Estimates of reservoir methane emissions based on a spatially balanced probabilistic-survey

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Abstract

Global estimates of methane (CH₄) emissions from reservoirs are poorly constrained, partly due to the challenges of accounting for intra-reservoir spatial variability. Reservoir-scale emission rates are often estimated by extrapolating from measurements made at a few locations; however, error and bias associated with this approach can be large and difficult to quantify. Here, we use a generalized random tessellation survey (GRTS) design to generate unbiased estimates of reservoir-CH₄ emissions rates (±95% CI) for areas below tributary inflows, open-waters, and at the whole-reservoir scale. Total CH₄ emission rates (i.e., sum of ebullition and diffusive emissions) were 4.8 (±2.1), 33.0 (±10.7), and 8.3 (±2.2) mg CH₄ m⁻² h⁻¹ in open-waters, tributary-associated areas, and the whole-reservoir for the period in August 2014 during which 115 sites were sampled across an 7.98 km² reservoir in Southwestern, Ohio, U.S.A. Tributary areas occupy 12% of the reservoir surface, but were the source of 41% of total CH₄ emissions, highlighting the importance of riverine-lacustrine transition zones. Ebullition accounted for >90% of CH₄ emission at all spatial scales. Overall, CH₄ emission rates were high for a temperate zone reservoir, possibly because earlier studies underestimated ebullition or did not include emission hot spots. Confidence interval estimates that incorporated spatial pattern in CH₄ emissions were up to 29% narrower than when spatial independence is assumed among sites. The use of GRTS, or other probabilistic survey designs, can improve the accuracy and precision of reservoir emission rate estimates, which is needed to better constrain uncertainty in global scale emission estimates.

Methane (CH₄) is an important greenhouse gas accounting for approximately 40% of global radiative forcing due to anthropogenic activities (Stocker et al. 2013). Microbial degradation of organic matter in reservoirs is a significant source of CH₄ to the atmosphere, but estimates of the magnitude of this source are poorly constrained, ranging from 20 Tg CH₄ yr⁻¹ to 70 Tg CH₄ yr⁻¹ (St. Louis et al. 2000; Bastviken et al. 2011), partly due to the large range of CH₄ emission rates reported for reservoirs. Some of the variability in reported emission rates among systems can be attributed to differences in water temperature, reservoir age, and productivity (Barros et al. 2011; West et al. 2012), but another potentially large source of variability among studies is differences in how intra-reservoir spatial patterns in emission rates are assessed and incorporated into system-scale estimates. This source of variability is attributable to methodology, rather than true differences in emission rates, and therefore obscures spatial and temporal patterns in emission rates and adds uncertainty to emission rate estimates.

The factors that govern CH₄ production and emission from aquatic systems can lead to pronounced spatial patterns in CH₄ emission rates. Methane is produced in reservoirs from the degradation of organic matter under anoxic conditions, therefore one factor that governs CH₄ production rates is the quantity and quality of carbon delivered to the sediments (Sobek et al. 2012). Sediment deposition rates in reservoirs are often greatest in the transition zone between tributaries and open waters where water velocities rapidly decrease and suspended solids consequently settle (Thornton 1990). Also,
littoral zone sediments are frequently enriched in organic material from senesced macrophytes (Polunin 1984) and dam forebays can be sites of rapid sediment accumulation in run of the river reservoirs (Maeck et al. 2013), all of which can lead to localized areas of elevated CH$_4$ production.

An important mechanism for the transport of CH$_4$ from sediments to the atmosphere is ebullition. Ebullition occurs when biogenic gas production raises the total dissolved gas pressure in sediment pore water above the hydrostatic pressure, leading to the formation of sedimentary gas bubbles. These bubbles can be released from the sediments, typically following a physical perturbation (Joyce and Jewell 2003), and dissolve in the water column as they rise toward the water surface where the residual content of the bubble is released to the atmosphere. The degree of dissolution that occurs is positively related to water depth, therefore a larger fraction of the original bubble mass directly escapes to the atmosphere in shallow compared with deep waters, leading to higher emissions from shallow waters. Additional spatial patterns in CH$_4$ emission rates within reservoirs can result from large plumes of inflowing river water with low CH$_4$ content (Hofmann 2013), point source discharges from waste water treatment plants with high organic matter content (DelSontro et al. 2010; Gonzalez-Valencia et al. 2014), and in sediment cohesiveness that partially regulate the release of sedimentary gas bubbles (Joyce and Jewell 2003). Together, these spatial patterns in reservoir CH$_4$ emissions complicate efforts to generate system-scale estimates.

Estimating system-scale emission rates is problematic for two reasons. First, most investigations of reservoir CH$_4$ emissions include only 2–8 sampling sites per reservoir (Chen et al. 2011; Beaulieu et al. 2014; Gonzalez-Valencia et al. 2014; Musenze et al. 2014; Sturm et al. 2014), which can lead to large uncertainties in emission rate estimates. Recent advances in hydroacoustics (Ostrovsky et al. 2008; Maeck et al. 2013) and air-side CH$_4$ sensors (Grinham et al. 2011) can allow for higher sampling densities, but these approaches face several limitations that restrict their application including high detection limits and minimum water-depth requirements. Second, many studies that have detected spatial patterns have used judgment or convenience sampling to locate sites. How representative those samples are of the system is unknown and this can introduce a bias into estimates of reservoir emissions (Lohr 2010; Reynolds 2012).

Generating system-scale estimates of CH$_4$ emission rates for reservoirs is a problem that can be addressed using statistical survey designs. A key feature of a strong survey design is that the samples (i.e., sample sites) are representative of the population (i.e., whole-reservoir), so that population level estimates can be made with a known degree of accuracy (Lohr 2010). One approach for generating representative samples is probability sampling, in which each unit in the population has a known probability of selection and a randomization procedure is used to choose the specific sample units. A probability sampling approach that has been widely used to assess the status of lakes, estuaries, rivers, and streams in the United States (US Environmental Protection Agency 2009, 2012, 2013) is a generalized random tessellation survey design (GRTS) (Stevens and Olsen 2004; Olsen et al. 2012). An important feature of GRTS designs is that they are spatially balanced, meaning that the samples have a spatial distribution similar to that of the population, whereas random sampling designs can produce clusters of sample sites. GRTS designs can also utilize spatial patterns in the process of interest to generate estimates with less uncertainty than simpler survey designs (Stevens and Olsen 2003).

