Drivers of methane flux differ between lakes and reservoirs, complicating global upscaling efforts

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Key Points:

- The best predictors of methane emission differ between lakes and reservoirs.
- Morphometric features better predict methane emission in lakes, whereas chlorophyll *a* is a better predictor in reservoirs.
- To improve global upscaling, we need more emission measurements from small reservoirs, large lakes, and natural and artificial ponds.

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1029/2019JG005600.

Abstract

Methane is an important greenhouse gas with growing atmospheric concentrations. Freshwater lakes and reservoirs contribute substantially to atmospheric methane concentrations, but the magnitude of this contribution is poorly constrained. Uncertainty stems partially from whether the sites currently sampled represent the global population as well as incomplete knowledge of which environmental variables predict methane flux. Thus, determining the main drivers of methane flux across diverse waterbody types will inform more accurate upscaling approaches. Here we use a new database of total, diffusive, and ebullitive areal methane emissions from 313 lakes and reservoirs (ranging in surface area from 6 m^2 to 5,400 km²) to identify the best predictors of methane emission. We found that the best predictors of methane emission differed by waterbody type (lakes vs. reservoirs), and that ecosystem morphometric variables (e.g., surface area and maximum depth) were more important predictors in lakes whereas metrics of autochthonous production (e.g., chlorophyll a) were more important in reservoirs. We also found that productivity strongly predicted methane ebullition, whereas ecosystem morphometry and waterbody type were more important predictors of diffusive methane flux. Finally, we identify several knowledge gaps that limit upscaling efforts. First, we need more methane emission measurements in small reservoirs, large lakes, and both natural and artificial ponds. Additionally, more accurate upscaling efforts require improved global information about waterbody surface area, waterbody type (lake vs. reservoir), ice phenology, and the distribution of productivityrelated predictor variables such as total phosphorus, DOC, and chlorophyll a.

Plain Language Summary

Methane is an important greenhouse gas, and its atmospheric concentrations are steadily rising. Inland waters, such as lakes and reservoirs, are an important source of methane, but there is uncertainty in the magnitude of emissions as well as the types of systems that emit more methane. Recent work suggests that high ecosystem productivity (e.g., high rates of photosynthesis) leads to high methane emission and that smaller waterbodies tend to emit more methane than larger ones. Still, the extent to which these patterns differ in lakes versus reservoirs (lakes formed behind dams) is not known. Here, we examined the best predictors of lake and reservoir methane flux using a new dataset of methane emissions from 313 lakes and reservoirs. The best predictors of methane emission differed between lakes and reservoirs: lake methane flux was more driven by waterbody shape and size, whereas reservoir methane flux was

related more to productivity. Future global-scale estimates of lake and reservoir methane emission should consider these systems separately. With improved understanding of the drivers of methane flux from lakes and reservoirs, we can better inform models of global methane emissions and target future emissions reductions.

1 Introduction

Freshwater lakes and reservoirs are an important but poorly constrained source of methane to the atmosphere. Recent emission estimates range from 72 - 185 Tg CH₄ yr⁴ (DelSontro et al. 2018; Rosentreter et al., In Press), or 10-34% of the 545-745 Tg CH₄ yr⁻¹ estimated from all natural and anthropogenic sources combined (Kirschke et al., 2013; Saunois et al., 2016, 2019). While differing estimates of lentic surface area cause some of this uncertainty (ranging from 3.23-5.36 x 10⁶ km², Messager et al. 2016; Verpoorter et al., 2014), extreme variability and skewed distributions of aquatic methane fluxes pose additional challenges to upscaling efforts (Rosentreter et al., In Press). Identifying and quantifying key methane sources is important given methane's potential to act as a "lever" on atmospheric greenhouse gas concentrations (wherein the combination of its potency and its short atmospheric residence time means that current changes in emission can have immediate consequences; Prather et al., 2012). While some recent work has suggested that methane emission dynamics are controlled by similar processes across lentic waterbody types (e.g. lakes vs. reservoirs, DelSontro et al. 2018), other work highlights important differences in waterbody properties (e.g. between ponds, natural lakes, and artificial reservoirs) that may ultimately affect methane efflux (Downing, 2010; Hayes et al., 2017; Holgerson & Raymond, 2016).

