spatial survey measurements to estimate annual emissions by applying the \( F_{CH₄} \) value determined by the first survey of the year to every day between 1 May and the first survey, interpolating between each of the three annual surveys, and then applying the \( F_{CH₄} \) value determined by the last survey of the year out through 15 October. We assumed an \( F_{CH₄} \) of zero between 15 October and 1 May.

For this analysis, we separated the year into different seasons, categorizing November thru March as “winter”, or the cold season. We refer to April and October as the “shoulder” season. The spring period is defined as 24 May thru 4 June. To upscale to whole-reservoir \( F_{CH₄} \), we used a hybrid approach, combining results from EC, the deep-site (U-12) AFT, and the spatial surveys. We stratified Acton Lake into shallow (>3 m) and deep (>6 m) areas and used reservoir bathymetry to determine the surface area for the shallow and deep portions: 0.8 km² and 1.6 km², respectively. The depth cut-off of 3 m roughly corresponds to the greatest depth of the EC footprint. We then used \( F_{CH₄} \) measured by EC to characterize the shallow portion of the reservoir. For the deep portion, we calculated the ratio (reservoir ratio, or RR) between the measured \( F_{CH₄} \) (ebullitive + diffusive) at the U-12 AFT (hereafter, deep AFT \( F_{CH₄} \)) and the mean of \( F_{CH₄} \) measured at the other deep sites (U-01, U-04, U-05, U-08, U-11, U-12, U-13, U-15, U-16, U-17, and U-18, see Fig. 1). We calculated this RR for each of the six spatial survey dates. To characterize \( F_{CH₄} \) in the deep portion of the reservoir, we applied the RR from the first survey to the deep AFT \( F_{CH₄} \).
continuous timeseries data collected before 10 July 2017, and likewise applied the RR from the last survey to the timeseries data collected after 20 September 2018. For the periods in-between, we used linear interpolation to produce a daily RR and applied that to the deep AFT $CH_4$ continuous timeseries. We weighted the cumulative shallow and deep $CH_4$ areal emissions by the shallow and deep fraction of the reservoir to determine the whole-reservoir $CH_4$ emissions. We refer to this estimate of whole-reservoir emissions as the “hybrid” upscaled estimate.

### 2.8 Uncertainty Analysis

We parameterized the uncertainty in the EC time series of $F_{CH_4}$ using three different measures: the random measurement error, the bias error of the gap-filled dataset, and the 95% confidence intervals of the gap-filled dataset. The random measurement error is calculated from the variance of the covariance (Finkelstein and Sims, 2001), and reflects instrument noise, variation in footprint over a given 30-minute flux integration period, and the stochastic nature of turbulence. As described in Jammet et al., (2017), the random error decreases with increasing dataset size and is negligible at the resolution of cumulative annual fluxes but can be substantial for individual flux measurements (Richardson et al., 2006; Moncrieff et al., 1996). The random error was calculated as part of the EddyPro processing, and we report the summary statistics in section 3.2. Unlike random errors, systematic biases can accumulate to affect the cumulative seasonal or annual flux. Although the measurement bias cannot be quantified, we calculated the systematic bias in the annual fluxes due to gap-filling following Moffat et al. (2007) and Jammet et al. (2017):

$$BE = \frac{1}{N} \sum (p_i - o_i)$$ (5)

where $N$ is the number of values in the validation time series, $p$ are the values predicted by the ANN, and $o$ are the observed values in the validation time series. The bias error was multiplied by the total number of gap-filled values to obtain the total annual bias. We calculated the 95% confidence interval of the gap-filled dataset using the distribution of the 20 ANN medians extracted from the 20 resamplings, which consider both sample and model uncertainty (Knox et al., 2016).

We used root-sum-squared error propagation of the error in $AFT_{vol}$ and $[CH_4]$ to characterize the uncertainty in ebullitive $F_{CH_4}$ measured by the AFTs. Compared to error in $AFT_{vol}$, the error contribution from other terms in Eqn 2 was negligible. As described in Varadharajan et al. (2010), we propagated the error in $m$, offset, and electronic noise through Eqn 1, adding a 2-ml dead volume error each time the AFTs flushed to account for gas that could be trapped in the fittings at the top of the collection chamber. Our mean slope and slope error were similar to those reported in the Varadharajan methods paper (31 and 0.31, respectively, compared to 28 and 0.5); the mean ($V_{osc}$) and standard deviation ($\Delta V_{osc}$) of the offset terms we used were slightly larger: 0.51V and 0.071V for the shallow site, 0.41V and 0.045V for the deep site (compared to 0.15 and 0.015); our calculated electronic noise ($\Delta V_{elec}$) was smaller (0.4 mV vs. 3 mV in Varadharajan), so we defaulted to their value. The standard deviation between the multiple trap gas samples was used as the uncertainty in $[CH_4]$. This term was generally small compared to the uncertainty due to AFTvol error. The cumulative errors were propagated by summing in quadrature.

The whole-reservoir lake surveys provide an estimate of $F_{CH_4}$ integrated across the entire reservoir surface area and a 95% confidence interval range (Beaulieu et al., 2016). Variance estimates calculated from GRTS incorporates spatial
autocorrelation, if present, resulting in smaller uncertainty ranges than survey approaches that ignore spatial autocorrelation (Stevens and Olsen, 2003). The GRTS design and data reduction were executed in R using the spsurvey package (Kincaid et al., 2019). We propagated the cumulative uncertainties across 2017 and 2018 by taking the 95% confidence interval of each survey and summing them in quadrature.

The uncertainty in the hybrid approach to the upscaled cumulative whole-reservoir emissions were also determined by error propagation, combining the uncertainty in the deep AFT measurements, the spatial surveys, and the EC measurements. We propagated the cumulative uncertainties across 2017 and 2018 by taking the 95% confidence interval of each survey and summing them in quadrature.

2.9 Statistical and Quantitative Analysis

For these analyses, we used the non-gap-filled measurement time series. We quantified the relationship between sediment temperature (sedT) and FCH4 using Q10 and breakpoint analyses. The concept of an “ecological Q10” (DelSontro et al., 2016) follows from the physiological exponential relationship between metabolic processes and temperature. In contrast to physiological Q10 values, ecological Q10, hereafter “ecoQ10” values are muddied by time-lags and competing rate enhancers and inhibitors (e.g. that temperature affects both methanogens and methanotrophs, Segers, 1998; Duc et al., 2010; Lofton et al., 2014). While the physiological Q10 value for methanogenesis converges around 4 (Yvon-Durocher et al., 2014), ecoQ10 values for methane fluxes have been reported to range from 1 – 35 (e.g. DelSontro et al., 2016; Wik et al., 2014; Duc et al., 2010). The concept of an “ecological Q10” (DelSontro et al., 2016) follows from the physiological exponential relationship between metabolic processes and temperature. In contrast to physiological Q10 values, ecological Q10, hereafter “ecoQ10” values are muddied by time-lags and competing rate enhancers and inhibitors (e.g. that temperature affects both methanogens and methanotrophs, Segers, 1998; Duc et al., 2010; Lofton et al., 2014). While the physiological Q10 value for methanogenesis converges around 4 (Yvon-Durocher et al., 2014), ecoQ10 values for methane fluxes have been reported to range from 1 – 35 (e.g. DelSontro et al., 2016; Wik et al., 2014; Duc et al., 2010). We calculated the ecological Q10 (DelSontro et al., 2016) using the equation:

\[ \text{ecoQ10} = 10^{10b} \]  

where b is the slope of the regression between temperature and FCH4.

We also used a two-dimensional Kolmogorov-Smirnov test (2DKS, Garvey et al, 1998) to quantify the temperature breakpoint distinguishing winter conditions where FCH4 is near zero and unrelated to temperature from warm weather conditions where FCH4 is elevated and positively correlated with temperature. The 2DKS test is a non-parametric statistic that uses measures of disagreement to define the largest difference between cumulative distribution functions, that is, a threshold or breakpoint (Lopes et al., 2008). We applied the 2DKS test to each of the continuous FCH4 monitoring datasets: EC, shallow AFT, and
This threshold temperature represents the temperature above which substantial \( F_{CH4} \) activity occurs.

We looked at diurnal patterns on monthly and daily timescales. For the monthly timescales we binned 30-minute periods and took the median. For daily timescales we adapted the methods used by Podgrajsek et al. (2014) to quantify “strong” diurnal patterns. For 24-hour periods with at least eight night-time and eight daytime non-gap filled 30-minute flux measurements, we compared the median of daytime \( F_{CH4} \) to night-time \( F_{CH4} \). The period was defined as having a strong diurnal pattern if 1) the difference between daytime vs night time \( F_{CH4} \) median was >50 \% the larger median was greater than the smaller median by more than 50\% of the value of the smaller median, and 2) the contiguous points in the 30-minute times series were smooth, i.e. more similar than points separated in time. We determined smoothness using visual inspection.

We compared the cumulative \( F_{CH4} \) measured from Acton Lake during each year of this study to output from the size-productivity model (Del Sontro et. al, 2018). This model uses the following equation to predict total \( CH_4 \):

\[
\log_{10}(total \ CH_4 + 1) \log_{10} = 0.778 + \log_{10}(chla) + 0.940 \ (7)
\]

where total \( CH_4 \) is in units of mg C m\(^{-2}\) d\(^{-1}\), and chla is in units of ug L\(^{-1}\).

### 3. Results

#### 3.3 EC gap filling and uncertainties

The overall \( F_{CH4} \) data acceptance rate for the two year monitoring period (26 January 2017 – 13 November 2018) was 31.3\% (Fig. S8). In 2017, the data acceptance rate was lower, 23.4\%, due to power issues and the need to filter for wind direction at the near-shore EC S-1 site where the instrumentation was located for the whole year vs. 39.8\% in 2018 when the instrumentation was relocated in the spring to the mid-lake EC S-2 site. The data coverage for the period of monitoring from EC S-2 (May thru November) was 52.8\%. Resiting removed the need to filter periods based on wind direction and coincided with an improvement to the battery system that reduced incidences of power failure. At EC S-1, non-operability of the LI7700 due to power loss or other issues caused the majority of data rejection (40.4\% of total monitoring periods), followed by filtering for wind direction (28.1\%), and quality control filtering (7.8\%). At EC S-2, power loss caused the majority of gaps (36.3\%), followed by quality control filtering (16.6\%).