The focus of this study was William H. Harsha Lake (hereafter called Harsha Lake) located in southwest Ohio, U.S.A. Previous research has shown that total CH$_4$ emission rates (i.e., sum of ebullition and diffusive emissions) are up to 1000 times greater in areas below the largest tributary inflow than in open-water portions of the reservoir (Beaulieu et al. 2014), but this was based on measurements made at only six sites. The objective of this study was to generate a system-scale estimate of the mean ($\pm$95% confidence interval) diffusive, ebullitive, and total (i.e., diffusion + ebullition) CH$_4$ emission rate for the reservoir. To meet this objective we used a GRTS design. We modified the basic GRTS design to accommodate an “open-water” and “tributary” stratum, which allowed for comparison of emission rates between these areas of the reservoir.

Methods

Site description

The study was conducted at Harsha Lake, a monomictic reservoir located in Ohio, U.S.A. (Fig. 1). Harsha Lake was constructed in 1978 for flood control, water supply, recreation, and wildlife habitat. It has a surface area of 7.9 km$^2$, water storage capacity of $1.1 \times 10^8$ m$^3$, max depth of 32.8 m, and mean depth of 12.8 m at summer pool elevation. Harsha Lake drains an 882 km$^2$ watershed managed primarily for agriculture (63% cultivated crops and pasture) and is frequently on the state’s advisory list for recreational contact due to the abundance of harmful blue-green algae (http://epa.ohio.gov/habalgae.aspx).

Survey design

The sample frame for a GRTS design is a geographic information system (GIS) layer (Olsen et al. 2012). We used a polygon shapefile of Harsha Lake obtained from the high resolution National Hydrography Dataset (http://nhd.usgs.gov) with an Albers equal area projection. We partitioned the reservoir into “open-water” and “tributary” strata. The tributary stratum contained areas of the reservoir extending from the points where the 13 largest tributaries enter the reservoir out to a depth of 8 m (Fig. 1) and covered 0.97 km$^2$ of the reservoir surface (Table 1). The boundary between the open-water and tributary strata was based on previous work.
which indicated that emission rates rapidly decreased at depths > 8 m (Beaulieu et al. 2014). All other portions of the reservoir were included in the open-water stratum which covered 7.01 km² of reservoir surface. We allocated sample sites across the sample frame using a GRTS survey design. To ensure that the design included sample points in some of the smaller areas of the reservoir, such as the upstream tips of the tributary-associated areas, the open-water and tributary-associated strata were subdivided into 5 and 20 polygons, respectively. Using an unequal probability GRTS survey design, we specified the number of sample sites to be allocated to each polygon. Previous research indicated that CH₄ emission rates were more spatially variable below tributaries than in open-waters in Harsha Lake (Beaulieu et al. 2014), we therefore adopted a sample density that was 10-fold greater in the tributary than open-water stratum. The multiple constraints we placed on the design (i.e., allocation of sample points to many separate tributary areas, sample points along the length of the largest tributary areas, etc.) resulted in a survey that included 65 and 50 sites in the open-water and tributary strata, respectively (Fig. 1). The GRTS survey was designed using the spsurvey package (Kincaid and Olsen 2015) in the statistical software R (R Development Core Team 2015).

The GRTS algorithm in the spsurvey package imposes a series of nested grids across the sample frame (i.e., reservoir surface area) which are used to map two-dimensional space into one-dimensional space. Sample sites are then allocated to a subset of these grids using a hierarchical randomization process which ensures a spatially well-balanced sample. The probability that a sample will be located in a specific grid cell is proportional to the area of the resource contained

Fig. 1. William H Harsha Lake (Harsha Lake), tributaries, outlet, and sampling sites. Colors differentiate the open-water and tributary strata. Sample sites were allocated to the polygons within each stratum using an unequal probability GRTS survey design. Letters identify the 13 areas below tributary inputs that were sampled.
Table 1. Watershed drainage area and reservoir surface area associated with the 13 largest tributaries draining into Harsha Lake. Tributary labels correspond to the site map in Fig. 1.

| Tributary | Surface area (km²) | Drainage area (km²) |
|-----------|--------------------|---------------------|
| A         | 0.47               | 665.0               |
| B         | 0.30               | 110.6              |
| C         | 0.13               | 65.0               |
| D         | 0.003              | 10.0               |
| E         | 0.010              | 9.1                |
| F         | 0.007              | 5.2                |
| G         | 0.009              | 3.5                |
| H         | 0.024              | 3.1                |
| I         | 0.003              | 2.6                |
| J         | 0.011              | 2.6                |
| K         | 0.002              | 2.0                |
| L         | 0.002              | 2.0                |
| M         | 0.007              | 1.0                |

within the cell. The specific location of a sample point within a cell is determined by selecting random x and y-coordinates while ensuring the coordinates fall within the resource (i.e., within the reservoir). The result is a spatially balanced probabilistic survey design. Consult Olsen et al. (2012), Stevens and Olsen (2004), and Kincaid and Olsen (2015) for a detailed description of the GRTS algorithm.

Methane and CO₂ emission rates, dissolved CO₂, dissolved CH₄, dissolved oxygen, alkalinity, pH, specific conductivity, water temperature, barometric pressure, and air temperature were measured once at each site between 18 August 2014 and 27 August 2014. Chlorophyll a (Chl a) samples were collected from one tributary and five open-water sites on 12 August 2014 and 02 September 2014.

Water sample collection

Samples for dissolved CH₄ analysis were collected in 160 mL glass infusion bottles. The infusion bottles were prepared in the laboratory by first adding 130 µL of a saturated mercuric chloride solution to the bottles, capping the bottles with gray butyl septa and aluminum crimps, and alternately evacuating to 6.6 Pa and filling with ultra-high purity dinitrogen (UHP N₂) to 101.3 kPa (101.3 kPa = 1 atm). After the third evacuation, 40 mL of UHP N₂ was added to each bottle.

Water samples were collected in the field by suspending the bottle below the water surface, puncturing the septa with a 27 gauge needle and allowing the vacuum in the bottle to draw water through the needle until the headspace pressure in the bottle was equal to the hydrostatic pressure at the needle inlet. The needle was removed underwater and the sample bottle stored in an opaque box during transport to the laboratory.