A variety of biological, morphometric, and physical properties have been suggested as important predictors of lentic methane flux to the atmosphere, with recent literature identifying temperature (DelSontro et al., 2016; Yvon-Durocher et al., 2014), latitude (Barros et al., 2011), ecosystem productivity (Deemer et al., 2016; DelSontro et al., 2016, 2018; West, Creamer, et al., 2015), surface area (Holgerson & Raymond, 2016; Rasilo et al., 2015) and water depth (Gorsky et al., 2019; West, Creamer, et al., 2015) as key predictors at regional to global scales. Ecosystem productivity, in particular, has been posited as a master regulator of methane emissions in wetlands, lakes, and reservoirs given its role in producing labile organic matter substrate critical to methanogenesis and its role in promoting anoxic conditions via associated organic matter respiration (Deemer et al., 2016; DelSontro et al., 2018; Whiting & Chanton, 1993). A number of smaller scale incubation studies support the idea that autochthonous organic matter can provide a more labile substrate than allochthonous material for methanogenesis (Grasset et al., 2018; West et al., 2012), but there is also evidence that some autochthonous and allochthonous organic matter are similarly labile (Grasset et al., 2018) and that the lability of autochthonous organic matter may decline with increasing productivity (West, McCarthy, et al., 2015). Thus, morphometric properties of waterbodies that help determine the degree of allochthonous organic matter inputs to the system may also be important predictors of methane flux. Such properties include surface area, catchment area : surface area ratios, and perimeter : water volume ratios. Waterbody depth may also affect the magnitude of methane emission by altering the degree of methane dissolution as bubbles rise through the water column (McGinnis et al., 2006), the region of the water column that can trap methane during stratified conditions, and the water volume that can support methane oxidation (i.e., deeper waterbodies have greater capacity for dissolution, trapping, and oxidizing methane).

Relating methane emissions to waterbody properties is important for resolving upscaling issues associated with disproportionate sampling of certain waterbody types and/or sizes. While traditional upscaling methods generally combine the arithmetic mean of flux estimates across the sample population with an estimate of global ecosystem surface area (Bastviken et al., 2011; Deemer et al., 2016), recent efforts to upscale greenhouse gases from freshwaters have suggested the potential disparity between the properties of the sample population versus the global population of sites (Holgerson & Raymond 2016; DelSontro et al., 2018; Rosentreter et al., In Press). To get around this, studies have scaled methane emissions based on waterbody surface area (Holgerson & Raymond 2016; Rosentreter et al., In Press) and chlorophyll a concentrations (DelSontro et al., 2018; Rosentreter et al., In Press). In reservoirs, more detailed models incorporate both waterbody and catchment characteristics to predict emissions in support of greenhouse gas inventory efforts (Prairie et al., 2017). Still, problems remain with these methods given current limitations with global lake and reservoir datasets. For example, satellitebased estimates of lentic waterbody properties cannot resolve the smallest systems (Verpoorter et al. 2014, Messager et al. 2016). In addition, biases in the waterbody characteristics that are most readily measured (and the types of systems in which they are measured) may limit our ability to identify the best predictors of lake and reservoir methane flux (Stanley et al., 2019).

While lakes and reservoirs are often lumped together for the purposes of estimating surface area (Verpoorter et al., 2014) and for upscaling fluxes (DelSontro et al., 2018), key differences in the ecosystem morphometry and hydrology of these systems may result in different mean emissions and different controls on emission between the two waterbody types. Reservoirs, which we define as any impounded waterbody, tend to have larger catchments, higher catchment area : surface area ratios, and longer perimeters (but with no significant difference in surface area or depth; Hayes et al., 2017). These morphometric attributes suggest more mass input from the watershed per unit waterbody in reservoirs, such that reservoirs are better situated to intercept more allochthonous inputs than natural lakes in the same region (Hayes et al., 2017). To this end, reservoirs experience higher areal sedimentation rates than natural lakes (Mendonca et al. 2017), and these high sedimentation zones can have particularly high rates of methane emission (Maeck et al. 2013). Reservoirs also generally experience a greater degree of water level fluctuation than natural lakes (Hayes et al., 2017; Zohary & Ostrovsky, 2011), and water level drawdowns are known to drive large methane emission events in some systems (Harrison et al., 2017; Maeck et al., 2014). Finally, there may be regional differences in ecosystem productivity between lakes and reservoirs; for example in the EPA National Lakes Assessment, natural lakes were generally more eutrophic than reservoirs (Doubek & Carey, 2017).

Here we use a recently compiled global dataset of total, ebullitive, and diffusive areal methane emission rates from lakes and reservoirs (as described in Rosentreter et al., In Press) to identify the best environmental predictors of methane emission and examine whether predictors differ between lakes and reservoirs. We end by discussing current challenges to upscaling efforts and critical future data needs.

2 Materials and Methods

2.1 Dataset

We used a dataset containing estimates of total, ebullitive, and diffusive methane flux from 227 lakes and 86 reservoirs from around the world, spanning a wide latitudinal gradient (Figure 1, Figure S1; Rosentreter et al., In Press). Fluxes were recorded on an areal basis (e.g. per m²), and "total flux" is used throughout the manuscript to refer to the sum of areal ebullitive and diffusive fluxes. The dataset also contains basic ancillary morphometric, biological, and

chemical data that may correlate with methane flux. The dataset is unique in that lentic methane flux studies reporting only one of the two main emission pathways (ebullition or diffusion) were excluded (but see Deemer et al., 2016). This was done given previous evidence that ebullition can make up anywhere from 0-99.6% of total emissions (Deemer et al., 2016).