The non-gap filled, quality filtered 30-minute \( F_{CH4} \) measurements had a mean random error (± SD) of 1.3 ± 1.9 and 1.8 ± 1.7 mg CH\(_4\) m\(^{-2}\) hr\(^{-1}\) in 2017 and 2018, respectively, or 15.5\% and 13.7\% of the mean annual fluxes. The fractional errors were larger in the winter months when \( F_{CH4} \) was small (mean winter random error: 23\%) and smaller during the warmer months when \( F_{CH4} \) was larger (mean summer random error: 15\%). Both the magnitudes and patterns in the random errors are similar to those observed by Jammet et al. (2017) in a subarctic aquatic ecosystem. Similarly, we found gap-filling our \( F_{CH4} \) time series with ANN worked well with a few exceptions. The median \( R^2 \)-value for the 20 extractions was 0.79, and the cumulative bias error was minimal: the 20 ANN extractions yielded a median bias of 0.25 (range of -3.7 to 3.5) g CH\(_4\) m\(^{-2}\) or up to 3.3\% of cumulative emissions over the two-year monitoring period. The ANN establishes non-linear predictive power to each of the driver inputs, defined as a “Variable Importance Factor” (VIF) in terms of a percent importance to the predictive power of the model. The median VIFs from the 20 ANN extractions are plotted in Fig 8; a consistently high ranking across runs indicates a strong relationship with \( F_{CH4} \).
3.1 Temporal patterns in FCH₄: warm season and annual budgets

We observed a consistent pattern of elevated FCH₄ during the warm season across all measurement methods (Fig. 2). In both monitoring years, the majority of cumulative total CH₄ emissions (>85%) occurred in the five-months between May 1 and September 30, when air and sediment temperatures were warmer (Fig. 4 (a)), and latent heat fluxes were elevated (Fig. 4 (b)). We observed larger-magnitude CH₄ emissions in 2018 relative to 2017 at Acton Lake across each observation type except for the deep site (Table 2). The EC and spatial survey results indicated similar warm-season mean fluxes in 2017: 9.73 ± 0.67 and 9.98 ± 6.2 mg CH₄ m⁻² hr⁻¹, results from both methods indicated larger-magnitude mean FCH₄ in 2018: 17.5 ± 0.38 mg CH₄ m⁻² hr⁻¹ per the EC system and 13.0 ± 6.6 mg CH₄ m⁻² hr⁻¹ per the spatial surveys (Table 2). Both the shallow site results also indicated elevated FCH₄ in 2018 relative to 2017, while the deep site results were effectively the same (Table 2). The lower-magnitude mean FCH₄ measured at the shallow site compared to the mean FCH₄ measured by EC is likely due to the under-representation of hot-spots (Wik et al., 2016). The wintertime FCH₄ measured by EC indicate that during the winter months FCH₄ dropped by more than an order of magnitude to a baseline close to zero: between 1 Nov and 1 April FCH₄ was 0.60 ± 0.69 mg CH₄ m⁻² hr⁻¹. The surface of Acton Lake was frozen for several periods during the 2017-2018 winter: 27 Dec 2017-10 Jan 2018; 13-21 Jan 2018; and 5-15 Feb 2018, during which FCH₄ was 0.08 ± 0.46 mg CH₄ m⁻² hr⁻¹.

The non-gap filled, quality filtered 30-minute FCH₄ measurements had a mean random error (± SD) of 1.3 ± 1.9 and 1.8 ± 1.7 mg CH₄ m⁻² hr⁻¹ in 2017 and 2018, respectively or 15.5% and 13.7% of the mean annual fluxes. The fractional errors were larger in the winter months when FCH₄ was small (mean winter random error: 23%) and smaller during the warmer months when FCH₄ was larger (mean summer random error: 15%). Both the magnitudes and patterns in the random errors are similar to those observed by Jammet et al. (2017) in a subarctic aquatic ecosystem. Similarly, we found gap-filling our FCH₄ time series with ANN worked well with a few exceptions. The median R² value for the 20 extractions was 0.79, and the cumulative bias error was minimal; the 20 ANN extractions yielded a median bias of 0.25 (range of -3.7 to 3.5) g CH₄ m⁻², or up to 3.3% of cumulative emissions over the two-year monitoring period. The ANN establishes non-linear predictive power to each of the driver inputs, defined as a “Variable Importance Factor” (VIF) in terms of a percent importance to the predictive power of the model. The median VIFs from the 20 ANN extractions are plotted in Fig 3; a consistently high ranking across runs indicates a strong relationship with FCH₄. The biophysical drivers with the highest variable importance were static pressure (the sum of water pressure and air pressure), change in static pressure, and sediment temperature.

The most substantial difference between the two monitoring years is the period of elevated emissions in late May to early June observed by the EC monitoring in 2018 but not 2017 (hereafter “spring burst”). We define the spring burst as the period from 24 May thru 4 June, where the daily average FCH₄ observed by EC was ≥ 25 mg CH₄ m⁻² hr⁻¹. Maximum FCH₄ of 62.0 mg CH₄ m⁻² hr⁻¹ occurred on 29 May 2018. While the 2017 EC monitoring does indicate a small burst in FCH₄ of 20.4 mg CH₄ m⁻² hr⁻¹ on 5 June, overall FCH₄ was much smaller; mean FCH₄ for 24 May - 4 June 2017 was 3.6 ± 1.8 mg CH₄ m⁻² hr⁻¹. Although the AFT at the shallow site was not operational during the spring burst, diffusive FCH₄ measurements indicate that FCH₄ was elevated at that site compared to the deep site. Although none of the spatial surveys coincided with the spring burst period, the deep site monitoring further indicates that the spring burst did not extend to the deeper parts of the reservoir. The cumulative CH₄ emission over the 2018 twelve-day spring burst period was 10.8 g CH₄ m⁻² which is 15% of the cumulative annual emissions measured by EC in 2018 (Table 2), and which accounts for 59% of the difference in the EC cumulative annual emissions between 2017 and 2018.
The differences between the 2017 and 2018 monitoring years continue past the early summer (Fig. 2, Fig. 4). During 2017, \( \text{F}_{\text{CH}_4} \) increased to a maximum in late summer, then declined back to the winter baseline. Maximum emissions at the deep site in 2017 lagged and were dampened compared to the shallow site. In contrast, the 2018 summer and fall in the shallow portion of the reservoir (EC and shallow site) were characterized by episodic emission pulses and declines before tapering down to the winter baseline. The deep site emissions were in phase with the shallow site but did not have the same pulses. There was a late season pulse at the deep site in 2018 that coincided with reservoir turnover (Fig. 4(g)), and a drop in dissolved \( \text{CH}_4 \) below the thermocline at the deep site (Fig. S3).

Approximately 87.5% of cumulative annual emissions to EC measurements is likely due to the under indicated elevated system and 13.0\( \pm \)3.0 \( \text{g CH}_4\text{-m}^{-2} \) in 2017 at 2018. We used the EC measurements of \( \text{F}_{\text{CH}_4} \) to look for diurnal patterns in emissions. We found that Acton Lake did not have a clear over-arching diurnal pattern when aggregated over monthly timescales. (Fig. S4), but out of the 168 days with adequate data coverage for diurnal analysis, 18.5\% (31 days) displayed strong diurnal patterns: sixteen with elevated daytime emissions and fifteen with elevated nocturnal emissions. Very few of these strong diurnal pattern days were contiguous: there were only four instances of strong diurnal patterns persisting for two or more consecutive days. The periods with strong diurnal patterns when \( \text{F}_{\text{CH}_4} \) peaked during the day were correlated with latent heat flux (Fig. S5, Fig. S6); while periods when \( \text{F}_{\text{CH}_4} \) peaked at night were correlated with air pressure (Fig. S5, Fig. S6). While we looked for evidence of synoptic patterns in \( \text{F}_{\text{CH}_4} \) due to changes in overlying pressure from frontal systems (c.f. Liu et al., 2016), and due to underwater turbulence (Fig. S7), we did not see evidence of impact on \( \text{F}_{\text{CH}_4} \) from these drivers during the study period.

### 3.2: Cumulative \( \text{F}_{\text{CH}_4} \)

There are notable differences in the cumulative annual areal emissions across methods and years (Table 2, Fig. 5). The impact of the spring burst is evident in the interannual difference between the EC cumulative emissions, which were 40.7 ± 5.88 and 71.4 ± 4.2 \( \text{g CH}_4\text{-m}^{-2} \) in 2017 and 2018, respectively. The cumulative areal emission measured by EC from 1 October 2017 through 1 May 2018 was 6.66 ± 3.1 \( \text{g CH}_4\text{-m}^{-2} \), on the same order as the uncertainty range in the annual values. As follows from the patterns in the mean fluxes discussed above, the results from the spatial surveys and the shallow trap also indicate elevated cumulative annual emissions in 2018 compared to 2017, while the results from the deep site indicate similar emissions over both years. The implications of the spring burst for whole-reservoir upscaled total annual \( \text{CH}_4 \) emissions is discussed below, but the best estimate of reservoir-wide cumulative annual areal emissions from the hybrid approach yields 45.6 ± 8.3 and 51.4 ± 4.3 \( \text{g CH}_4\text{-m}^{-2} \) for 2017 and 2018, respectively (Fig. 5). The larger magnitude \( \text{F}_{\text{CH}_4} \) emissions observed in 2018 relative to 2017 at Acton Lake carry through to the warm-season and annual budgets across measurement methods. The EC and GRTS survey results indicated similar warm-season mean fluxes in 2017: 9.69 ± 0.67 and 9.08 ± 6.5 \( \text{mm CH}_4\text{hr}^{-1} \text{m}^{-2} \) (Table 2). Results from both methods indicated larger-magnitude mean \( \text{F}_{\text{CH}_4} \) in 2018: 17.45 ± 0.38 \( \text{mm CH}_4\text{hr}^{-1} \text{m}^{-2} \) for the EC system and 13.01 ± 6.6 \( \text{mm CH}_4\text{hr}^{-1} \text{m}^{-2} \) pet the GRTS surveys (Table 2). Both the shallow-site and deep-site results also indicated elevated \( \text{F}_{\text{CH}_4} \) in 2018 relative to 2017 (Table 2). The lower-magnitude mean \( \text{F}_{\text{CH}_4} \) measured by these methods relative to EC measurements is likely due to the under-representation of hot spots (Wik et al., 2016).

Approximately 87.5\% of cumulative annual \( \text{F}_{\text{CH}_4} \) occurred during the five-month warm-season period from May thru September in 2017, and 89.7\% in 2018 per the EC results. The cumulative areal emissions during the warm-season in 2017 were 35 ± 3.5 \( \text{g CH}_4\text{-m}^{-2} \) (Fig. 9(a)), while the annual cumulative areal emissions in 2017 were 40.6 ± 5.9 \( \text{g CH}_4\text{-m}^{-2} \). Similarly, in 2018 the cumulative areal emissions during the warm season were 61.1 ± 1.4 \( \text{g CH}_4\text{-m}^{-2} \) (Fig. 9(b)), compared to the annual rate of...
21.1±1.2 g CH₄ m⁻² yr⁻¹: Scaling up to the 2.4 km² area of Acton Lake, the hybrid approaches measurements indicate that this reservoir was a source of 22.4±14.109±14 and 127±10 Mg CH₄ to the atmosphere in 2017 and 2018, respectively.

3.3: Spatial patterns in FCH₄

The results from the six spatial surveys indicate an inconsistent spatial pattern in FCH₄ that differs from previous findings on CH₄ emissions from temperate, eutrophic reservoirs which has shown that the river – reservoir transition zone near the tributary inlets tends to be a hot spot for emissions compared to the lacustrine zone (Beaulieu et al., 2014; Beaulieu et al., 2016; DeSoutro et al., 2011; Tuser et al., 2017). The survey results from Acton Lake indicate relatively similar rates of FCH₄ across most of the reservoir surface area (Fig. 6), and a weak but significant (n=90, R² = 0.1, p < 0.005) positive relationship between ebullition and reservoir depth (Fig. S8).

At the whole- reservoir scale, ebullition was a dominant emission pathway for CH₄ relative to diffusion, accounting for 82-94% of total FCH₄. However, at certain sites diffusive FCH₄ contributed a larger proportion of the total flux (Fig. S9). The four sites with mean ebullitive to total FCH₄ ratios less than 0.8 are also the four shallowest sites (see Fig. 1): U-09, U-14, U-07, and U-06, with mean observed depths of 1, 1.3, 1.5, and 2 m respectively. This pattern from the spatial surveys is also reflected in the results from the more frequent measurements made at the shallow and deep site: ebullition accounted for 58% of the total FCH₄ at the shallow site in both 2017 and 2018, while ebullition accounted for 86% and 88% of total FCH₄ at the deep site in 2017 and 2018, respectively. Emission behaviour at sites U-09 and U-06 was substantially different than at other sites: these two sites had consistently low FCH₄ and tend to have higher rates of CH₄ diffusion than ebullition. Much of this behaviour is likely explained by the proximity of these sites to Acton Lake’s swimming beach, which has a sandy substrate that likely inhibits methanogenesis at these sites. These sites were included as part of the random GRTS sampling design.