Within 10 d of collection, the infusion bottles were placed on a shaker table for 1 h to equilibrate the gases between the aqueous and gas phase. Immediately after the headspace equilibration, the septa was punctured with a 27 gauge needle connected to a two-way stopcock and 60 mL syringe. The syringe plunger was withdrawn to 40 mL, the stopcock closed, and the plunger allowed to relax until the pressure in the syringe was equal to that of the lab atmosphere, typically resulting in a 25 mL gas sample at approximately 101.3 kPa (101.3 kPa = 1 atm) pressure. Twenty milliliters of the sample was then transferred to a pre-evacuated (<6.6 Pa) 12 mL glass vial capped with a teflon backed silicon septa stacked on top of a chlorobutyl septa (order code 736W, Labco Ltd, UK) for analysis. Gas samples were analyzed for CH₄ partial pressure ($P_{CH_4}$) using a gas chromatograph (Bruker 450, Massachusetts, U.S.A.) equipped with an autosampler (PAL LH-xt, CTC Analytics, Switzerland) and flame ionization detector. The dissolved CH₄ concentration in the original water sample was calculated from the Bunsen solubility coefficient at the temperature of the headspace equilibration and a mass-balance for the headspace equilibration system.

The mercuric chloride preservative depressed the pH of the water sample in the infusion bottles, therefore dissolved CO₂ in the reservoir could not be determined from the headspace equilibration. We calculated dissolved CO₂ from alkalinity, water temperature, pH, and specific conductivity using the seacarb package (Gattuso et al. 2015) in R.

Alkalinity was measured on unfiltered water samples using the titration method and Chl a was measured via the spectrophotometric method following acetone extraction (APHA 2012). We measured pH, water temperature, dissolved oxygen, and specific conductivity using a data sonde (YSI 6600, Yellow Springs, Ohio, U.S.A.). Air temperature was measured using an alcohol thermometer and pressure was measured using a barometer (YSI MDS, Yellow Springs, Ohio, U.S.A.).

Emission rate measurements

We measured CO₂ and CH₄ emission rates using 20 L floating acrylic chambers tethered to a drifting boat via a 1 m long boom. The chamber headspace was recirculated through a portable CH₄ and CO₂ analyzer (Ultraportable Greenhouse Gas Analyzer, Los Gatos Research, Los Gatos, Colorado, U.S.A.) carried on-board the boat and powered with a 12 V battery. The analyzer measures CO₂ and CH₄ partial pressures ($P_{CO_2}$ and $P_{CH_4}$, respectively) at 1 Hz using off-axis integrated cavity output spectroscopy. To minimize analytical noise, we averaged partial pressure measurements made at a frequency of 1 Hz for 20 s before recording a value. The chamber was deployed for 5 min at each site, resulting in 15 recorded partial pressure values per deployment.

We calculated diffusive CO₂ and CH₄ emissions, and when possible, CH₄ ebullition. Methane ebullition was apparent as an abrupt $P_{CH_4}$ increase in the chamber headspace, whereas diffusive emissions caused $P_{CH_4}$ and $P_{CO_2}$ to change at a relatively constant rate (Supporting Information Fig. S1). Diffusive emission rates ($E_{gas,t0}$) were calculated from a
minimum of five partial pressure measurements recorded prior to ebullition following:

\[ E_{\text{gas},D} = \frac{dP_{\text{gas}}}{dt} \left( \frac{V}{A} \right) \left( \frac{P}{RT} \right) \]  

(1)

where \( \frac{dP_{\text{gas}}}{dt} \) is the rate of change of \( P_{\text{CH}_4} \) or \( P_{\text{CO}_2} \) in the chamber headspace, \( V \) is the chamber volume, \( A \) is the area of the chamber opening, \( P \) is the pressure in the chamber headspace, \( R \) is the universal gas constant, and \( T \) is temperature in the chamber headspace. The rate of change of \( P_{\text{gas}} \) in the chamber headspace was calculated using simple linear regression and a non-linear model. Linear models underestimate \( \frac{dP_{\text{gas}}}{dt} \) at \( t = 0 \) when the rate of change of \( P_{\text{gas}} \) decreases during the deployment, which can occur in response to the lessening of the concentration gradient between the headspace and the water body during the deployment. The non-linear model took the form:

\[ P_{\text{gas},t} = P_{\text{gas},\text{max}} - \left( P_{\text{gas},\text{max}} - P_{\text{gas},0} \right) \exp\left( -\frac{t}{K} \right) \]  

(2)

where \( P_{\text{gas},t} \) and \( P_{\text{gas},0} \) are \( P_{\text{CH}_4} \) or \( P_{\text{CO}_2} \) at time \( t \) and time \( 0 \), respectively, \( P_{\text{gas},\text{max}} \) is the maximum \( P_{\text{CH}_4} \) or \( P_{\text{CO}_2} \) observed during the deployment, and \( K \) is a rate constant (Demello and Hines 1994; Stolk et al. 2009). These terms are regression parameters that were estimated using non-linear curve fitting procedures in the minpackIm library (Elzhov et al. 2013) in the statistical software R. The regression parameters were used to calculate the rate of change of \( P_{\text{gas}} \) at \( t = 0 \) following:

\[ \frac{dP_{\text{gas}}}{dt} = K \left( P_{\text{gas},\text{max}} - P_{\text{gas},0} \right) \]  

(3)

Akaike information criterion (AIC) was used to determine whether the linear or non-linear model best described the data and only models with an \( r^2 > 0.9 \) were retained.

When fewer than five \( P_{\text{CH}_4} \) measurements were recorded prior to a \( \text{CH}_4 \) ebullition event, or the \( \text{CH}_4 \) model had an \( r^2 < 0.9 \), \( E_{\text{CH}_4,D} \) was calculated from the measured dissolved \( \text{CH}_4 \) concentration and an estimated \( \text{CH}_4 \) gas transfer velocity (\( k_{\text{CH}_4} \)):

\[ E_{\text{CH}_4,D} = k_{\text{CH}_4} \left( C_{\text{CH}_4,\text{w}} - C_{\text{CH}_4,\text{eq}} \right) \]  

(4)

where \( C_{\text{CH}_4,\text{w}} \) is the measured \( \text{CH}_4 \) concentration in the water (see below) and \( C_{\text{CH}_4,\text{eq}} \) is the concentration of \( \text{CH}_4 \) in the surface water at equilibrium with the atmosphere (Wanninkhof et al. 2009). The equilibrium dissolved \( \text{CH}_4 \) concentration was calculated from the \( \text{CH}_4 \) partial pressure in the atmosphere (assuming 100% humidity) and the temperature specific Bunsen solubility coefficient (Colt 2012). The \( \text{CH}_4 \) gas transfer velocity was calculated one of two ways. In the first approach, \( k_{\text{CH}_4} \) was estimated from \( k_{\text{CO}_2} \), which was calculated by rearranging Eq. 4 and substituting \( \text{CO}_2 \) for \( \text{CH}_4 \).