In this dataset, each site was categorized into one of two waterbody types: lake or reservoir. A reservoir was defined as a system whose primary outflow was dammed, excluding beaver ponds and river reaches upstream of weirs, however, larger run of river reservoirs were included. The lake category encompassed a large size gradient ($0.000006 - 2500 \text{ km}^2$), including small waterbodies that may be considered ponds (e.g., 51 sites < 0.01 km^2), and was largely composed of natural lakes, although a small subset (n=23) were artificial. Sites that were dominated by emergent vegetation were considered wetlands and excluded from the dataset.



Figure 1. Global distribution of total methane emissions from lakes (blue, n=227) and reservoirs (red, n=86). The size of each point is scaled to the magnitude of emission.

2.2 Predictors of Methane Flux

Using this dataset, we examined eight potential predictors of waterbody methane flux. These predictor variables related to ecosystem productivity (chlorophyll *a*, dissolved organic carbon, and total phosphorus concentrations), morphometric features (mean depth,

maximum depth, surface area), and climatic features (water temperature and latitude). Generally, these variables were from the same study that reported methane emission. However, given previous evidence that chlorophyll *a* concentrations were strong predictors of total lentic methane emissions at the global scale (Deemer et al., 2016; DelSontro et al., 2018), the database we used mined the literature for other studies of the same system that reported chlorophyll *a* within a +/- five-year time period of the primary study (Rosentreter et al. In Press). Because TP and chlorophyll *a* were correlated in waterbodies where both were measured (r = 0.71, n=50), we used statistical relationships between total phosphorus (TP) and chlorophyll *a* concentrations to model missing chlorophyll *a* data for temperate and boreal systems (Dallon and Rigler 1974), for subtropical systems (Cunha et al., 2013), and for tropical systems (Salas and Martino 1991). As we used TP measurements to model chlorophyll *a* values, our models do not consider individual effects of TP. Due to the potential confounding effect of elevation on the latitude-temperature relationship, our analysis excluded latitude from 19 systems located >1000m above sea level. Highly skewed variables were natural log transformed and residual plots were examined to check for normality.

We conducted multivariate regression models as well as individual least squares regression models to evaluate how environmental variables predicted total, ebullitive, and diffusive areal methane fluxes. First, we tested for correlations between predictor variables using Pearson correlations in the corrplot package (Table S1; Wei and Simko 2017). We identified strong correlations among maximum depth, mean depth, and surface area ($r \ge 0.73$) as well as between latitude and water temperature (r = -0.88). In multiple linear regression models, we avoided collinearity by selecting the variable with the highest sample size (surface area and latitude). Our multiple linear regression model also excluded DOC due to low sample sizes. As DOC was correlated with surface area (r=-0.66, Table S1), we can interpret an area effect to potentially indicate effects of both depth and DOC. Because our multivariate regression model used only a subset of our data (due to missing data among predictor variables), we also ran individual least square regression models with all available data to test the relationship between methane flux and each predictor variable. As our multivariate analysis highlighted interactions with waterbody type (lake vs. reservoir), we also used linear models to test for a waterbody type interaction for each predictor variable. All analyses were run in R (Version 3.3.1, R Core Team 2020).

3 Results

3.1 Total Methane Flux

The multivariate regression model for total areal methane flux included 165 waterbodies, and the five best models included interactions between waterbody type and latitude, area, and/or chlorophyll a (Table 1). Total areal methane flux increased with chlorophyll *a*, decreased with surface area and latitude, and effects varied between lakes and reservoirs (Table 1). The effect of chlorophyll *a* was stronger in reservoirs compared to lakes, while area and latitude had stronger effects in lakes. This could be due to the fact that more reservoirs were large, while more lakes were at high latitudes (Figure 2a, b).





Figure 2. Total (ebullitive + diffusive) areal CH₄ emission in reservoirs (black squares) and lakes (open circles) plotted against predictor variables: surface area (a), absolute latitude (b), maximum depth (c), DOC (d), chlorophyll a (e), and waterbody type (f). In panels a, c, and e, two regression lines depict a significant interaction with waterbody type (Table S2). In panel f, boxes demarcate the 25th and 75th percentiles, horizontal lines indicate median concentrations, diamonds indicate mean concentrations, whiskers extend to the largest value less than 1.5 times the interquartile range, and data extending beyond this range are plotted as individual points. All available data are plotted (with no sub-setting based on input to the multivariate regressions).