3.1: Seasonal patterns in FCH₄

We observed a consistent pattern of elevated FCH₄ during the warm season and low-magnitude FCH₄ during the cold season between the two monitoring years (Fig. 2) per the EC results. In both monitoring years, the majority of cumulative total CH₄ emissions (88%) occurred in the five-month period between May 1 and September 30, when air and sediment temperatures were warmer (Fig. 3 (a)), and latent heat fluxes were elevated (Fig. 3 (b)). The mean (± SD) warm season FCH₄ was 14.6±12.4 mg CH₄ m⁻² hr⁻¹ in 2017 and 17.3±14.5 mg CH₄ m⁻² hr⁻¹ in 2018. During the winter months FCH₄ dropped by more than an order of magnitude to a baseline close to zero: between 1 Nov and 1 Apr 2018 was 0.60±0.69 mg CH₄ m⁻² hr⁻¹. The surface of Acton Lake was frozen for several periods during the 2017-2018 winter: 27 Dec 2017-10 Jan 2018; 13-21 Jan 2018; and 5-15 Feb 2018, during which FCH₄ was 0.08±0.46 mg CH₄ m⁻² hr⁻¹. The most substantial difference between the two monitoring years is the period of elevated emissions in late May to early June observed in 2018 but not 2017 (hereafter “spring burst”).

We define the 2018 spring burst as the period from 21 May thru 4 June, during which the daily average FCH₄ observed by EC was ≥ 25 mg CH₄ m⁻² hr⁻¹. Maximum FCH₄ of 62.0 mg CH₄ m⁻² hr⁻¹ occurred on 29 May 2018. While the 2017 EC monitoring does indicate a small burst in FCH₄ of 20.4 mg CH₄ m⁻² hr⁻¹ on 5 June, overall FCH₄ was much smaller: mean FCH₄ for 21 May – 4 June 2017 was 3.6±1.8 mg CH₄ m⁻² hr⁻¹. This difference was likely due to differences in available carbon and sedT, driven by differences in precipitation patterns in the two years (Fig. 3 (a) and (c)), discussed further in Section 5.2.1. The cumulative CH₄
emission over the 2018 twelve-day spring burst period was 10.8 g CH$_4$ m$^{-2}$, which is 17% of the total 2018 emission, and which accounts for 50% of the difference in cumulative annual emissions between 2017 and 2018. The differences between the 2017 and 2018 monitoring years continue past the early summer. During 2017, $F_{CH_4}$ increased to a maximum in late summer, then declined back to the winter baseline. In contrast, the 2018 summer and fall were characterized by episodic emission pulses and decline before tapering down to the winter baseline. These patterns are reflected in the AFT results for the co-located shallow site, although the pattern is dampened (Fig. 7 (b)).

3.2 Spatial patterns in $F_{CH_4}$

The results from the six spatial surveys indicate a consistent spatial pattern in $F_{CH_4}$ that differs from previous findings on CH$_4$ emissions from temperate, eutrophic reservoirs which has shown that the river – reservoir transition zone near the tributary inlets tends to be a hot spot for emissions compared to the lacustrine zone (Beaulieu et al., 2014; Beaulieu et al., 2016; DelSontro et al., 2011; Tuer et al., 2017). The survey results from Acton Lake indicate relatively consistent rates of $F_{CH_4}$ across most of the reservoir surface area (Fig. 5), and a weak but significant ($n=90, R^2=0.1, p<0.005$) positive relationship between ebullition and reservoir depth (Fig. 6).

At the whole lake scale, ebullition was a dominant emission pathway for CH$_4$, relative to diffusion, accounting for 82–94% of total $F_{CH_4}$. However, at certain sites, diffusive $F_{CH_4}$ contributed a larger proportion of the total flux (Fig. 7). The four sites with mean ebullitive to total $F_{CH_4}$ ratios less than 0.8 are also the four shallowest sites (see Fig. 1): U-09, U-14, U-07, and U-06, with mean observed depths of 1.1, 1.3, 1.5, and 2.0 m, respectively. Emission behaviour at sites U-09 and U-06 was substantially different than at other sites; these two sites had consistently low $F_{CH_4}$ (Fig. 5) and tend to have higher rates of CH$_4$ diffusion than ebullition. Much of this behaviour is likely explained by the proximity of these sites to Acton Lake’s swimming beach, which has a sandy substrate. This difference in sediment composition likely inhibits methanogenesis at these sites.

Lower magnitude mean fluxes in the warm season of 2017 relative to 2018 correspond to lower mean air temperature (airT), sediment temperature (sedT), and latent heat flux (LE) during warm season 2017 than 2018 (Fig. 3 (a) and (b)). Mean warm season values for airT were 21.0 and 22.9°C in 2017 and 2018, respectively, for sedT were 22.0 and 24.8°C in 2017 and 2018, respectively, and for LE were 80.7 and 97.3 Wm$^{-2}$ in 2017 and 2018, respectively. Both quantitative analyses of the relationship between $F_{CH_4}$ and sedT yielded statistically significant results (Table 2). We observed $ecO_{10}$ values ranging from 6 to 35, with correlation coefficient values that indicate a strong relationship for all observation sets (Table 2, Fig. 4). In both 2017 and 2018, the shallow AFT (water depth ~ 1.3 m) had a higher sedT threshold per the 2DKS test than the deep AFT (water depth ~ 8 m, Table 2, Fig. 4). The warm season period corresponds with the period of lake stratification (Fig. 3 (g)): the thermocline developed in early May in both years; turnover occurred on 30 September in 2017 (with a weak turnover event occurring between 8–24 September), and on 7 October in 2018 (see Fig. S3 for more detail). Although we observed elevated levels of hypolimnetic dissolved CH$_4$ at the deep site in 2018 (Fig. S4), we did not observe a substantial increase in $F_{CH_4}$ coincident with turnover.

The Bowen ratio (the ratio of sensible heat flux to latent heat flux, H:LE, the proportion of warming to evaporation in the energy budget) observed at our site was low in the summer (~0.1–0.2) and increased in the winter (~1.0), similar to what has been reported in other flux studies over open water (Liu et al., 2012; Vesala et al., 2006). Although we observed seasonal and interannual differences in the Brunt–Väisälä frequency (Fig. 3 (f)), the indicator of underwater turbulence did not correlate with
F_max (Fig. S5, S6), in contrast to the findings of other studies of water-atmosphere trace gas exchange (c.f. Webb et al., 2010; MacIntyre et al., 2010). During the winter months, F_max dropped by more than an order of magnitude to a baseline close to zero between 29 May 2017 and 1 April 2018 (0.6-0.65 mg CH₄·hr⁻¹·m⁻²). The surface of Acton Lake was frozen for several periods during the 2017-2018 winter: 27 Dec 2017-10 Jan 2018; 13-21 Jan 2018; and 5-15 Feb 2018, during which F_max was 0.08-0.09 mg CH₄·hr⁻¹·m⁻².

The most substantial difference between the two monitoring years is the period of elevated emissions in late May to early June observed in 2018 but not 2017 (hereafter “spring burst”). We define the 2018 spring burst as the period from 24 May thru 4 June, when the daily average F_max observed by EC was ≥ 25 mg CH₄·hr⁻¹·m⁻². Maximum F_max of 0.65 mg CH₄·hr⁻¹·m⁻² occurred on 29 May 2018. While the 2017 EC monitoring does indicate a small burst in F_max of 0.4 mg CH₄·hr⁻¹·m⁻² on 5 June, overall F_max was much smaller mean F_max for 24 May-4 June 2017 was 0.6 ± 0.8 mg CH₄·hr⁻¹·m⁻². This difference was likely due to differences in available carbon and 02 driven by differences in precipitation patterns in the two years (Fig. 2 (a) and (c), discussed further in Section 4.1). The cumulative CH₄ emission over the 2018 twelve day spring burst period was 40.8 mg CH₄·m⁻² which is 17% of the total 2018 emission and which accounts for 50% of the difference in cumulative annual emissions between 2017 and 2018.

The differences between the 2017 and 2018 monitoring years continue past the early summer. During 2017, F_max increased to a maximum in late summer, then declined back to the winter baseline. In contrast, the 2018 summer and fall were characterized by episodic emission pulses and declines before tapering down to the winter baseline. These patterns are reflected in the AFT results for the co-located shallow site, although the pattern is dampened (Fig. 2 C). We found that the F_max observations at Acton Lake did not have a clear over-arching diurnal pattern when aggregated over monthly timescales. (Fig. 5), but out of the 168 days with adequate data coverage for diurnal analysis, 18.5% (31 days) displayed strong diurnal patterns, sixteen with elevated daytime emissions and fifteen with elevated nocturnal emissions. Very few of these strong diurnal pattern days were contiguous; there were only four instances of strong diurnal patterns persisting for two or more consecutive days. While we looked for evidence of synoptic patterns in F_max due to changes in overlying pressure from frontal systems (c.f. Liu et al., 2016), we did not see this during the study period.

3.2 Spatial patterns in F_max

The results from the six spatial surveys indicate a consistent spatial pattern in F_max that differs from previous findings on CH₄ emissions from temperate, eutrophic reservoirs which has shown that the river—reservoir transition zone near the tributary inlets tends to be a hot spot for emissions compared to the lacustrine zone (Beaulieu et al., 2014; Beaulieu et al., 2016; DeSontto et al., 2011; Tuser et al., 2017). The survey results from Acton Lake indicate relatively consistent rates of F_max across most of the reservoir surface (Fig. 5), and a weak but significant (r² = 0.1, p < 0.005) positive relationship between ebullition and mean observed depths (Fig. 5).

At the whole lake scale, ebullition was a dominant emission pathway for CH₄ relative to diffusion, accounting for 89.94% of total F_max. However, at certain sites, diffusive F_max contributed a larger proportion of the total flux (Fig. 7). The four sites with mean ebullition to total F_max ratios less than 0.8 were also the four shallowest sites (see Fig. 1): U09, U14, U1107, and U106, with mean observed depths of 1.1, 1.3, 1.5, and 2 m respectively. Emission behaviour at sites U09 and U106 was substantially different than at other sites; these two sites had consistently low F_max (Fig. 5) and tend to have higher rates of CH₄ diffusion
than ebullition. Much of this behaviour is likely explained by the proximity of these sites to Acton Lake’s swimming beach which has a sandy substrate. This difference in sediment composition likely inhibits methanogenesis at these sites.

### 3.3 EC gap filling and uncertainty

The overall \( F_{CH4} \) data acceptance rate for the two-year monitoring period (26 January 2017 – 13 November 2018) was 31.3% (Fig. S8). In 2017, the data acceptance rate was lower, 23.4%, due to power issues and the need to filter for wind direction at the near-shore ECS-1 site where the instrumentation was located for the whole year vs. 10.6% in 2018 when the instrumentation was relocated to the mid-lake ECS-2 site. The data coverage for the period of monitoring from ECS-2 (May thru November) was 58%. Reacting removed the need to filter periods based on wind direction and coincided with an improvement to the battery system that reduced incidence of power failure. At ECS-1, non-operability of the LI7700 due to power loss or other issues caused the majority of data rejection (40.4% of total monitoring periods), followed by filtering for wind direction (28.1%), and quality control filtering (7.8%).