This approach was employed when the chamber data allowed for the calculation of \( E_{\text{CO}_2,D} \) and the water pH < 8.5. At high pH, \( k_{\text{CO}_2} \) is enhanced relative to \( k_{\text{CH}_4} \) by the reaction of \( \text{CO}_2 \) with hydroxide, which maintains a steeper \( \text{CO}_2 \) concentration profile at the air–water interface (Schindler et al. 1972; Bade and Cole 2006; Wanninkhof et al. 2009). The \( \text{CH}_4 \) gas transfer velocity was calculated from \( k_{\text{CO}_2} \) according to:

\[ k_{\text{CH}_4} = k_{\text{CO}_2} \left( \frac{S_{\text{CH}_4}}{S_{\text{CO}_2}} \right)^{-0.5} \]  

(5)

where \( S_c \) is the Schmidt number for \( \text{CH}_4 \) (\( S_{\text{CH}_4} \)) and \( \text{CO}_2 \) (\( S_{\text{CO}_2} \)) (Wanninkhof et al. 2009). Schmidt numbers were calculated following Wanninkhof (1992). If \( E_{\text{CO}_2,D} \) could not be calculated or the water pH > 8.5, \( k_{\text{CH}_4} \) was assumed to be equal to the average of the \( k_{\text{CH}_4} \) values measured at the 2–3 closest sites on the same day.

The total \( \text{CH}_4 \) emission rate (\( E_{\text{CH}_4,T} \)) represents the sum of the ebullitive (\( E_{\text{CH}_4,E} \)) and diffusive (\( E_{\text{CH}_4,D} \)) emission rates. In the instances where no ebullition was observed, \( E_{\text{CH}_4,T} \) was equal to \( E_{\text{CH}_4,D} \). When ebullition was observed, however, \( E_{\text{CH}_4,T} \) was calculated from the difference between the initial and final \( P_{\text{CH}_4} \) measurement. The ebullition rate was calculated as the difference between \( E_{\text{CH}_4,T} \) and \( E_{\text{CH}_4,D} \).

Data analysis

We calculated population level estimates of the mean \( E_{\text{CH}_4,T} \), \( E_{\text{CH}_4,E} \), and \( E_{\text{CH}_4,D} \) at the stratum (i.e., open-water, tributary) and whole-reservoir scale using an approach based on the Horvitz–Thompson theorem as described in Stevens and Olsen (2003). Population level estimates of variance (i.e., 95% confidence interval) were calculated using the local neighborhood variance estimator (95% CI_LS) (Stevens and Olsen 2003) and the Horvitz–Thompson variance estimator, which is based on the assumption of independent random sampling (95% CI_RS). The local neighborhood variance estimator is designed for surveys conducted over space as it can incorporate spatial patterns of the data thereby producing narrower confidence limits than other variance estimators (Stevens and Olsen 2003). Differences in emission rates between the open-water and tributary strata were determined to be statistically significant if the population mean ± 95% CI_LS did not overlap. Population level estimates were made using the spsurvey package (Kincaid and Olsen 2015) in R.

We calculated extent estimates of the proportion of the three spatial areas (e.g., open-water, tributary, and whole-reservoir) that supported ebullition. The analysis was based on whether or not ebullition was observed at each site (i.e., coded as True or False) and was executed using the cat.analysis function in spsurvey package.

To detect spatial patterns in \( \text{CH}_4 \) ebullition, we created Thiessen polygons around the sample sites, clipped those...
polygons to the contour of the lake, and used the polygons to define neighborhoods around the sampling sites based on rook-style contiguity (Bivand et al. 2008). We used a join count statistic to determine if the presence or absence of ebullition in the polygons exhibited spatial autocorrelation (de Smith et al. 2013).

To determine whether differences in CH₄ emission rates between strata could be explained by depth, or whether factors other than depth played a role, we used a generalized least squares model to compare CH₄ emission rates measured at similar depths in the two stratum. We only used observations made at sites with water depths that were represented in both strata, therefore all sites < 1 m (i.e., sites < 1 m deep occurred exclusively in the tributary stratum) and > 4 m (i.e., sites > 4 m deep occurred predominantly in the open-water stratum) in depth were excluded from the analysis. The analysis was done using the nlme package (Pinheiro et al. 2011) in R.

To examine the relationship between sampling effort and population estimates of the total CH₄ emission rate, we calculated the mean and 95% CILN using subsets of the survey data. Each sample subset was created by selecting the first “n” and “m” points from the list of open-water and tributary sites used in the full survey, respectively. Each sample subset created in this manner represents a spatially balanced probabilistic survey design. Each sample subset had the same ratio of open-water to tributary sites (65: 50) used in the full survey.

Results
Dissolved gases and water chemistry

Dissolved CH₄ was supersaturated at all sites (range: 139–3117% saturation) and concentrations ranged from 0.14–3.1 μM in the open-water stratum and 0.31–2.9 μM in the tributary stratum (Table 2). Carbon dioxide was undersaturated at all open-water sites (range: 8–54% saturation, 0.9–5.8 μM), but was more variable in the tributary-area stratum with concentrations ranging from 0.8 μM to 129 μM (7.5–11,470% saturation; median = 129% saturation). All sites in the open-water stratum had a pH in excess of 8.8 (range: 8.8–9.4), while lower pH values were observed at some sites in the tributary-area stratum (range: 7.5–9.4). Alkalinity ranged from 82 to 144 mg CaCO₃ (mean: 96 mg CaCO₃), and was very similar among strata. Dissolved oxygen saturation ranged from 51% to 166% (3.4–10.5 mg L⁻¹) across the reservoir and tended to be higher in the open-water (mean: 128%) than tributary-area (mean: 104%) stratum. The mean surface water temperature was 27.3°C and was very similar among strata. Mean Chl a was 26 μg L⁻¹ and 20 μg L⁻¹ on 12 August 2014 and 02 September 2014, respectively.

Emission rates

Linear and non-linear models were fit to the 86 chamber deployments where five or more P_CH₄ measurements were recorded prior to ebullition. Forty five of these 86 P_CH₄ profiles were best described by the non-linear model, according to AIC, and the others were best described by the linear model. Only two of the models had an r² value < 0.90 (0.80 and 0.89) and the mean r² of the best model was 0.98.