Using individual least squares regressions, we found that total areal methane flux was related to six of our seven predictor variables (all but mean depth; Table 2). The best predictors were maximum depth ($R^2 = 0.18$) and chlorophyll *a* ($R^2 = 0.13$), indicating that methane flux decreases with increasing waterbody size and increases with increasing productivity (Table 2, Figure 2). We found that waterbody type significantly interacted with surface area, maximum depth, and chlorophyll *a*, but not latitude, mean depth, or DOC (Figure 2, Table S2). Specifically, area and maximum depth drove methane flux in lakes with weaker effects in reservoirs, whereas chlorophyll *a* had a stronger effect in reservoirs than in lakes. As four of the seven predictor variables had significant interactions with waterbody type (Figure 2, Table S2), we conducted additional least squares regressions to explore relationships between predictor variables and methane flux in lakes and reservoirs separately (Table 2). In lakes, total areal methane flux was driven by maximum depth, DOC, and area, with weaker (yet significant) relationships to chlorophyll *a* (Table 2).

3.2 Diffusive Methane Flux

The multivariate regression model for areal diffusive methane flux included 131 waterbodies, and two top models included interactions between waterbody type and latitude, area, and chlorophyll *a* (R^2 =0.26, Table S3). Diffusive fluxes increased with increasing chlorophyll *a* in reservoirs but not lakes, whereas diffusive fluxes decreased with increasing surface area in lakes but not reservoirs.

Using individual linear regression models, we found that lakes and reservoirs differed in predictors of diffusive flux (Figure 3, Table S4), with 5 of the 7 predictor variables significantly interacting with waterbody type (Table S5). Across both waterbody types, diffusive fluxes increased with increasing DOC concentrations (Figure 4a) and decreased with increasing area and maximum depth (Figure 4b). These dynamics appear to be strongly driven by lakes (which represented much higher sample sizes), with lake diffusive flux being most strongly related to DOC (R^2 =0.28), followed by area (R^2 =0.22). In reservoirs, diffusive flux actually increased with increasing maximum depth (Figure 4b, R^2 =0.56), and flux was most strongly related to chlorophyll *a* (R^2 =0.62).



Figure 3. Diffusive (left) and ebullitive (right) areal CH₄ emission in reservoirs (black squares) and lakes (open circles) plotted against the top predictors of flux as identified in the multivariate regression analysis: chlorophyll (a, b), surface area (c, d), absolute latitude (e, f), and waterbody type (g, h). In panels a, c, and e, two regression lines depict a significant interaction with waterbody type (Tables S5 and S8). In panels g and h, boxes demarcate the 25th and 75th percentiles, horizontal lines indicate median concentrations, diamonds indicate mean concentrations, whiskers extend to the largest value less than 1.5 times the interquartile range,

and data extending beyond this range are plotted as individual points. All available data are plotted (with no sub-setting based on input to the multivariate regressions).



Figure 4. Diffusive areal CH₄ emission in reservoirs (black squares) and lakes (open circles) plotted against the best predictors of flux as identified by linear regression analysis: DOC (a) and maximum depth (b). Two regression lines indicate a significant interaction with waterbody type (Table S5).

3.3 Ebullitive Methane Flux

The multivariate regression model for areal ebullitive methane flux included 130 waterbodies, and the three best models included latitude, area, and an interaction between waterbody type and chlorophyll *a* (R^2 =0.29, Table S6). Specifically, ebullitive flux was higher in reservoirs, increased with chlorophyll *a*, and decreased with area and latitude.

Using individual linear regression models, we found that areal ebullitive flux in lakes and reservoirs responded similarly to predictor variables (Figure 3, Table S7), with no interactions between waterbody type and predictor variables (Table S8). The strongest predictor of ebullitive flux was chlorophyll *a* (Table S6, Figure 3b). Ebullitive flux increased with chlorophyll *a* when waterbody types were pooled (R^2 =0.18), and when lakes (R^2 =0.16) and reservoirs (R^2 =0.28) were analyzed separately (Table S7).

4 Discussion

We found that the best predictors of methane emission differed between lakes and reservoirs, and also differed when considering ebullitive versus diffusive flux. Total lake methane fluxes and diffusive fluxes were more strongly related to lake morphometry, whereas productivity was more important in predicting reservoir flux and overall ebullitive flux. Our results suggest that lumping lakes and reservoirs together for the purposes of determining drivers and/or upscaling may obscure important differences between the systems. Identifying and understanding the drivers of lentic methane flux is paramount to increasing certainty in global upscaling efforts, and for informing management actions to minimize emissions. Here, we report on the environmental variables correlated with methane flux in lakes and reservoirs, discuss the implications for management and the challenges associated with current global upscaling efforts, and conclude with future research needs.

4.1 Drivers of Methane Flux

Waterbody type, surface area, chlorophyll *a* concentration, and latitude consistently emerged as important predictor variables in multivariate models regardless of methane pathway (total, diffusive, or ebullitive). Due to both sample size and collinearity issues, these four variables were the only predictors included in our multivariate analyses--- and each were retained in top models. Still, the relative strength and even the direction of the surface area, chlorophyll *a*, and latitude effects varied by both methane emission pathway and waterbody type.