The non-gap filled, quality filtered 30-minute \( F_{CH4} \) measurements had a mean random error (± SD) of 1.3 ± 1.9 and 1.8 ± 1.7 mg CH\(_4\) m\(^{-2}\) hr\(^{-1}\) in 2017 and 2018, respectively or 15.5% and 13.7% of the mean annual fluxes. The fractional error was larger in the winter months when \( F_{CH4} \) was small (mean winter random error: 23%) and smaller during the warmer months when \( F_{CH4} \) was larger (mean summer random error: 15%). Both the magnitude and patterns in the random error are similar to those observed by Jammet et al. (2017) in a subarctic aquatic ecosystem. Similarly, we found gap filling our \( F_{CH4} \) time series with ANN worked well with a few exceptions. The median \( R^2 \) values for the 20 extractions was 0.79, and the cumulative bias error was minimal; the 20 ANN extractions yielded a median bias of 0.25 (range of -3.7 to 3.5) g CH\(_4\) m\(^{-2}\) or up to 3.3% of cumulative emissions over the two-year monitoring period. The ANN establishes non-linear predictive power to each of the 20 driver inputs, defined as “Variable Importance Factor” (VIF) in terms of a percent importance to the predictive power of the model. The median VIFs from the 20 ANN extractions are plotted in Fig 8; a consistently high ranking across runs indicates a strong relationship with \( F_{CH4} \).

### 3.4 \( F_{CH4} \) warm season and annual budgets

The larger magnitude \( F_{CH4} \) emissions observed in 2018 relative to 2017 at Acton Lake carry through to the warm-season and annual budgets across measurement methods. The EC and GRTS survey results indicated similar warm-season mean fluxes in 2017: 0.89 ± 0.67 and 0.89 ± 0.62 mg CH\(_4\) m\(^{-2}\) hr\(^{-1}\) (Table 2). Results from both methods indicated larger magnitude mean \( F_{CH4} \) in 2018: 12.9 ± 0.38 mg CH\(_4\) m\(^{-2}\) hr\(^{-1}\) per the EC system and 13.01 ± 6.6 mg CH\(_4\) m\(^{-2}\) hr\(^{-1}\) per the GRTS surveys (Table 2). Both the shallow site and deep site results also indicated elevated \( F_{CH4} \) in 2018 relative to 2017 (Table 2). The lower magnitude mean \( F_{CH4} \) measured by these methods relative to EC measurements is likely due to the under representation of hot spots (Wik et al., 2016).

Approximately 87.5% of cumulative annual \( F_{CH4} \) occurred during the five-month warm season period from May thru September in 2017 and 89.7% in 2018 per the EC results. The cumulative areal emissions during the warm season in 2017 were 15 ± 0.5 g CH\(_4\) m\(^{-2}\) (Fig. 9(a)), while the annual cumulative areal emissions in 2017 were 10.6 ± 5.9 g CH\(_4\) m\(^{-2}\). Similarly, in 2018 the cumulative areal emissions during the warm season were 11.1 ± 1.4 g CH\(_4\) m\(^{-2}\) (Fig. 9(b)), compared to the annual rate of

18
4. Discussion

4.1 Comparison with other systems and methods

The hybrid upscaling approach we used in this study leverages the best available information from our measurements to characterize both the spatial and temporal variability of Acton Lake. EC monitoring for the shallow portion of the reservoir, and the continuous deep site monitoring scaled by the spatial survey site measurements for the deep portion of the reservoir. If we used the EC monitoring results alone to upscale to whole-reservoir emissions, that would assume the spring burst pattern affected the whole reservoir (Fig. 5). However, we know the spring burst did not affect the deep site (Fig. 2). Thus, a key uncertainty around this upscaling method is estimating what portion of the reservoir was affected by the spring burst of emissions in 2018. The cumulative FCH4 measured by EC was 77% greater in 2018 than 2017, compared to a difference of only 11% per the hybrid approach. Adding one or more AFT sites along the depth gradient of the reservoir would be one way to decrease uncertainty in the extent of the spring burst and improve confidence in upscaled FCH4 estimates.

The cumulative annual CH4 areal emissions were 40.6 ± 5.9 g CH4 m⁻² in 2017 and 71.4 ± 4.2 g CH4 m⁻² in 2018 at Acton Lake, based on the gap-filled continuous EC monitoring results (Fig. 9). Comparing cumulative annual areal emissions from the hybrid upscaling approach (45.6 ± 8.3 and 51.4 ± 4.3 g CH4 m⁻² for 2017 and 2018, respectively) there values to other reservoir CH4 emission rates reported in the literature is not straightforward due to differences in monitoring methods and temporal coverage. One important reason earlier studies of reservoir FCH4 may be biased low is that they only measured CH4 diffusion. Deemer et al. found that the mean FCH4 reported in studies measuring ebullition and diffusion was over double of diffusion-only FCH4 studies. Another potentially important source of bias is temporal coverage. Most studies that report FCH4 from inland waters monitor during the warm season, with less than six months of measurements (cf. Deemer et al., 2016; DelSontro et al., 2018; Bastviken et al., 2011), and the mean FCH4 value is then extrapolated to annual total emissions. It may however be better to assume zero FCH4 during wintertime months for temperate reservoirs, given the very low (on the same order as the warm-season uncertainty) wintertime FCH4 measured in this study. On the other hand, the spring burst phenomenon we observed demonstrates the importance of continuous monitoring of mid-latitude eutrophic reservoirs during the full warm season to capture hot-moments of FCH4. A related consideration is a method’s ability to capture spatial and temporal variability of FCH4 during the study period. Deemer et al. noted that studies using the eddy covariance method reported substantially higher values of FCH4: ~92.5 g CH4 m⁻² yr⁻¹ (Deshmukh et al., 2014) and ~160 g CH4 m⁻² yr⁻¹ (Eugster et al., 2011), which are on the same order as the Acton Lake cumulative annual emissions (Table 2). The two open-water sites included in the CH4 EC meta-analysis by Knox et al. (2019) were natural lakes in temperate regions with cumulative annual emissions of ~15 g CH4 m⁻² yr⁻¹. This difference in FCH4 speaks to the need for building a representative dataset across both methods and ecoregions. Nevertheless, Acton Lake’s annual FCH4 is relatively high compared to other reservoirs. It falls in the 4th quintile (≥60%) of the reservoir emission rates that included ebullition reported in Deemer et al. (2016); the warm season FCH4 fall in the upper quintile (≥80%) of those reservoirs. The warm season FCH4 also falls into the upper quartile (≥75%) of the 32 temperate reservoirs surveyed by Beaulieu et al. (2020). This result strengthens the finding that midlatitude, eutrophic reservoirs

4.2 Comparison with other systems and methods
in the Midwest US can support high CH₄ emission rates (cf. Beaulieu et al., 2014, 2016), and also supports the emerging body of knowledge around the importance of reservoir productivity as a key indicator for FCH₄ (cf. Deemer et al., 2016; West et al., 2012; DesOnstro et al., 2018b) in contrast to the earlier assessment of age and latitude as the main drivers (Barros et al., 2012). Due in large part to the temporal coverage: the majority of studies that report FCH₄ from inland waters monitor during the warm season, with less than six months of measurements (cf. Deemer et al., 2016; DesOnstro et al., 2018 Bastviken et al., 2011). Lack of shoulder-season and winter measurements could bias the mean or cumulative FCH₄ high: lack of continuous measurements that miss hot moments could bias mean/cumulative FCH₄ low. Upscaling survey-style methods is analogous to gap-filling pseudo-continuous methods like EC, but there is currently a disconnect in terms of how the uncertainty in the two processes is characterized. Within the flux community, ANN methods for gap-filling FCH₄ time series are being adopted, but it is an area of ongoing research (Nemitz et al., 2018; Knox et al. 2019). While several studies over wetlands and rice have used ANN to gap-fill FCH₄ (e.g. Dengel et al., 2014; Morin et al., 2014; Knox et al., 2015, Rev-Sanchez et al., 2017; Knox et al., 2016), to our knowledge, Jummet et al. (2017) is the only other study that has gap-filled open water FCH₄ measurements using ANN. Gap-filling with ANN gives non-linear weighted best estimates of FCH₄ in relation to the drivers for that time period. The ANN also enables us to characterize uncertainty by looking at the upper and lower confidence intervals of the ensemble models. This gives us a continuous time series of uncertainty integrated over the footprint of the EC system. In contrast, the uncertainty of survey-style methods often derives from spatial heterogeneity. The GRTS surveys are characterizing the lake-scale FCH₄ (and uncertainty) at a snapshot in time. Thus, upscaling these survey results temporally is a matter of gap-filling by linear interpolation.

While these methodological differences are noted, nevertheless Acton Lake’s annual FCH₄ is relatively high. It falls in the 4th quantile (60%) of the reservoir emission rates that included ebullition reported in Deemer et al. (2016); the warm season FCH₄ fall in the upper quantile (80%) of those reservoirs. Deemer et al. (2016) also discuss how methods matter in characterizing FCH₄ from reservoirs. The main consideration is the importance of measuring ebullition; Deemer et al. found that the mean FCH₄ reported in studies measuring ebullition and diffusion was over double of diffusion-only FCH₄ studies. A secondary consideration is a method’s ability to capture spatial and temporal variability of FCH₄. Deemer et al. noted that studies using the eddy-covariance method reported substantially higher values of mean FCH₄ (~190 mg CH₄-C m⁻² d⁻¹) (Deshmukh et al., 2014) and ~328 mg CH₄-C m⁻² d⁻¹ (Eugster et al., 2011), which are comparable to the Acton Lake annual FCH₄ values converted to daily mean fluxes: 9.4 and 14.7 mg CH₄-C m⁻² d⁻¹ in 2017 and 2018, respectively. The two open-water sites included in the Knox et al. (2019) analysis had mean annual FCH₄ of 15±4 mg CH₄-C m⁻² d⁻¹ or 5.5 mg CH₄-emiss⁻¹. These sites are natural lakes in temperate regions. This difference in FCH₄ speaks to the need for building a representative dataset across both methods and ecologies.

The difference in FCH₄ between the different methods in 2017 versus 2018 (Table 2) illustrates how methods matter in capturing hot spots and hot moments. In 2017, the warm-season FCH₄ measured by EC and the GRTS surveys are not significantly different, and FCH₄ measured at the two AFT sites is within 30% of this value. This suggests that the GRTS surveys adequately captured hot spots of emissions and did not under represent hot moments. In 2018, by contrast, the warm-season FCH₄ measured by EC is 34% larger than the GRTS survey results, and more than double what was measured at the AFT sites. Using a literature model to estimate FCH₄ also yields estimates that agree relatively well with 2017 EC results, but not 2018. 11.4 and 10.3 mg
CH$_4$ m$^2$ hr$^{-1}$, respectively (DelSontro et al., 2018). This reflects the limitations in the datasets used to train the model: the model uses chla levels to predict $F_{\text{CH}_4}$. Mean chla levels were higher in 2017 than 2018 for Acton Lake, but as we saw here, the timing of the elevated chla levels was key in how that input translated to $F_{\text{CH}_4}$. The difference in uncertainty between the methods should also be noted. While we report a larger uncertainty range for the GRTS survey results than either the EC results or the AFTs and chambers (Table 2, Fig. 9), the GRTS uncertainty is the only one that encompasses the whole lake.

Integrating spatially over the 2.4 km$^2$ surface area of the lake, these results suggest Acton Lake emits 111 – 155 Mg CH$_4$ yr$^{-1}$.

This loss of mineral carbon (C) is non-trivial term in the reservoir C budget, constituting ~7% (range: 4% - 12%) of Acton Lake's annual C retention over 2007 and 2008 reported in Knoll et al. (2013). The Knoll study did not measure $F_{\text{CH}_4}$ and thus did not include it in their budget. They did include losses of C as CO$_2$, which tended to be much smaller in magnitude than CH$_4$ emissions: 2 and 56 Mg C yr$^{-1}$ in 2007 and 2008, respectively, compared to 83 and 116 Mg C yr$^{-1}$.