In 29 of the 115 chamber deployments, four or fewer P_CH₄ measurements were recorded prior to rising bubbles emerging into the chamber headspace. Since we required five or more P_CH₄ measurements to calculate diffusive emissions (see “Emission rate measurements” section) from the chamber deployments, E_CH₄,D was calculated using an alternative method. In six of these instances, E_CH₄,D was estimated from K_CO₂ and the dissolved CH₄ concentration. All six chamber P_CO₂ profiles used to calculate K_CO₂ had r² values > 0.93. In the remaining 23 sites, plus the two sites where the model fit to the P_CH₄ data had an r² < 0.9, E_CH₄,D was estimated from K_CH₄ measured at nearby sites.

Diffusive CH₄ emission rates were more variable in the tributary-areas (range (sd): 0.07–6.18 (1.38) mg CH₄ m⁻² h⁻¹; Fig. 2A) than open-water areas (range (sd): 0.03–2.18 (0.43) mg CH₄ m⁻² h⁻¹). The population mean E_CH₄,D (±95% CI_LN) was 0.47 (±0.16), 1.61 (±0.95), and 0.60 (±0.25) mg CH₄ m⁻² h⁻¹ in the open-water, tributary, and whole-reservoir areas, respectively (Table 3). The tributary-areas were the source of 22% of diffusive emissions at the reservoir scale.

There was significant positive spatial autocorrelation in the presence or absence of ebullition across the 115 sites.

Table 2. Mean, range, and standard deviation (SD) of dissolved methane (CH₄), dissolved carbon dioxide (CO₂), pH, alkalinity, dissolved oxygen (DO), and water temperature at the study sites.
Sites that had ebullition were more likely to have neighboring sites with ebullition than predicted by chance alone (Join count $= 25.1$, $p < 0.0001$) and sites without ebullition were more likely to have neighboring sites without ebullition than predicted by chance alone (Join count $= 13.6$, $p < 0.0001$). The population extent estimate ($\pm 95\%$ CI) for the occurrence of ebullition was 47% ($\pm 9$), 84% ($\pm 9$), and 51% ($\pm 9$) for the open-water, tributary, and reservoir areas, respectively. Ebullition rates ranged from 0–136.1 mg CH$_4$ m$^{-2}$ h$^{-1}$ in the open-water areas and 0–186.1 mg CH$_4$ m$^{-2}$ h$^{-1}$ in the tributary areas. Ebullition rates were highly variable at sites < 10 m deep (range: 0–186.1 mg CH$_4$ m$^{-2}$ h$^{-1}$), although the highest rates (i.e., those in the upper 15th percentile of the distribution) were strictly limited to these shallow waters (Fig. 4A). Overall, ebullition rates were weakly correlated with water depth (Spearman’s $\rho = -0.15$). The population mean $E_{\text{CH}_4,E}$ $\pm 95\%$ CI was 4.4 $\pm 2.1$, 31.4 $\pm 10.8$, and 7.7 $\pm 2.2$ mg CH$_4$ m$^{-2}$ h$^{-1}$ in the open-water, tributary areas, and reservoir strata, respectively (Table 3). The tributary-areas were the source of 43% of the ebullitive CH$_4$ emissions at the reservoir scale.

Total CH$_4$ emissions reflect the sum of diffusive emissions and ebullition (Fig. 2). The population mean $E_{\text{CH}_4,T}$ $\pm 95\%$ CI was 4.8 $\pm 2.1$, 33.0 $\pm 10.7$, and 8.3 $\pm 2.2$ mg CH$_4$ m$^{-2}$ h$^{-1}$ in the open-water, tributary, and reservoir areas, respectively (Table 3). The gls model indicated that $E_{\text{CH}_4,T}$ at 1–4 m depths was greater in the tributary than open-water stratum ($p = 0.0006$, Fig. 4B). Ebullition represented $> 90\%$ of

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**Table 3.** Population estimates of the mean and 95% confidence interval (mg CH$_4$ m$^{-2}$ h$^{-1}$) methane emission rate for the reservoir, open-water, and tributary stratum. Confidence interval is calculated with the local neighborhood variance estimator ($95\%$ CI$_{\text{LN}}$) and the independent random sample estimator ($95\%$ CI$_{\text{IRS}}$). Percent reduction is the CI$_{\text{LN}}$ estimate compared with the CI$_{\text{IRS}}$ estimate.

| Stratum   | Emission type | Population mean | 95% CI$_{\text{IRS}}$ | 95% CI$_{\text{LN}}$ | Percent reduction |
|-----------|---------------|-----------------|------------------------|-----------------------|-------------------|
| Reservoir | Diffusion     | 0.60            | 0.48–0.73              | 0.51–0.7              | 24                |
| Open-water|               | 0.47            | 0.36–0.57              | 0.38–0.55             | 19                |
| Tributary-area |            | 1.61            | 1.09–2.13              | 1.13–2.08             | 9                 |
| Reservoir | Ebullition     | 7.66            | 4.54–10.79             | 5.43–9.9              | 28                |
| Open-water|               | 4.38            | 1.84–6.92              | 2.28–6.48             | 17                |
| Tributary-area |            | 31.4            | 17.8–44.93             | 20.55–42.18           | 20                |
| Reservoir | Total         | 8.27            | 5.11–11.42             | 6.04–10.5             | 29                |
| Open-water|               | 4.84            | 2.3–7.39               | 2.74–6.94             | 18                |
| Tributary-area |            | 33.0            | 19.41–46.53            | 22.27–43.67           | 21                |
total CH₄ emissions from each strata and the tributary stratum was the source of 42% of total CH₄ emissions at the reservoir scale.

All emission pathways (i.e., diffusion, ebullition, and total emissions) exhibited a strong spatial pattern with the highest rates generally occurring in the three large eastern tributary arms and the lowest rates occurring in the western open-water basin (Figs. 2, 3). The local neighborhood variance estimator took advantage of these patterns and produced confidence intervals that were up to 29% lower than those calculated using the IRS procedure (Table 3).