In lakes, total and diffusive areal methane flux was best predicted by waterbody morphometry, including surface area and maximum depth, with DOC also emerging as an important predictor despite its small sample size (n=73 for lakes). All three of these variables are highly correlated (Table S1), likely because smaller waterbodies are often shallow with a greater edge effect that increases terrestrial carbon loads (Holgerson and Raymond 2016). Added DOC may provide a substrate for methanogenesis in anoxic conditions; however, it can also provide electron acceptors for methane oxidation (Reed et al. 2017) and it is not often a predictor of increased methane flux (Bastviken et al., 2004; Holgerson, 2015; Kankaala et al., 2013). We hypothesize that the observed relationship between DOC and methane flux may reflect lake morphometry more than DOC. Small and shallow lakes are often polymictic, allowing methane production from anoxic sediments to influence more of the water column (Holgerson, 2015; Juutinen et al., 2009). Additionally, there is less potential for methane oxidation in smaller, shallower lakes (Bastviken et al., 2004).

Productivity (e.g. chlorophyll *a*) emerged as a significant predictor in all the best multivariate models for total, ebullitive, and diffusive methane fluxes, but the relative strength of this driver varied by waterbody type (stronger in reservoirs than lakes) and by pathway (more important for ebullitive than diffusive flux). In lakes, chlorophyll a weakly predicted total methane flux, which was driven by a strong relationship with ebullitive flux but was unrelated to diffusive flux. In contrast, chlorophyll a was the strongest predictor of total, ebullitive and diffusive methane fluxes in reservoirs. The strong relationship between chlorophyll a and reservoir methane flux is consistent with previous work (Deemer et al. 2016) and suggests that morphometric controls are less important drivers of methane emission in reservoirs than in lakes, although more studies are needed in small and shallow reservoirs. Autochthonous production may be a more important regulator of methane dynamics in reservoirs given that these systems generally have lower residence times (Hayes et al., 2017) and thus possibly less time to process allochthonous carbon inputs. In contrast to lakes, reservoir methane emissions were not significantly related to DOC, further suggesting a less important role for watershed carbon inputs. Reservoirs also tended to have a higher fraction of methane as ebullition (median: 78%, n=59 vs. median of 54% n=172 in lakes; Figure S2), with chlorophyll a emerging as the single best predictor of ebullitive flux regardless of waterbody type (Table S7). Autochthonous carbon may generally provide more labile substrate for methanogenesis (West et al. 2012 but see West, McCarthy et al. 2015 and Berberich et al. 2019) resulting in more ebullitive flux, but longer residence times and more stable water levels in lakes may promote greater fractional methane oxidation than in reservoirs with shorter residence times. In other words, for every unit of methane produced, methanotrophs in lakes may remove a greater fraction before it reaches the atmosphere, serving as a more efficient buffer to atmospheric emissions.

We also report several unexpected relationships between morphometry and flux when comparing lakes and reservoirs. While methane flux decreased in larger lakes, larger reservoirs tended to have higher diffusive and total emissions (Figure 2, Figure 4). While more research is needed to elucidate the mechanisms driving this relationship, we have several hypotheses. First, reservoirs generally have longer, more complex perimeters than natural lakes (Hayes et al., 2017), a phenomenon which may be most dramatic in larger reservoirs that have flooded more

complex river valleys. In these systems, increased shallow edge habitats may promote productivity and associated methane production that can largely bypass oxidation due to shorter bubble travel times from the sediments to the atmosphere. In contrast larger lakes are often deeper, which reduces the methane that is able to reach the atmosphere (Bastviken et al., 2004; McGinnis et al., 2006). Secondly, large reservoirs may be used more for water storage, and thus experience greater water level fluctuations than some smaller run-of-river-type systems (although this hypothesis has not been tested). Such water level fluctuations may lead to elevated ebullition as hydrostatic pressure drops (Harrison et al., 2017; Maeck et al., 2014). It's important to note that our discussion of morphometric controls is limited as we lack measurements from small and shallow reservoirs (n=16 for reservoirs <1 km² in this study) as well as from the largest lakes (n=3 for lakes >100 km² in this study). We stress the need for more methane emission measurements from small reservoirs, especially given the ongoing global proliferation of small hydropower facilities (Couto and Olden 2018) as well as a need for more measurements from the largest lakes.