4.2 Implications for upscaling

The key question in upscaling any set of measurements to characterize an ecosystem is “what is representative?”. This study leveraged a combination of continuous and spatially extensive monitoring methods to investigate the spatial and temporal variability in a reservoir. The spring burst of elevated emissions that we observed in 2018 but not 2017, and in the shallow portion of the reservoir but not at the deep site, is the largest contributor to the spatial and temporal variability in this study. In this section we will analyse the spring burst and factors that could have contributed to it. We will also discuss other patterns in intra-reservoir spatial and temporal variability linked to sediment T and other biophysical drivers are also discussed.

4.2.1 Spring burst

Differences in phytoplankton populations and sediment temperature, partially driven by precipitation differences, provide insight into why the spring burst of emissions occurred 1) in 2018 but not 2017, and 2) in the littoral area of the reservoir but not the deeper areas. Chlorophyll a (chla) levels measured a few days before the spring burst period show elevated levels in the shallow portion of the reservoir in 2018 compared to 2017, while levels near the outflow were similar between the two years (Fig. 7 (a)). This increase in chla levels coincided with an increase in shallow sed T to 27°C (Fig. 7 (b)). These differences in chla and sedT near the inflow can be tied to differences in precipitation between the two years: Our analysis suggest that precipitation dynamics drove differences in algal populations that lead to both the 2018 spring burst and the subsequent differences in warm season emission patterns between years. The spring burst period of elevated $F_{\text{CH}_4}$ in late May thru early June of 2018 indicates that environmental conditions were more favourable for CH$_4$ production and emission in the late spring of 2018 compared to the same period in 2017. Spring of 2017 was relatively wet, with 31.0 cm of rainfall and 20.9*10$^6$ m$^3$ of stream inflow in May (Fig. 4 (c), (d)) which drove substantial fluctuations in reservoir water level (Fig. 4 (e)). These rain events also led to a decrease in sedT from 22.5 to 18°C prior to the onset of the spring burst timeframe (Fig. 7 (ba)) due to the inflow of cooler stream water and the cooling of ambient air temperature. In contrast, May of 2018 was relatively dry, with 12.3 cm of rain, 9.45*10$^6$ m$^3$ of stream inflow (Fig. 4 (c), (d)), and stable reservoir water levels (Fig. 4 (e)). Prior to the spring burst in 2018, sedT rose from 22.5 to 27°C (Fig. 11 (a)). Chlorophyll levels in spring 2018 were elevated compared to spring 2017 (Fig. 11 (b)). The phytoplankton bloom suggests enhanced production.
of algal biomass in the shallow portion of the reservoir leading up to the spring burst period was likely catalyzed by the conducive water temperature, turbidity, presumably due to differences in precipitation, turbidity, and water level stability. Elevated levels of dissolved ammonium (NH$_3$), total phosphorus (TP), soluble reactive phosphorus (SRP), and particulate organic carbon (POC) near the inflow during the 2018 spring burst support that the conditions in the littoral area in 2018 were different than those in 2017, and that this interannual difference did not occur in the deep portion of the reservoir (Table 3).

There are at least two established mechanistic connections between phytoplankton blooms and enhanced CH$_4$ production and emission, and either or both could have driven the spring burst observed in this study. One mechanistic connection between autochthonous organic carbon (autoOC, i.e. phytoplankton-derived) and F$_{CH_4}$ is the stimulation of methanogenesis from the input of this labile C source as the phytoplankton die and settle to the sediment. Several lab studies have demonstrated that the addition of autoOC can lead to enhanced CH$_4$ production rates (Schwartz et al., 2008; West et al. 2012, 2015; Grasset et al., 2018). A recent study using in-situ measurements found that heatwave-induced cyanobacterial blooms and subsequent input of autoOC to the sediment could lead to pulses of CH$_4$ emissions up to an order of magnitude larger than baseline levels (Bartosiewicz et al., 2021). The 2018 crash in phytoplankton that coincided with the spring burst (as indicated by chla measurements, Fig. 7 a)) evidences a large input of autoOC to the sediment during the spring burst. A second possible mechanistic connection is production of CH$_4$ by phytoplankton in the oxic surface water. A recent study by Hartmann et al. (2020) combined in-situ measurements of phytoplankton communities, CH$_4$, and CH$_4$ isotopes with lab incubations and demonstrated that all major phytoplankton classes could produce CH$_4$ under oxic conditions. Phytoplankton CH$_4$ production in the surface mixed layer super-saturates the upper water column with CH$_4$ and leads to enhanced diffusive emissions, and phytoplankton biomass has been found to be the primary driver of diffusive F$_{CH_4}$ in some reservoir systems (McClure et al., 2020). Strong diurnal patterns in F$_{CH_4}$ surrounding the spring burst correlated with latent heat flux (LE), an indicator of warm, windy, convective conditions of enhanced air-water gas exchange (Fig. S5, S6). This suggests that during the spring burst the surface waters were super-saturated with CH$_4$ and diffusive emissions were the dominant pathway during that time. Including measures of phytoplankton CH$_4$ production in the surface mixed layer in future studies would be helpful in differentiating which production pathway led to elevated dissolved CH$_4$.

The difference in hydrologic regimes and subsequent availability of autoOC versus allochthonous OC (alloOC, i.e. particulate or dissolved C derived from terrestrial plant tissue) also sheds light on interannual differences beyond the spring burst. The lab study by Grasset et al. (2018) found that while additions of autoOC led to pulses of F$_{CH_4}$, alloOC took longer to decompose and additions led to more gradual but sustained F$_{CH_4}$. Thus, the wet spring of 2017 loaded the reservoir with slow-burning alloOC, and F$_{CH_4}$ was more stable, tracking with sedT to peak emissions in early fall (Fig. 2). Precipitation and stream inflows have been shown to have contrasting effects on reservoir carbon dynamics. An increase in precipitation can increase allochthonous carbon (C) availability in the reservoir due to inflow of dissolved and particulate C in the stream discharge, but enhanced turbidity from stream discharge can decrease autochthonous C availability due to shading. Another study at Acton Lake found that storm events led to suppression of lake metabolism, likely due to the flushing removal of autotrophic biomass (Williamson et al., 2020). Thus, precipitation can shift the balance between autochthonous C (autoOC) and allochthonous C (alloOC), and the source of C can impact CH$_4$ production and emission. Several lab studies have found that additions of...
autochthonous C (autoOC), such as algal cells, stimulate CH₄ production rates (Schwarz et al., 2008; West et al., 2012, 2015) and West et al., (2012) found that additions of autoOC lead to a greater increase in CH₄ production than additions of allochthonous C (alloOC). Grasset et al., (2018) found that autoOC decomposed more rapidly than alloOC and that additions of the former lead to pulses of FCH₄, while additions of the latter lead to slower and more constant CH₄ production and emission. This would be consistent with the emission patterns in 2018 and 2017, respectively, warm temperatures and low turbidity in May 2018 lead to an algal bloom and high levels of autoOC resulting in the spring burst of FCH₄, while a wet spring in 2017 lead to cool, turbid inflow that suppressed an algal bloom, but loaded the reservoir with slow-burning alloOC. Hence, in 2017 the steady increase in FCH₄ tracked with sedT and accumulating algal biomass to a maximum in late fall.

The implications of the spring burst phenomenon on upscaling to total FCH₄ are twofold. In terms of characterizing current total reservoir FCH₄, the spatial and temporal variability of the spring burst mitigate its influence. This is illustrated by comparing the lake-wide survey results to the hybrid upscaling results, which agree well in both 2017 and 2018 (Fig. 5). However, in predicting future reservoir FCH₄ under changing climatic regimes, it is important to characterize underlying processes that relate to the climatic drivers of precipitation and temperature. Using reservoir productivity to predict FCH₄ is a good place to start: the size-productivity model (Del Sontro et al., 2018) uses annual mean chla levels to predict FCH₄ (Eqn 7). Acton Lake’s mean chla was higher in 2017 than 2018 (Fig. 7), and the model predicts 11.1 and 10.3 mg CH₄ m⁻² hr⁻¹, respectively for 2017 and 2018. These values agree well with our estimates using the hybrid upscaling approach (Table 2) but flip the finding of which year had larger CH₄ emissions, which was driven by sub-annual productivity dynamics. A burgeoning body of knowledge points to the importance of phytoplankton ecology on lake and reservoir CH₄ production, in terms of both the amount (Hartman et al., 2020; McClure et al., 2020; Zhang et al., 2021) and type (Bartosiewicz et al., 2021). Furthermore, warmer springs have increased the frequency and intensity of cyanobacterial blooms in midwestern US reservoirs over the past two decades (Smucker et al., 2021), and continued warming will likely intensify this phenomenon. Thus, the underlying factors that led to the 2018 spring burst at Acton Lake may be more common in the future and have a greater effect on the reservoir CH₄ budget.