**Discussion**

In this study, we used a spatially balanced probabilistic survey design to estimate the mean (±95% CI) CH₄ emission rate for a reservoir at multiple spatial scales (e.g., whole-reservoir, tributary stratum, open-water stratum). The results support our hypothesis that reservoir areas below tributary inflows support higher and more variable emission rates than open-water areas, highlighting the importance of including tributary areas in reservoir CH₄ surveys. We also found that ebullition comprised >90% of total CH₄ emissions at all spatial scales, indicating that surveys which only capture diffusive emissions, such as those based on measurement of dissolved CH₄ concentration (Hofmann 2013), may greatly underestimate total CH₄ emissions. Finally, we demonstrate how GRTS, a well-developed and readily accessible statistical survey design, can be used to generate system-scale estimates of CH₄ emissions rates that (1) build on expert knowledge through the incorporation of strata hypothesized to be important in the system and (2) utilize spatial patterns to reduce uncertainty.
The areas of the reservoir associated with tributaries had diffusive, ebullitive, and total CH4 emission rates that were 3.4, 7.2, and 6.8 times higher than that of the open-water areas, respectively. Overall, the tributary associated areas were the source of 42% of total emissions, despite comprising only 12% of the total reservoir surface area. This finding is consistent with a growing body of evidence indicating that areas below tributary inputs can be hot-spots of CH4 emissions from reservoirs (DelSontro et al. 2011; Grinham et al. 2011; Musenze et al. 2014; Sturm et al. 2014). This pattern has been shown for subtropical reservoirs in Australia of different sizes and draining different land-use types (0–65% agriculture) (Grinham et al. 2011; Musenze et al. 2014; Sturm et al. 2014), a very large tropical reservoir (5400 km² surface area) in Africa (DeLsontro et al. 2011), and has been previously reported for Harsha Lake (Beaulieu et al. 2014). One factor which likely contributes to differences in emission rates between open-waters and areas below tributary inflows is depth. Open-water areas are typically deeper than tributary-associated areas (mean depth of 2.6 and 13.4 m in tributary and open-water areas in this study, respectively) resulting in longer rise time and enhanced dissolution and oxidation of CH4 in bubbles released from sediment (Bastviken et al. 2008). When we restrict the data set to observations made at depths included in both strata (i.e., 1–4 m water), however, total CH4 emission rates were significantly greater in the tributary strata than open-waters (Fig. 4B), suggesting that factors other than depth contribute to the difference in emission rates between these strata. Another probable difference between these strata is organic matter loading rates. The tributary areas are a transitional zone between the upstream river and downstream lacustrine zones. This transitional zone is characterized by rapidly decreasing water velocities that cause a large fraction of the river suspended solids, which contains watershed-derived organic matter (i.e., plant residues, eroded soil), to settle out, resulting in high sedimentation rates (Thornton 1990). These higher organic loadings to sediment likely enhance CH4 production rates (DelSontro et al. 2010; Maeck et al. 2013) relative to the open-water portions of the reservoir.

Methane emission rates below tributary inflows

While the tributary stratum supported higher emission rates than the open-water stratum, emission rates varied considerably within individual tributary areas. Some insight into this variability can be assessed using measurements made within the largest tributary arm (tributary area A in Fig. 1) which had sample sites distributed throughout its length. The data indicate a strong spatial pattern of increasing emission rates with increasing distance from the tributary inflow (Fig. 2), possibly because the extreme upper reaches of the tributary arm are periodically scoured by high flows, thereby limiting sediment accumulation and CH4 production, whereas locations further downstream are areas of persistent sediment deposition and therefore support high CH4 production rates. The presence of a strong emission hot spot in the lower reaches of the largest...
trIBUTARY AREA SUGGESTS THAT THESE AREAS SHOULD BE WELL CHARACTERIZED IN EFFORTS TO GENERATE SYSTEM-SCALE ESTIMATES.

WE ALSO OBSERVED VARIABILITY IN CH₄ EMISSION RATES AMONG THE 13 TRIBUTARY AREAS SAMPLED IN THIS SURVEY (FIG. 4A). NINE OF THE TEN HIGHEST EMISSION RATES OBSERVED IN THE TRIBUTARY STRATUM OCCURRED BELOW THE THREE TRIBUTARIES WITH THE LARGEST DRAINAGE AREAS (FIG. 4A; TABLE 1), SUGGESTING THAT WATERSHED AREA MIGHT PLAY A ROLE IN REGULATING CH₄ EMISSION RATES FROM AREAS BELOW TRIBUTARY INFLOWS, POSSIBLY BECAUSE THE AMOUNT OF ORGANIC MATTER TRANSPORTED BY RIVERS SCALES WITH WATERSHED AREA (MOELLER ET AL. 1979). NOT ONLY DID THE AREAS BELOW THE THREE LARGEST TRIBUTARIES SUPPORT THE HIGHEST EMISSION RATES OBSERVED WITHIN THE TRIBUTARY STRATUM, THEY ALSO COMPRISÉ OVER 90% OF THE CUMULATIVE SURFACE AREA OF THE 13 TRIBUTARY AREAS (TABLE 1). THIS SUGGESTS THAT THE VAST MAJORITY OF CH₄ EMISSIONS FROM THE TRIBUTARY STRATUM EMBRANNE FROM THE AREAS BELOW THE THREE LARGEST TRIBUTARIES WITH THE REMAINING 10 TRIBUTARIES MAKING A COMPARETIVELY SMALL CONTRIBUTION. FROM A SURVEY DESIGN PERSPECTIVE, THIS FINDING INDICATES THAT WHETHER THESE 10 SMALLER AREAS WERE INCLUDED IN THE TRIBUTARY STRATUM AND ALLOCATED SAMPLING POINTS, AS WAS DONE HERE, OR MERGED WITH THE OPEN-WATER STRATUM AND SAMPLED ON AN EQUAL PROBABILITY BASIS, WOULD HAVE LITTLE EFFECT ON THE SYSTEM-SCALE EMISSION ESTIMATE. THEREFORE TO OPTIMIZE THE TRADE-OFF BETWEEN SAMPLING EFFORT AND OBTAINING A CONRAINED VARIANCE ESTIMATE IN THIS RESERVOIR, SURVEY DESIGNS SHOULD INCLUDE THE GREATEST SAMPLING DENSITY BELOW THE LARGEST TRIBUTARIES WHERE EMISSION RATES ARE HIGHEST AND MOST VARIABLE, WHILE SAMPLING THE BALANCE OF THE RESERVOIR AT A LOWER DENSITY.