While global datasets that cross ecosystem types have shown that methane emissions are highly temperature dependent (Yvon-Durocher et al. 2014), we found only a weak climatic effect on methane flux in reservoirs and lakes. Latitude emerged in all the best models of total, diffusive, and ebullitive flux, but was not as strong a covariate as either chlorophyll a or surface area (Table 1, Table S4, Table S7). When broken down by waterbody type, the relationship between methane emission and water temperature was not significant in reservoirs and was only weakly significant in lakes ($R^2 = 0.08$; Table 2). Previous research suggests that latitude predicts methane emissions, with tropical reservoirs often releasing more methane than temperate and boreal systems (Barros et al., 2011; Bastviken et al., 2011; but see Deemer et al., 2016) and temperate lakes emitting more methane than boreal lakes (Bastviken et al., 2011; Holgerson & Raymond 2016). Recent work in lakes suggests a synergistic link between productivity and water temperature that is generally consistent with the weak but significant link between methane emission and latitude that we report here (DelSontro et al. 2016, Davidson et al. 2018, Jansen et al. 2020). Still, the strongest latitude effect we report here is for diffusive flux from reservoirs (R²=0.14, n=67, Table S4) which is somewhat surprising given that ebullitive flux has often been found to be more sensitive to temperature than diffusive flux (Davidson et al. 2018, Jansen et al. 2020). Seasonal sampling bias (where sites are sampled more in the summer than in

the winter) can substantially overestimate flux in northern systems (Jansen et al. 2020) and may be masking a stronger latitude effect than we report here. The extent to which the latitude effect we report here may have to do with temperature versus other ecosystem properties is an important area for future work.

4.2 Implications for Managing Methane Emissions from Lakes and Reservoirs

Our results inform the management of aquatic methane emissions, particularly with respect to eutrophication and the widespread construction of reservoirs and ponds. Chlorophyll *a* concentrations were strongly correlated with ebullition across waterbody types and for diffusive flux in reservoirs, suggesting that future emissions from these systems may be particularly sensitive to aquatic eutrophication (Beaulieu et al., 2019; Deemer et al., 2016). Methane emissions may be reduced by strategies to site new reservoirs and artificial ponds in locations where they are less likely to intercept nutrient runoff (Almeida et al. 2019), as well as through watershed nutrient management efforts to reduce runoff. Limiting nutrient loads to ponds may be particularly difficult as created ponds are often in agricultural (Webb et al., 2019) and urban (Peacock et al., 2019) landscapes, while natural upland ponds are critical storage sites for phosphorus and sediment that would otherwise enter lakes and rivers (Schmadel et al., 2019).

Beyond eutrophication, we found that small lakes (i.e., ponds) had high methane emissions, which raises concern surrounding the global expansion of constructed farm ponds and retention ponds (Downing, 2010; Downing et al., 2006; Fairchild et al., 2013; Ollivier et al., 2018). Pond creation is prevalent because ponds can provide important ecosystem services, ranging from sediment, nutrient, and water retention to water supply, aesthetic value, and recreation (Fairchild et al., 2013; Schmadel et al., 2019). We did not evaluate methane emissions from natural vs. artificial ponds due to the low (n=23) sample size and geographical bias of artificial ponds, but this is an important future research question. Preliminary evidence suggests that artificial ponds may have higher methane fluxes, even in cases where diffusion was the only pathway measured (Gorsky et al., 2019; Ollivier et al., 2018, but see Miller et al. 2019), and that artificial pond type matters (Grinham et al., 2018). In cases where ponds are constructed, methane emissions may be managed through morphometric design as deeper ponds often emit less methane than shallower ones (Gorsky et al., 2019; Webb et al., 2019).

4.3 Challenges with Global Upscaling

There are numerous challenges associated with upscaling methane fluxes measured in individual lakes and reservoirs to estimates of global methane flux. Currently upscaling is affected by biases in the types of waterbodies we sample, our limited understanding of methane flux and drivers over space and time, and the coarse resolution of global lake and reservoir databases. In the following section we discuss some of these challenges and highlight potential avenues for future work to resolve areas of limited understanding (Table 3).

4.3.1 Across site sampling

Arguably one of the most critical challenges to global upscaling efforts is a bias in the types of waterbodies sampled. While our sample size of 227 lakes and 86 reservoirs is on par with other global upscaling efforts, it is miniscule compared to an estimated 22.6 - 27.5 million lakes and 17,356 reservoirs larger than 0.1 km² (sites < 0.1 km² substantially more uncertain, with lakes estimated between 647 million - 3.48 billion; reservoirs estimated at 16.7 million) (Downing, 2010; Downing et al., 2006; Holgerson & Raymond, 2016; Lehner et al., 2011; Messager et al., 2016; Verpoorter et al., 2014). While this dataset appears to represent the latitudinal distribution of lakes and reservoirs globally (Figure S1), it does not likely represent the global size distribution of lakes and reservoirs. For instance, the dataset only includes 20 large lakes $\geq 1 \text{ km}^2$, with only three $\geq 100 \text{ km}^2$. In contrast, we have only 16 small reservoirs < 1km². Additionally, we do not know the global area or distribution of the smallest waterbodies < 0.1 km², which comprise most of the world's lakes. Lastly, these study sites may not proportionately represent the global distribution of waterbodies in terms of chemical and biological characteristics. We suggest that future studies focus on large lakes (>1 km²), small reservoirs (<1 km²), and the smallest lakes (e.g. ponds, <0.01 km²), as well as select sites randomly to avoid sampling bias (Table 3).