**4.2.2 Additional intra-lake variability:**

Beyond the spring burst, we observed additional patterns of intra-lake spatiotemporal variability in FCH₄ related to sediment temperature (sedT). Temperature is an important control on metabolic processes such as methanogenesis, but other signals can complicate the relationship between temperature and FCH₄ at the scale of ecosystem fluxes. Nevertheless, sedT emerged as a key predictor of FCH₄ in this study. The ANN model used to gap-fill the EC monitoring ranked sedT as one of the most important biophysical predictors of FCH₄ alone with absolute static pressure, change in static pressure, and latent heat flux (Fig. 3). A strong indication of the intra-lake patterns in drivers and emissions is that maximum ebullitive FCH₄ observed by the AFTs coincided with maximum sedT at both the shallow (U-14) and deep (U-12) monitoring sites in 2017 (Fig. 8). This maximum occurs in early August at U-14 versus mid-September at U-12, a phase-shift that reflects the time delay in heat transfer to the deeper sediment. This phase shift could also (speculatively) have been affected by the time delay in nutrient and OC transfer...
We used ecoQ10 and 2DKS threshold analysis to further investigate the role of sediment temperature on regulating $F_{CH_4}$ in both the deep and shallow portions of Acton Lake. Both of these quantitative analyses of the relationship between $F_{CH_4}$ and SedT yielded statistically significant results (Table 4), and each monitoring method had consistentThe concept of an "ecological Q10" (DelSontro et al., 2016) follows from the physiological exponential relationship between metabolic processes and temperature. In contrast to physiological Q10 values, ecological Q10, hereafter "ecoQ10" values are modified by time-lags and competing rate enhancers and inhibitors (e.g. that temperature affects both methanogens and methanotrophs). Soenen, 1998; Duc et al., 2010; Lothon et al., 2014). While the physiological Q10 value for methanogenesis converges around 4 (Yvon, Durocher et al., 2014), ecoQ10 values for methane fluxes have been reported to range from 1 – 35 (e.g. DelSontro et al., 2016; Wik et al., 2014; Duc et al., 2010). ecoQ10 values and 2DKS threshold temperatures across the two study years (Table 4, Fig S11). The EC method had a much lower ecoQ10 value than the AFT sites, the latter of which were comparable to maximum ecoQ10 values reported in other studies (DelSontro et al., 2016). The relatively low ecoQ10 value for the EC method may be due to different T response of ebullitive vs. diffusive emission pathways, or to a spatial mis-match between the measured sedT and the EC flux footprint. For these reasons, we will focus on the AFT sites in interpreting the ecoQ10 and threshold temperature results in terms of intra-lake spatial variability. The ecoQ10 values indicate a stronger relationship between sedT and ebullitive $F_{CH_4}$ at the shallow site than the deep site. Despite a greater ecoQ10 value, ebullitive $F_{CH_4}$ at the shallow site didn't respond to warming in the spring until water temperatures reached a threshold of -22.5 $^\circ$C, whereas ebullitive $F_{CH_4}$ at the deep site responded to warming at a much lower temperature threshold (13 – 18 $^\circ$C, Table 4). Furthermore, mean ebullitive $F_{CH_4}$ was very similar between the two sites (Table 2), despite a 6-degree difference in maximum sediment temperature. These patterns suggest that methanogens at the deep site may be better adapted to the consistently cooler conditions found in the hypolimnion of Acton Lake, which has important implications for predictive models employing ecoQ10 or threshold values to parameterize $F_{CH_4}$ as a function of sedT. Alternatively, the differences in temperature sensitivity between the deep and shallow site may reflect differences in substrate quality and/or quantity related to spatial patterns in sedimentation and productivity (Berberich et al. 2019). Regardless of the underlying mechanism, these patterns illustrate strong spatial patterning in $CH_4$ biogeochemistry within this 2.4 km$^2$ reservoir. In terms of biophysical drivers, sediment temperature, absolute static pressure, change in static pressure, and latent heat flux were ranked as the top drivers (Fig. 8). We used ecoQ10 and 2DKS threshold analysis to further investigate the role of sediment temperature on regulating $F_{CH_4}$. Static pressure and latent heat flux are important drivers of diurnal patterns in $F_{CH_4}$ (Section 4.2.2). Biophysical drivers We intensively monitored one small eutrophic reservoir, Acton Lake, over two years in this study with the goal of improving our understanding of the patterns and drivers of $F_{CH_4}$ from reservoirs. The drivers we used to run the ANN to gap-fill the EC time series (Section 2.7) were chosen because of their known biophysical links to either $CH_4$ production (sediment temperature and air temperature) or emission across the air-water interface (change in static pressure, absolute static pressure, and latent heat flux). We also included empirical factors that do not fall into either category: a location indicator (Site 1 vs. Site 2) and indicators for day of year and hour of day. Day of year (DOY) was the top predictor, likely reflecting the strong seasonal pattern in $F_{CH_4}$ (Fig. 8). That "Site", an indicator of where the flux tower was located, came out as the second most important input is likely reflective of the difference between years. While the re-siting of the tower (even given the mitigating factor of
overlapping footprints) does make it difficult to disentangle some spatial and temporal differences, the spring burst is a clear signal we did not see in 2017 and constitutes the majority of the difference between years. In terms of biophysical drivers, sediment temperature, absolute static pressure, change in static pressure, and latent heat flux were ranked as the top drivers (Fig. 8). We used ecoQ10 and 2DKS threshold analysis to further investigate the role of sediment temperature on regulating $F_{\text{CH}_4}$. Static pressure and latent heat flux were important drivers of diurnal patterns in $F_{\text{CH}_4}$ (Section 4.2.2).

The ecoQ10 values and 2DKS threshold temperatures were consistent across years among the three continuous monitoring methods (Table 2). The EC method had the lowest ecoQ10 value (~6), indicating the weakest relationship between sediment T and observed emissions. This may be due to two factors: the first is the spatial decoupling of the EC measurements from the sedT thermistor, as the EC measurement footprint encompasses a wider swath of the reservoir, much of which may have different sedT conditions. The second factor is that the EC measurements integrate ebullitive and diffusive emissions. While diffusive emissions are dependent on methanogenesis and thus sedT, the relationship may be confounded by methanotrophy, which is temperature dependent as well (Fuchs et al., 2016). The shallow site AFT had a consistently higher ecoQ10 value than the deep AFT site, indicating a stronger relationship between sedT and ebullitive $F_{\text{CH}_4}$ at the shallow site than the deep site. Despite a greater ecoQ10 value, ebullitive $F_{\text{CH}_4}$ at the shallow site didn’t respond to warming in the spring until water temperatures reached ~22.5°C, whereas ebullitive $F_{\text{CH}_4}$ at the deep site responded to warming at a much lower temperature threshold (13–18°C). Furthermore, mean ebullitive $F_{\text{CH}_4}$ was very similar between the two sites (Table 3), despite a 6-degree difference in maximum sediment temperature. These patterns suggest that methanogens at the deep site may be better adapted to the consistently cooler conditions found in the hypolimnion of Acton Lake, which has important implications for predictive models employing ecoQ10 or threshold values to parameterize $F_{\text{CH}_4}$ as a function of sedT. Alternatively, the differences in temperature sensitivity between the deep and shallow site may reflect differences in substrate quality and/or quantity related to spatial patterns in sedimentation and productivity (Berberich et al. 2019). Regardless of the underlying mechanism, these patterns illustrate strong spatial patterning in CH$_4$ biogeochemistry within this 2.4 km$^2$ reservoir.

Another indication of the intra-lake variability is the time lag between the shallow and deep site in both maximum sedT and maximum $F_{\text{CH}_4}$. Maximum ebullitive $F_{\text{CH}_4}$ observed by the AFTs coincided with maximum sedT at both the shallow (U-14) and deep (U-12) monitoring sites in 2017 (Fig. 10). This maximum occurs in early August at U-14 versus mid-September at U-12, a phase shift that reflects the time delay in heat transfer to the deeper sediment, and nutrient transfer due to the distance from the inlet. This pattern was not as pronounced in 2018 (Fig. S9), likely because other drivers played a larger role in $F_{\text{CH}_4}$ that season, in line with the results of the ecoQ10 analysis indicating a stronger relationship between $F_{\text{CH}_4}$ and sedT in 2017 than in 2018 (Table 3, Fig. 4).

4.2 Temporal Patterns

4.2.1: Interannual & Spring Burst

Our analysis suggest that precipitation dynamics drove differences in algal populations that lead to both the 2018 spring burst and the subsequent increase in warm season emission patterns between years. The spring burst period of elevated $F_{\text{CH}_4}$
late May thru early June of 2018 indicates that environmental conditions were more favorable for \( \text{CH}_4 \) production and emission in the late spring of 2018 compared to the same period in 2017. Spring of 2017 was relatively wet, with 31.0 cm of rainfall and 20.9 \( \times 10^6 \) m\(^3\) of stream inflow in May (Fig. 3 (c), (d)) which drove substantial fluctuations in reservoir water level (Fig. 3 (a)). These rain events also led to a decrease in sedT from 22.5 to 18°C prior to the onset of the spring burst timeframe (Fig. 1 (a)) due to the inflow of cooler stream water and the cooling of ambient air temperature. In contrast, May of 2018 was relatively dry, with 12.3 cm of rain, 9.45 \( \times 10^6 \) m\(^3\) of stream inflow (Fig. 3 (c), (d)), and stable reservoir water levels (Fig. 3 (a)).

Prior to the spring burst in 2018, sedT rose from 22.5 to 27°C (Fig. 1 (a)). Chlorophyll levels in spring 2018 were elevated compared to spring 2017 (Fig. 1 (b)). This suggests enhanced production of algal biomass, presumably due to differences in precipitation, turbidity, and water level stability.

Precipitation and stream inflows have been shown to have contrasting effects on reservoir carbon dynamics. An increase in precipitation can increase allochthonous carbon (C) availability in the reservoir due to inflow of dissolved and particulate C in the stream discharge, but enhanced turbidity from stream discharge can decrease autochthonous C availability due to shading. Another study at Acton Lake found that storm events led to suppression of lake metabolism, likely due to the flushing removal of autotrophic biomass (Williamson et al., 2020). Thus, precipitation can shift the balance between autochthonous C (autoOC) and allochthonous C (alloOC), and the source of C can impact \( \text{CH}_4 \) production and emission. Several lab studies have found that additions of autochthonous C (autoOC), such as algal cells, stimulate \( \text{CH}_4 \) production rates (Schwarz et al. 2008; West et al. 2012, 2015), and West et al. (2013) found that additions of autoOC led to a greater increase in \( \text{CH}_4 \) production than additions of allochthonous C (alloOC). Gignac et al. (2018) found that autoOC decomposed more rapidly than alloOC and that additions of the former lead to pulses of \( \text{F}_{\text{CH}_4} \) while additions of the latter lead to slower and more constant \( \text{CH}_4 \) production and emission.

This would be consistent with the emission patterns in 2018 and 2017, respectively. Warm temperatures and low turbidity in May 2018 lead to an algal bloom and high levels of autoOC resulting in the spring burst of \( \text{F}_{\text{CH}_4} \), while a wet spring in 2017 lead to cool, turbid inflow that suppressed an algal bloom, but loaded the reservoir with slow-burning alloOC. Hence in 2017 the steady increase in \( \text{F}_{\text{CH}_4} \) tracked with sedT and accumulating algal biomass to a maximum in late fall.

### 4.2.2: Diurnal patterns

Diurnal patterns in \( \text{F}_{\text{CH}_4} \) were less prevalent at Acton Lake than in some other systems reported on in the literature. Understanding the amplitude and direction of any diurnal pattern in \( \text{F}_{\text{CH}_4} \) helps to reduce bias in upscaled survey-style measurements of \( \text{F}_{\text{CH}_4} \), which for convenience and safety are almost always collected during the daytime. It is noteworthy that Acton Lake could switch diurnal pattern phases, which we propose is due to shifts in biophysical controls on \( \text{CH}_4 \) production and emission. We only observed strong diurnal patterns 18.5% of the time, compared to reports of consistent diurnal patterns observed in other eddy covariance studies of \( \text{F}_{\text{CH}_4} \) in a nutrient-rich Swedish lake (Podgrajsek et al., 2014), a mesotrophic subtropical reservoir (Deshmukh et al., 2014), and a subarctic pond (Jammet et al., 2017). The lack of a diurnal pattern >80% of the time and the lack of a relationship between \( \text{F}_{\text{CH}_4} \) and underwater turbulence (Fig. 3 (f), S5, S6) indicate factors that do not vary diurnally are important in controlling \( \text{CH}_4 \) production and emission at Acton Lake and perhaps in warm, eutrophic reservoirs more broadly. While sedT, LE, and static pressure all contribute to the regulation of \( \text{F}_{\text{CH}_4} \), the roles of substrate
availability and microbial community dynamics, which may not vary on a diel basis, may play a larger role than the physical factors at Acton in regulating $F_{CH4}$.

Although periods of contiguous diurnal patterns were relatively rare at Acton Lake, they co-occurred with diurnal patterns in potential drivers. Contiguous daytime peaks in $F_{CH4}$ correlated with peaks in latent heat flux (LE), a measure of the heat energy used in evaporation of liquid water from the surface (Fig. 12 (a), (c), Fig. S10). This is consistent with the ANN results, which identified LE as an important predictor variable (Fig. 8). While LE is not a direct biophysical driver of $CH4$ production or emission, it is enhanced under warm, windy, convective conditions (Liu et al., 2012). These same conditions may enhance diffusive $CH4$ emissions by 1) causing deeper, $CH4$-rich water to upwell toward the water surface, and 2) enhancing the air-water gas exchange rate. Periods of nighttime $F_{CH4}$ peaks (Fig. 12 (b), (d)) co-occurred with nighttime minima in atmospheric pressure, consistent with static pressure serving as an important predictor in the ANN (Fig. 8, Fig. S11). Drops in overlying static pressure can trigger the release of sediment bubbles (Beaulieu et al., 2018; Harrison et al., 2017; Varadharajan and Hemond, 2012), thereby greatly enhancing ebullitive $F_{CH4}$. A similar result was reported for a tropical reservoir, but in that case atmospheric pressure was typically lower during the day than at night, resulting in consistent daytime peaks in $F_{CH4}$ (Deshmukh et al., 2014). Diurnal patterns in static $P$ do not necessarily result in a corresponding patterning in $F_{CH4}$ at Acton Lake, however, likely because other factors also exert control on $F_{CH4}$. The period shown in Fig. 12 b, d had high, stable sedT (not shown) which may have minimized the role of temperature as a limiting factor, enhancing the role of static $P$.