THE IDEAL SURVEY DESIGN WILL VARY AMONG INDIVIDUAL RESERVOIRS BASED ON NUMEROUS FACTORS, BUT PRACTITIONERS SHOULD CAREFULLY CONSIDER WHETHER THE SYSTEM OF INTEREST IS LIKELY TO CONTAIN CH₄ EMISSION HOT SPOTS. EVEN RELATIVELY SMALL HOT SPOTS CAN BE THE DOMINANT SOURCE OF RESERVOIR-SCALE EMISSIONS AND SHOULD BE INCLUDED IN SURVEY DESIGNS. IN AN EXTREME EXAMPLE OF THIS PATTERN, GRINHAM ET AL. (2011) REPORTED THAT THE 2–7% OF THE SURFACE AREA OF A RESERVOIR BELOW THE MAIN TRIBUTARY IN A SUBTROPICAL RESERVOIR IN AUSTRALIA WAS THE SOURCE OF UP TO 97% OF RESERVOIR-SCALE EMISSIONS. EMISSION HOT SPOTS ARE NOT ALWAYS CONFINED TO THE AREAS BELOW TRIBUTARIES, HOWEVER. SEDIMENT TRAPPING IMMEDIATELY ABOVE DAMS IN SMALL RESERVOIRS SEPARATED BY STRETCHES OF FLOWING WATERS ALONG RIVERS CAN LEAD TO CH₄ EMISSION HOT SPOTS (DELSONTRO ET AL. 2010; SOBEK ET AL. 2012; MAECK ET AL. 2013). OTHERS HAVE REPORTED EMISSION HOT SPOTS ASSOCIATED WITH SHALLOW LITTORAL (KELLER AND STALLARD 1994) AND DRAW DOWN (CHEN ET AL. 2009) ZONES.

RELATIVE IMPORTANCE OF EBULLITION AND DIFFUSION

THE HIGHEST EBULLITION RATES (I.E., > 30 mg CH₄ m⁻² h⁻¹) WERE RESTRICTED TO SITES WITH WATER DEPTHS < 10 m (FIG. 4A), WHICH IS CONSISTENT WITH REPORTS FROM MANY OTHER LAKES AND RESERVOIRS (OSTROVSKY ET AL. 2008; GUNKEL 2009; DELSONTRO ET AL. 2011). THIS PATTERN IS GENERALLY ATTRIBUTED TO LOWER HYDROSTATIC PRESSURE AT DEEPER DEPTHS WHICH ALLOWS BUBBLE FORMATION TO OCCUR AT LOWER TOTAL DISSOLVED GAS PRESSURES IN SEDIMENT POREWATERS (BASTVIKEN ET AL. 2004; OSTROVSKY ET AL. 2008; STURM ET AL. 2014). FURTHERMORE, CH₄ DIFFUSES FROM BUBBLES INTO THE SURROUNDING WATER AS THEY RISE THROUGH THE WATER COLUMN. THE AMOUNT OF CH₄ THAT IS REMOVED FROM BUBBLES DURING THEIR RISE IS PROPORTIONAL TO THE RISE HEIGHT, SUCH THAT THE FRACTION OF THE ORIGINAL BUBBLE-CH₄ TRANSPORTED TO THE WATER SURFACE IS INVERSELY RELATED TO WATER DEPTH (OSTROVSKY ET AL. 2008). WHILE PREVIOUS STUDIES HAVE USED THE NEGATIVE RELATIONSHIP BETWEEN DEPTH AND EBULLITION RATES TO UPSCALE EBULLITION TO AN ENTIRE WATER BODY (BASTVIKEN ET AL. 2004; MARTINEZ AND ANDERSON 2013), WE FOUND THAT THE CORRELATION WAS RELATIVELY WEAK (SPEARMAN’S ρ = −0.15) IN THIS STUDY, PARTLY DUE TO THE EXTREME VARIABILITY OF EBULLITION RATES IN THE SHALLOW WATERS. THIS SUGGESTS THAT WHILE WATER DEPTH MAY EXERT A STRONG CONTROL ON EBULLITION RATES, OTHER FACTORS, SUCH AS SEDIMENTATION RATES, ARE ALSO IMPORTANT (JOYCE AND JEWELL 2003; DELSONTRO ET AL. 2015). AN IMPORTANT IMPLICATION OF THE HIGH VARIABILITY OF EBULLITION RATES IN SHALLOW WATERS OBSERVED IN THIS STUDY IS THAT SURVEY DESIGNS SHOULD INCLUDE A HIGH DENSITY OF SAMPLING SITES IN THESE AREAS TO REDUCE UNCERTAINTY IN POPULATION ESTIMATES. THIS IS HIGHLIGHTED BY THE TWOFOOLD LARGER 95% CI FOR THE TRIBUTARY STRATA AS COMPARED WITH THE OPEN-WATER STRATA, DESPITE THE TRIBUTARY STRATA BEING SAMPLED AT A 10-FOLD GREATER DENSITY THAN THE OPEN- WATERS.

THE POPULATION EXTENT ESTIMATES INDICATE THAT EBULLITION WAS PERVERSIVE THROUGHOUT THE TRIBUTARY STRATUM (I.E., 84% OF THE SURFACE AREA EMITTING BUBBLES), WHICH IS CONSISTENT WITH REPORTS FOR TRIBUTARY ASSOCIATED AREAS IN OTHER RESERVOIRS (DELSONTRO ET AL. 2011; GRINHAM ET AL. 2011). THE PROPORTION OF THE OPEN-WATER STRATUM EMITTING BUBBLES (I.E., 47% OF SURFACE AREA) WAS SURPRISINGLY HIGH, HOWEVER. FOR EXAMPLE, EBULLITION WAS FOUND TO BE VERY UNCOMMON IN BAYS (MAX DEPTH: 20 m DEPTH) NOT RECEIVING DIRECT RIVER INFLOWS IN A TROPICAL RESERVOIR (DELSONTRO ET AL. 2011) AND AT DEPTHS GREATER THAN 12 m IN A SUBTROPICAL RESERVOIR (GRINHAM ET AL. 2011). THE RELATIVELY HIGH FREQUENCY OF EBULLITION IN THE OPEN WATER STRATUM IN HARSHA LAKE MAY BE A RESULT OF HIGH ALGAL BIOMASS DENSITIES WHICH ENRICH THE SEDIMENTS WITH AUTOCHTHONOUS CARBON THAT CAN GREATLY STIMULATE CH₄ PRODUCTION (WEST ET AL. 2012, 2015). ALTHOUGH EBULLITION EXTENT AND CH₄ FLUX WAS MUCH LOWER IN THE OPEN-WATER THAN TRIBUTARY STRATUM, EBULLITION WAS THE SOURCE OF 90% OF TOTAL OPEN-WATER CH₄ EMISSIONS AND 93% OF WHOLE-RESERVOIR CH₄ EMISSIONS. THIS FINDING IS CONSISTENT WITH REPORTS THAT EBULLITIVE EMISSIONS FAR EXCEED DIFFUSIVE EMISSIONS IN MANY TEMPERATE, SUBTROPICAL, AND TROPICAL RESERVOIRS (KELLER AND STALLARD 1994; JOYCE AND JEWELL 2003; DELSONTRO ET AL. 2010; DELSONTRO ET AL. 2011; GRINHAM ET AL. 2011; SOBEK ET AL. 2012; STURM ET AL. 2014), HIGHLIGHTING THE IMPORTANCE OF INCLUDING EBULLITION IN EMISSION SURVEYS. IT SHOULD BE NOTED, HOWEVER, THAT EMISSIONS FROM COLD AND WELL OXYGENATED BOREAL...
reservoirs appear to be dominated by diffusive emissions (Teodoru et al. 2012).