4.3.2 Within site sampling

Current upscaling efforts are limited by the scope of smaller-scale field studies in terms of the environmental variables measured, the methane flux pathways measured (e.g. ebullitive vs. diffusive vs. total), and spatial and temporal coverage. We suggest that gas sampling studies measure and report DOC, chlorophyll a, surface area, and maximum depth, which were our

strongest predictors of methane fluxes (Table 2). In our dataset, only 32% of lakes and 19% of reservoirs reported DOC concentrations, while maximum depth was reported for 61% of lakes and only 10% of reservoirs (Table 2). Under-sampling of DOC is not unique to methane flux datasets and may be universal in lake sampling efforts (Stanley et al. 2019). The limited data we do have suggest that reservoirs are low DOC systems, begging the question: do reservoirs tend to have less DOC than natural lakes? In a global study, low DOC was correlated with larger watersheds, higher shoreline complexity, and longer shorelines (Toming et al., 2020), which are all characteristics of reservoirs compared to lakes (Hayes et al. 2017). Yet, the same global study also found higher DOC in smaller, shallower systems (Toming et al., 2020), emphasizing the need for more DOC and flux measurements from small reservoirs. While depth and productivity metrics are more commonly reported than DOC, greater measurements (particularly in reservoirs) are needed given the strong patterns we observed.

Secondly, future studies should measure both diffusive and ebullitive pathways in order to aid upscaling efforts. This is because 1.) the fractional contribution of each pathway to total flux is highly variable by system (ranging from 0-100% in this dataset; Figure S2) and 2.) the controls on each flux pathway differ (Figure 3, Table S4, Table S7). While some methods cannot easily differentiate diffusive and ebullitive fluxes (e.g. eddy covariance), other methods can discern pathways (e.g. floating chambers). Studies that examine each pathway independently allow a better understanding of specific mechanisms driving fluxes via each pathway and will possibly support upscaling each flux pathway separately.

Lastly, the high degree of sampling needed to resolve waterbody methane fluxes (see Wik et al., 2016 and Jansen et al., 2020) poses a significant challenge to the research community. Methane emissions can be highly variable through space (DelSontro et al., 2011) and on diel (Podgrajsek et al., 2014, Sieczko et al. 2020), seasonal (Jansen et al., 2020; Denfeld et al., 2018; Jammet et al., 2015; Schubert et al., 2012), and event-based timescales (Harrison et al., 2017). For example, a water level drawdown event lasting a few weeks was responsible for >90% of the annual methane emission from a temperate reservoir (Harrison et al., 2017). This variability can make the use of average open water flux values problematic given that very large fractions of an annual waterbody's methane budget can be emitted over very short time frames. General increases in the sampling effort put forward within single systems will help to better narrow in on the actual average fluxes (Wik et al., 2016) as will efforts to better synthesize the average effect of short-term or seasonal events (e.g. as in Denfeld et al., 2018 and Jansen et al., 2020) and diel patterns in flux (Sieczko et al. 2020, Podgrajsek et al. 2014).

4.3.3 Global database needs

The accuracy of global methane emission upscaling efforts is currently limited by global estimates of environmental predictors and lake and reservoir surface area and distribution. First, relating methane emissions to widely measured predictor variables may resolve some of the problems associated with sample representativeness (DelSontro et al., 2018). In the last five years, global databases have been created for both chlorophyll *a* (using satellite-based estimates; Sayers et al., 2015) and DOC (using machine learning; Toming et al. 2020). These databases are excellent advances considering the importance of both chlorophyll *a* and DOC in predicting reservoir and lake methane fluxes, respectively, and the chlorophyll *a* database was recently used to predict lentic water greenhouse gas emissions (DelSontro et al. 2018) and large reservoir greenhouse gas emissions (Rosentreter et al. In Press).

However, these databases still have major limitations for upscaling greenhouse gas emissions. The chlorophyll *a* database is based on chlorophyll *a* concentrations from a single year in August (Sayers et al., 2015), while the DOC database was built from DOC measurements only in lakes, most of which were only measured once (Sobek et al., 2007). Both datasets ignore small waterbodies with minimum size thresholds of 1 km² for the chlorophyll *a* database (Sayers et al., 2015) and 0.1 km² for the DOC database (Toming et al. 2020). Lastly, both databases lump together lakes and reservoirs. Yet our analysis indicates that lakes and reservoirs respond differently to chlorophyll *a* and DOC, with chlorophyll *a* strongly predicting methane flux in reservoirs but not lakes (with the exception of ebullition), and DOC strongly predicting flux in lakes but not reservoirs (Table 1). While regional analyses suggest different distributions of chlorophyll *a* in reservoirs compared to that in lakes (Doubek and Carey 2017), it is not known how this plays out at the global scale. Similarly, improvements to spatially explicit models of watershed nutrient transport may allow improved global modeling of lentic waterbody trophic status, although at present these models are not resolved enough to be useful at the scale of single waterbodies (Deemer et al., 2016).