4.3 Comparison with other systems and methods

The cumulative annual $CH4$ areal emissions were 10.6 ± 0.4 g $CH4$ m$^{-2}$ in 2017 and 7.1 ± 0.7 g $CH4$ m$^{-2}$ in 2018 at Acton Lake, based on the gap-filled continuous EC monitoring results (Fig. 9). Comparing these values to others reported in the literature is not straightforward, due in large part to the temporal average: the majority of studies that report $F_{CH4}$ from inland waters monitor during the warm season, with less than six months of measurements (cf. Deemer et al., 2016; DelSontro et al., 2013; Brath et al., 2012). Lack of shoulder season and winter measurements could bias the mean or cumulative $F_{CH4}$ high; lack of continuous measurements that miss hot moments could bias mean/cumulative $F_{CH4}$ low.

Upscaling survey-style methods is analogous to gap-filling pseudo-continuous methods like EC, but there is currently a disconnect in terms of how the uncertainty in the two processes is characterized. Within the flux community, ANN methods for gap-filling $F_{CH4}$ time series are being adopted, but it is an area of ongoing research (Nemitz et al., 2018; Knox et al., 2019). While several studies over wetlands and rice have used ANN to gap-fill $F_{CH4}$ (e.g. Dengel et al., 2013; Morris et al., 2014; Knox et al., 2015; Rey-Sanchez et al., 2017; Knox et al., 2016), to our knowledge, Jørgensen et al. (2017) is the only other study that has gap-filled open-water $F_{CH4}$ measurements using ANN. Gap-filling with ANN gives non-linear weighted best estimates of $F_{CH4}$ in relation to the drivers for that time period. The ANN also enables us to characterize uncertainty by looking at the upper and lower confidence intervals of the ensemble models. This gives us a continuous time series of uncertainty integrated over the footprint of the EC system. In contrast, the uncertainty of survey-style methods often derives from spatial heterogeneity. The GRTS surveys are characterizing the lake-scale $F_{CH4}$ (and uncertainty) as a snapshot in time. Thus, upscaling these survey results temporally is a matter of gap-filling by linear interpolation.
While these methodological differences are noted, nevertheless Acton Lake’s annual $\text{F}_{\text{CH4}}$ is relatively high. It falls in the 4th quartile (60%) of the reservoir emission rates that included ebullition reported in Deemer et al. (2016); the warm season $\text{F}_{\text{CH4}}$ fell in the upper quartile (70%) of those reservoirs. Deemer et al. (2016) also discuss how methods matter in characterizing $\text{F}_{\text{CH4}}$ from mean rates. The main consideration is the importance of measuring ebullition. Deemer et al. found that the mean $\text{F}_{\text{CH4}}$ reported in studies measuring ebullition and diffusion was over double of diffusion-only $\text{F}_{\text{CH4}}$ studies. A secondary consideration is a method’s ability to capture spatial and temporal variability of $\text{F}_{\text{CH4}}$. Deemer et al. noted that studies using the eddy covariance method reported substantially higher values of mean $\text{F}_{\text{CH4}}$ (150 mg $\text{CH}_4$ m$^{-2}$ d$^{-1}$) (Dodson et al., 2014) and 225 mg $\text{CH}_4$ m$^{-2}$ d$^{-1}$ (Dupont et al., 2013), which are comparable to the Acton Lake annual $\text{F}_{\text{CH4}}$ values converted to daily mean fluxes, 83.4 and 147 mg $\text{CH}_4$ m$^{-2}$ d$^{-1}$ in 2017 and 2018, respectively. Two open water sites included in the Knox et al. (2019) analysis had mean annual $\text{F}_{\text{CH4}}$ of 15.4 mg $\text{CH}_4$ m$^{-2}$ d$^{-1}$ or 5.5 mg $\text{CH}_4$ m$^{-2}$ hr$^{-1}$. These sites are natural lakes in temperate regions. This difference in $\text{F}_{\text{CH4}}$ speaks to the need for building a representative dataset across both method and ecosystem.

The differences in $\text{F}_{\text{CH4}}$ between the different methods in 2017 versus 2018 (Table 2) illustrate how method matter in capturing hot spots and hot moments. In 2017, the warm-season $\text{F}_{\text{CH4}}$ measured by EC and the GRTS surveys are not significantly different, and $\text{F}_{\text{CH4}}$ measured at the AFT sites is within 10% of this value. This suggests that the GRTS survey adequately captured hot spots and emissions and did not underrepresent hot moments. In 2018, by contrast, the warm-season $\text{F}_{\text{CH4}}$ measured by EC is 3% larger than the GRTS survey results, and more than double what was measured at the AFT site. Using a literature model to estimate $\text{F}_{\text{CH4}}$ also yields estimates that agree relatively well with 2017 EC results, but not 2018: 11.1 and 10.3 mg $\text{CH}_4$ m$^{-2}$ d$^{-1}$, respectively (DaSilva et al., 2018). This reflects the limitations in the datasets used to train the model: the model uses chlorophyll levels to predict $\text{F}_{\text{CH4}}$. Mean chlorophyll levels were higher in 2017 than 2018 for Acton Lake, but as we have here, the timing of the elevated chlorophyll levels was key in how that input translated to $\text{F}_{\text{CH4}}$. The differences in uncertainty between the methods should also be noted. While we report a larger uncertainty range for the GRTS survey results than either the EC results or the AFTs and chambers (Table 2, Fig. 9), the GRTS uncertainty is the only one that encompasses the whole lake.

Integrating spatially over the 2.4 km$^2$ surface area of the lake, these results suggest Acton Lake emits 111–155 Mg $\text{CH}_4$ yr$^{-1}$. This loss of mineral carbon CH4 is non trivial term in the reservoir C budget, constituting 76% (range 41%–123%) of Acton Lake’s annual C retention over 2007 and 2008 reported in Knoll et al. (2013). The Knoll study did not measure $\text{F}_{\text{CH4}}$ and thus did not include it in their budget. They did include losses of C via CO2 which tended to be much smaller in magnitude than $\text{CH}_4$ emissions: 7 and 56 Mg C yr$^{-1}$ in 2007 and 2008, respectively, compared to 83 and 116 Mg C yr$^{-1}$.

5. Conclusions

In this study we investigated temporal patterns and biophysical drivers of $\text{CH}_4$ fluxes from a eutrophic temperate reservoir using multiple methods including eddy covariance. Sediment temperature and the overlying static pressure were the most important biophysical drivers of $\text{F}_{\text{CH4}}$ per the ANN model results. Water chemistry and chla measurements indicate that the spring burst of elevated $\text{F}_{\text{CH4}}$ coincided with a phytoplankton bloom. Comparing the two observation years indicated that the climatic conditions of precipitation and temperature were more conducive to a phytoplankton bloom in 2018 than 2017. Precipitation patterns were found to be important because of how inflow affected both sediment temperature and algal biomass.
In contrast to previous studies, we saw a weak positive correlation between \( F_{\text{CH}_4} \) and reservoir depth, but did not find a strong relationship between \( F_{\text{CH}_4} \) and underwater turbulence, nor did we observe consistent diurnal patterns in \( F_{\text{CH}_4} \).

We found that the study system, Acton Lake, had cumulative annual \( \text{CH}_4 \) areal emissions of \( 45.6 \pm 8.3 \) and \( 51.4 \pm 4.2 \) g \( \text{CH}_4 \) \( \text{m}^2 \) in 2017 and 2018, respectively. These levels of emissions place Acton Lake in the upper quartile of emission rates reported from reservoirs (Deemer et al., 2016), further supporting the concept that system productivity is a more important factor than latitude in predicting \( \text{CH}_4 \) emission rates (Del Sontro et al., 2018). A spring burst of \( F_{\text{CH}_4} \) observed over a two-week period in 2018 but not 2017 accounted for 59% of the difference in cumulative emissions between years. This difference between consecutive years highlights the importance of multi-year studies (c.f. Room et al., 2014), and the importance of characterizing temporal variability in open water systems, which Williamson et al. (2020) illustrated exceeded spatial variability for several physical, chemical, and biological metrics.

The EC technique holds much promise for improving our understanding of the biophysical drivers of gaseous fluxes, with a few caveats. In addition to the pseudo-continuous temporal coverage, the EC measurement footprint encompasses a much larger area than traditional gas flux measurement techniques (e.g. dissolved gas sampling, chambers, inverted funnel traps), increasing the likelihood of integrating fluxes over a distribution of hot spots. However, care must be taken in the siting, quality control, and interpretation of results. The authors reemphasize the recommendation given by Vesala et al., (2012): for best results, close collaboration is needed between biometeorologists and limnologists, to understand what is going on both above and below the water. For future studies of reservoir \( F_{\text{CH}_4} \) using EC, we recommend siting the monitoring tower in the area of the reservoir with the highest variability in \( \text{CH}_4 \) emissions, likely near the inlet, and setting up multiple AFTs across the reach of the reservoir to constrain spatial patterns. Future studies that incorporate more direct measurements of phytoplankton dynamics would also be useful to improve our understanding of drivers of \( \text{CH}_4 \) production and emission that may be more common with future warmer springs and extremes in precipitation patterns.

The EC results in this study further our understanding of the interaction between precipitation, sediment temperature, algal productivity levels, and \( F_{\text{CH}_4} \). This study adds to our understanding of open water flux processes at appropriate spatial and temporal scales, while highlighting a way to present and compare EC and whole reservoir lake survey data in appropriate contexts.

**Code and Data Availability**

The datasets and R code used for the analysis in this study are available on Zenodo. The raw data and R code are available under: R Code for: Temporal patterns and biophysical controls on methane emissions from a small eutrophic reservoir: insights from two years of eddy covariance monitoring, doi: 10.5281/zenodo.4540271; and supplemental ANN resampling data is available under: Artificial Neural Network (ANN) Resampling Results for Gap Filling Eddy Covariance Data, doi: 10.5281/zenodo.4540271.
Author Contributions

1. S. Waldo: conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, visualization, writing – original draft, writing – review & editing
2. J.J. Beaulieu: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, writing – review & editing
3. W. Barnett: formal analysis, methodology, software, writing – review & editing
4. D.A. Balz: conceptualization, data curation, investigation, methodology, project administration, resources, supervision
5. M.J. Vanni: data curation, formal analysis, investigation, resources, writing – review & editing
6. T. Williamson: data curation, formal analysis, investigation, resources
7. J.T. Walker: conceptualization, funding acquisition, investigation, methodology, project administration, resources, supervision, writing – review & editing

Disclaimer

The views expressed in this article are those of the authors and do not necessarily reflect the views and policies of the US Environmental Protection Agency. Any mention of trade names, manufacturers or products does not imply an endorsement by the United States Government or the US Environmental Protection Agency. EPA and its employees do not endorse any commercial products, services, or enterprises.