Comparison to other studies

Several literature reviews suggest that total CH₄ emission rates from temperate reservoirs are typically less than 1 mg CH₄ m⁻² h⁻¹ (Barros et al. 2011; Bastviken et al. 2011). The total CH₄ emission rate reported here (8.3 ± 2.2 mg CH₄ m⁻² h⁻¹) is well above that value and is in the range more frequently reported for tropical reservoirs. However, recent studies that included hot spots in temperate zone reservoirs have reported emission rates ranging from 4 mg CH₄ m⁻² h⁻¹ to 13 mg CH₄ m⁻² h⁻¹ (DelSontro et al. 2010; Maeck et al. 2013; Beaulieu et al. 2014) (excluding CH₄ released during passage through the dam), suggesting that emissions from temperate systems may have been systematically underestimated.

Bias in the selection of sample sites can affect system-scale estimates, possibly contributing to some of the variability among previously published estimates. To explore potential bias in emission estimates for Harsha Lake, we calculated the total CH₄ emission rate following the survey design presented in Beaulieu et al. (2014). In this study, one sampling site was established in the largest tributary area and five sites in open-water areas. Reservoir scale estimates were calculated by weighting the tributary site by 0.05, the proportion of the reservoir surface attributed to the tributary area. Using measurements made at locations nearby these six sites in this study, we calculate total CH₄ emission rates ranging from 4.1 mg CH₄ m⁻² h⁻¹ to 7.1 mg CH₄ m⁻² h⁻¹, depending on which site is used to represent the tributary area [i.e., three sites in this study are located nearby the tributary site used in Beaulieu et al. (2014)]. This range of values reflects the spatial variability in the tributary areas, further highlighting the importance of sampling these areas at a high spatial density. Regardless of which site is used to represent the tributary area, the estimates are biased low compared with the GRTS results (8.3 ± 2.2 mg CH₄ m⁻² h⁻¹) and this bias would be even more extreme if the original survey had not included a tributary site (2.1 mg CH₄ m⁻² h⁻¹). While this analysis highlights how judgment samples can produce biased estimates, it also demonstrates how judgment samples can be critically important for identifying spatial patterns (i.e., hot spots) that can inform the design of subsequent probabilistic survey designs.

The survey design used in this work included more sample sites and a higher sample density than any previously published investigation using similar measurement methods. One reason for the large sample size is that we placed multiple constraints on the survey design including the requirement that samples be distributed throughout the length of the largest tributary areas and within many separate tributary areas (i.e., 13 areas, Table 1). As discussed above, the inclusion of very small tributary areas likely did not improve system-scale estimates, suggesting that future surveys could employ fewer samples with minimal loss of information. Given limited resources, investigators must optimize survey designs to meet their data quality needs with the minimum sample size. This consideration becomes even more apparent when designs are expanded to include a temporal element (i.e., detection of seasonal patterns or long-term trends). Our analysis of subsets of the survey data indicate that estimates of the mean total CH₄ emission rate stabilized at sample sizes of ~15 and ~20 in the tributary and open-water stratum, respectively (Fig. 5); however, at this sample size the confidence interval for the system-scale emission rate was a factor of 1.15 greater than the mean (i.e., 9.62 ± 5.53 mg CH₄ m⁻² h⁻¹). With further increases in sampling effort the 95% CI declined to a minimum of 54% of the mean at a sample size of 115. These results suggest that generating well-constrained emission estimates requires a larger sampling effort than is needed to generate accurate estimates, therefore investigators should consider their data quality needs with respect to both accuracy and precision when designing surveys. We recommend conducting preliminary surveys to generate information regarding spatial patterning and variability that can be used to design efficient surveys that meet data quality needs (Reynolds 2012).

Spatial pattern and monitoring

System-scale estimate of CH₄ emission rates convey little information if not accompanied by clearly defined and well-constrained estimates of uncertainty. One feature of GRTS designs is that they allow for uncertainty estimation using a local neighborhood (LN) variance estimator (Stevens and
Beaulieu et al. Reservoir methane emissions

reports indicating that CH4 emission rates can exhibit strong

gations have underestimated emissions from these systems.

including emission hot-spots, suggesting that previous investi-

for a temperate zone reservoir, likely because our survey

estimates at multiple spatial scales. GRTS designs produce

reservoir-scale CH4 emission rate estimate was relatively high

dominant emission mechanism throughout the reservoir,

emission rates from areas below tributary inflows are greater

Conclusions

Spatial patterns in CH4 emission rates within reservoirs

may be induced by spatial patterns in the factors that control

methane production and evasion (sensu Fortin et al. 2002).

For example, spatial patterns in water depth and sediment

characteristics (Pearson and Rose 2001) likely conspire to

generate spatial patterns in CH4 emission rates. Spatial pat-

terns in CH4 emission rates have been reported by numerous

investigators and may be quite common. For example, Hof-

mann (2013) reported a strong offshore-directed gradient in

CH4 emissions between the littoral and open-water areas of a

reservoir in Western Europe. Several investigators have

reported a gradient in emission rates between river inflows

and open-water areas (DelSontro et al. 2011; Grinham et al.

2011; Musenze et al. 2014; Sturm et al. 2014) while others

have reported spatial gradients between dams and river seg-

ments in run of the river reservoirs (Maek et al. 2013).

In all of these cases, uncertainty estimation could benefit from

a computational approach that utilizes spatial patterns.

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