Acknowledgements

We thank David Wesler and other personnel at Hueston Wood State Park for all of their support in our monitoring efforts at Acton Lake. We are very grateful to the members of the EPA Scientific Dive Unit for their assistance in installing the mid-lake tower: Steve Donahue, Brad White, Frank Borsuk, David Light, Nathan Doyle, and Leah Ettema. We also thank Gil Bohrer and Jorge Villa for their guidance and assistance with the mid-lake tower. We thank Ryan Daly, Bill Mitchell, and Garrett Wiley for assistance with design and fabrication of tower hardware and power systems. We are grateful for the additional laboratory and field support provided by Karen White, Paul Trygstad, Eleanor Silver, Megan Berberich, Keith Bisbe, Aiden Pemberton, Page Jordan, and Tom Radford. We acknowledge that Acton Lake is located within the traditional homelands of the Myaamia and Shawnee people, who along with other indigenous groups ceded these lands to the United States in the first Treaty of Greenville in 1795.
References


Grasset, C., Mendonça, R., Villamor Sucedo, G., Bastviken, D., Roland, F., & Sobek, S. (2018). Large but variable methane production in anoxic freshwater sediment upon addition of allochthonous and autochthonous organic matter:


Table 1: Measurement methods summary

<table>
<thead>
<tr>
<th>Method</th>
<th>Flux Measured</th>
<th>Spatial Coverage</th>
<th>Frequency</th>
<th>Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eddy Covariance (EC)</td>
<td>total net</td>
<td>~100s m², north sector of the lake</td>
<td>pseudo-continuous, 30-min timestep</td>
<td>• annual budgets</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• diurnal patterns</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• biophysical drivers: ANN, Q10, 2DKS</td>
</tr>
<tr>
<td>Active Funnel Traps (AFT)</td>
<td>ebullition</td>
<td>0.3 m², two locations</td>
<td>pseudo-continuous, 30-min timestep</td>
<td>• annual budgets</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• diurnal patterns</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• biophysical drivers: Q10, 2DKS</td>
</tr>
<tr>
<td>Flux Chamber</td>
<td>diffusion</td>
<td>0.2 m² per site</td>
<td>2 sites bi-weekly, 15 sites sampled during 6 GRTS surveys</td>
<td>• annual budgets</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• emission pathway</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>relative importance</td>
</tr>
<tr>
<td>Passive Funnel Traps</td>
<td>ebullition</td>
<td>0.3 m²</td>
<td>15 sites sampled during 6 GRTS surveys</td>
<td>• annual budgets</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• spatial patterns</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• emission pathway</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>relative importance</td>
</tr>
</tbody>
</table>
Table 2: Seasonal methane fluxes reported as mean fluxes and cumulative areal emissions from Acton Lake characterized by different measurement techniques. The eddy covariance method measures total (diffusive + ebullitive + other) fluxes.

<table>
<thead>
<tr>
<th>Observation Type</th>
<th>Warm Season(^1) Mean Flux (mg CH(_4) m(^{-2}) hr(^{-1}))</th>
<th>Cumulative Annual Emissions (g CH(_4) m(^{-2}))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Diffusive</td>
<td>Ebullitive</td>
</tr>
<tr>
<td>2017</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eddy Covariance</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Shallow Site</td>
<td>3.2</td>
<td>4.47 ± 0.63</td>
</tr>
<tr>
<td>Deep Site</td>
<td>0.89</td>
<td>5.76 ± 0.54</td>
</tr>
<tr>
<td>Lake Surveys</td>
<td>1.28 ± 0.52</td>
<td>8.71 ± 6.1</td>
</tr>
<tr>
<td>Hybrid Upscaled</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>2018</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eddy Covariance</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Shallow Site</td>
<td>3.55</td>
<td>5.68 ± 0.11</td>
</tr>
<tr>
<td>Deep Site</td>
<td>0.96</td>
<td>6.65 ± 0.05</td>
</tr>
<tr>
<td>Lake Surveys</td>
<td>1.87 ± 1.2</td>
<td>11.1 ± 6.1</td>
</tr>
<tr>
<td>Hybrid Upscaled</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

\(^1\)“Warm Season” is defined as 1 May - 30 September

Table 3: Dissolved nutrient and carbon data for the inflow and outflow
Table 43: Summary statistics describing the relationship between FCH4 and sediment temperature per the ecoQ10 analysis and the two-dimensional Kolmogov-Smirnov test (2DKS) threshold analysis

<table>
<thead>
<tr>
<th></th>
<th>Eddy Covariance</th>
<th>AFT Shallow</th>
<th>AFT Deep</th>
</tr>
</thead>
<tbody>
<tr>
<td>ecoQ10 2017 value</td>
<td>6.96</td>
<td>35.1</td>
<td>30.4</td>
</tr>
<tr>
<td>ecoQ10 2017 R²</td>
<td>0.85</td>
<td>0.48</td>
<td>0.60</td>
</tr>
<tr>
<td>ecoQ10 2018 value</td>
<td>5.64</td>
<td>35.8</td>
<td>30.7</td>
</tr>
<tr>
<td>ecoQ10 2018 R²</td>
<td>0.83</td>
<td>0.85</td>
<td>0.38</td>
</tr>
<tr>
<td>2017 sedT threshold</td>
<td>14.1</td>
<td>22.2</td>
<td>17.9</td>
</tr>
<tr>
<td>2017 test statistic</td>
<td>0.226</td>
<td>0.166</td>
<td>0.204</td>
</tr>
<tr>
<td>2018 sedT threshold</td>
<td>17.4</td>
<td>23.0</td>
<td>13.3</td>
</tr>
<tr>
<td>2018 test statistic</td>
<td>0.234</td>
<td>0.190</td>
<td>0.138</td>
</tr>
</tbody>
</table>

Table 44: Seasonal methane fluxes reported as mean fluxes and cumulative areal emissions from Acton Lake characterized by different measurement techniques. The eddy covariance method measures total (diffusive + ebullitive + other) fluxes.
Figure 1: Map of Acton Lake (a), showing the location of multiple monitoring methods: eddy covariance flux tower sites (red circles), active funnel traps and bi-weekly chamber measurements (dark blue squares), and spatially extensive survey sites (light blue circles), and the weather station and thermistors operated by Miami University (purple triangles). The lake contour lines represent ~ 1m depth increments. Inset image shows the location of Acton Lake in southwest Ohio. The Google Earth image (b) shows the 80% cumulative footprint probability distribution at each eddy covariance flux tower site at 10% intervals.
Figure 2: Time series of $F_{\text{CH}_4}$ monitored via multiple methods: eddy covariance (panel violet), the sum of the shallow AFT and interpolated chamber measurements (blue, panel b, site U-14), and the sum of the deep AFT and interpolated chamber measurements (green, panel c, site U-12), and via the spatially integrated lake-wide surveys (yellow, panel d). Black circles are observed fluxes, and red traces show the daily mean (sum of ebullition and interpolated chamber diffusion measurements for panels b) and c). The error bars for the lake surveys in panel d.
indicate the 95% confidence interval of the mean. Error margins for the other measurements are omitted for figure legibility. The Vertical grey bars indicate the 2018 spring burst period was 24 May - 4 June 2018.

Figure 3: Median variable importance ranking for the drivers of the artificial neural network gap-filling model in terms of percent importance to the predictive power of the model. This ranking is based both on intra-model variability (i.e., the effect of model architecture and random seed selection) and on inter-model variability (i.e., the effect of data selection for the training, testing, and validation datasets). DOY = day of year; Delta static P is change in overlying static pressure; Sed T is sediment temperature; LE is latent heat flux; Static P is static pressure; Wind Dir is wind direction; H is sensible heat flux; u Star is friction velocity; PAR is photosynthetically active radiation; HOD is hour of day.
Figure 42: Meteorological and limnological conditions over the study period: (a) daily mean of air (red) and sediment (black) temperature; (b) daily mean latent and sensible heat fluxes (LE, black, and H, red, respectively); (c) daily cumulative precipitation (mm); (d) stream inflow (m³ s⁻¹); (e) water depth in the footprint of the flux tower (m); (f) Brunt Väisälä frequency, a measure of water column mixing potential (s⁻¹); and (g) the water temperature profile at the deep site (U-12). Grey bars indicate the time frame of the 2018 spring burst of CH₄ emissions.
Figure 4: $F_{CH4}$ measured by EC (top), the shallow AFT (middle) and the deep AFT (bottom) in 2017 and 2018 as a function of sedT. The panel (a) shows linear regressions of log-transformed $F_{CH4}$ vs sedT to determine the ecoQ10 (Table 3). The panel (b) shows the threshold values for $F_{CH4}$ as a function of sedT; the dotted lines are the x- and y-breakpoints determined via two-
Figure 5: Cumulative areal emissions in 2017 and 2018 from EC, sum of AFT and chamber, and spatial survey monitoring, and hybrid upscaling results (g CH$_4$ m$^{-2}$). Vertical lines intersecting the Lake Survey trace represent the 95% confidence interval of the lake-wide FCH$_4$ estimate.
Figure 65: Total (ebullitive + diffusive) F\textsubscript{CH4} measured during mid-summer, late-summer, and fall spatial surveys at Acton Lake during 2017 (top row) and 2018 (bottom row). Dots indicate magnitude of F\textsubscript{CH4} per the z-axis scale and vertical black lines connect red dots to their corresponding sampling location. Dot color indicates whether a sampling site is in the shallow (< 3 m, lavender) or deep (> 3 m, royal purple) area of the reservoir.

Figure 7: Daily air and sediment temperature (a, left) and chlorophyll a (an indicator for algal biomass, b, right) in 2017 and 2018. The grey bar indicates the spring burst period of elevated F\textsubscript{CH4} in 2018, likely supported by elevated sediment temperature and algal biomass levels that year.
Figure 6: Linear regression of the spatial survey $\text{CH}_4$ ebullition results ($n=90$, measured with PFTs) as a function of water depth at the site. $R^2 = 0.1, p<0.005$.

Figure 7: Mean, interquartile range, and standard deviation of the fraction of ebullitive $\text{F}_\text{CH}_4$ to total $\text{F}_\text{CH}_4$ at each of the survey sites ($n=6$ at each site). Sites U-06 and U-09 are near the swimming beach and have sandy sediments. Site U-14 is in the EC flux tower footprint.
Figure 8: Median variable importance ranking for the drivers of the artificial neural network gap-filling model in terms of percent importance to the predictive power of the model. This ranking is based on both intra-model variability (i.e., the effect of model architecture and random seed selection) and inter-model variability (i.e., the effect of data selection for the training, testing, and validation datasets). DOY = day of year; Delta Static P is change in overlying static pressure; Sed T is sediment temperature; LE is latent heat flux; Static P is static pressure; Wind Dir is wind direction; H is sensible heat flux; u Star is friction velocity; PAR is photosynthetically-active radiation; HOD is hour of day.
Figure 9: Cumulative areal emissions in 2017 and 2018 from EC, sum of AFT and chamber, and spatial survey monitoring results (g CH₄ m⁻²). Vertical lines intersecting the “GRTS Surveys” trace represent the 95% confidence interval of the lake-wide flux estimate from the GRTS surveys.
Figure S14: Time series of sedT and ebullition in 2017 at the shallow (a, U-14) and deep (b, U-12) sites. The light grey bar highlights the period of maximum ebullition and sedT at the shallow site; the dark grey bar highlights the corresponding period at the deep site.
Figure 11: Daily air and sediment temperature (a, left) and chlorophyll a (an indicator for algal biomass, b, right) in 2017 and 2018. The grey bar indicates the spring burst period of elevated FCH4 in 2018, likely supported by elevated sediment temperature and algal biomass levels that year.
Figure 12: Examples of strong diurnal patterns with $F_{CH4}$ peaking during the day (a, top) and at night (b, bottom). Blue dots connected with lines in a) and b) are individual 30-minute measurements of $F_{CH4}$. Grey boxes indicate period between local sunset and sunrise. The relative mean (line) and standard deviation (shaded region) of the bin-averaged 30-minute $F_{CH4}$ values for these periods are shown in c) and d). The biophysical driver of latent heat flux (LE, grey) is also plotted in c), and air pressure (air P, green) in d).