Global databases of lake and reservoir surface area coverage are also critical to upscaling efforts. Current global databases contain lake and reservoir surface area estimates that can differ

dramatically among size classes, with 7% to 95% differences in lakes greater than 0.1 km² (comparing Messager et al., 2016 and Downing et al., 2006) and even greater uncertainty in the smaller size classes (34% - 141% differences comparing Downing et al., 2006, Downing 2010, and extrapolations from Verpoorter et al., 2014). Without accurate estimates of global lake size distribution, particularly for small waterbodies, upscaling results in uncertain estimates. This includes problems with differentiating ponds from wetlands and lakes from reservoirs as well as identifying waterbodies under forest cover. Advancing technologies that support mapping small waterbodies is critical for upscaling efforts, and there are some promising advancements at local scales using LiDAR (Wu et al., 2014), real-color aerial images (Halabisky, 2011) and leaf-off color-infrared aerial imagery (Van Meter et al., 2008). In addition, recent regional-scale studies have improved waterbody mapping by digitizing high-resolution (1:24,000) paper maps (Schmadel et al., 2019) and using color-infrared imagery (Kyzivat et al., 2019). In addition to estimating the global size distribution of waterbodies, more accurate annual flux estimates will require a better understanding of changing surface areas due to drying as well as reduced flux during periods of ice cover.

4.4 Conclusions

While there remain significant challenges to upscaling global methane emissions from inland waters, we are in the midst of an incredible growth of methane measurements: of the 313 lakes and reservoirs considered here, 205 (65%) were published since 2015 (Rosentreter et al., In Press). As increased effort is put into methane measurements, more thought could be given to the types of waterbodies sampled and the types of supplemental data gathered at each waterbody (Table 3). Here we highlight the potential for different types of systems to behave very differently with respect to both ecosystem drivers and overall magnitude of methane emissions and suggest the utility of further delineating and quantifying these differences to inform future upscaling efforts.

Acknowledgments, Samples, and Data

Thank you to Peter Raymond for catalyzing this collaboration and to Chunlin Song for compiling the initial dataset. We are grateful for helpful discussions with Judith Rosentreter and her global aquatic methane emissions team, who synthesized cross-system methane emission estimates, including the dataset we analyzed here. We especially appreciate helpful conversations with John Melack. We thank Tom Gushue for his help with ArcGIS. We also thank Kim Wickland and two anonymous reviewers for their helpful reviews of this manuscript. Data associated with this manuscript can be found in the FigShare repository DOI: 10.6084/m9.figshare.13611296 associated with Rosentreter et al. In Press. Any use of trade, product, or firm names is for descriptive use only and does not imply endorsement by the U.S. Government.

References

Almeida, R. M., Nóbrega, G. N., Junger, P. C., Figueiredo, A. V., Andrade, A. S., de Moura, C. G. B., et al. (2016). High primary production contrasts with intense carbon emission in a eutrophic tropical reservoir. *Frontiers in Microbiology*, 7. https://doi.org/10.3389/fmicb.2016.00717

Barros, N., Cole, J. J., Tranvik, L. J., Prairie, Y. T., Bastviken, D., Huszar, V. L. M., et al. (2011). Carbon emission from hydroelectric reservoirs linked to reservoir age and latitude. *Nature Geoscience*, *4*(9), 593–596. https://doi.org/10.1038/ngeo1211

Bastviken, D., Tranvik, L. J., Downing, J. A., Crill, P. M., & Enrich-Prast, A. (2011). Freshwater methane emissions offset the continental carbon sink. *Science*, *331*(6013), 50–50. https://doi.org/10.1126/science.1196808

Bastviken, D., Cole, J., Pace, M., & Tranvik, L. (2004). Methane emissions from lakes: Dependence of lake characteristics, two regional assessments, and a global estimate. *Global Biogeochemical Cycles*, *18*(4). https://doi.org/10.1029/2004GB002238

Beaulieu, J. J., DelSontro, T., & Downing, J. A. (2019). Eutrophication will increase methane emissions from lakes and impoundments during the 21st century. *Nature Communications*, *10*(1), 1375. https://doi.org/10.1038/s41467-019-09100-5

Cunha, D. G. F., Calijuri, M. do C., & Lamparelli, M. C. (2013). A trophic state index for tropical/subtropical reservoirs (TSI_{tsr}). *Ecological Engineering*, *60*, 126–134. https://doi.org/10.1016/j.ecoleng.2013.07.058

Davidson, T. A., Audet, J., Jeppesen, E., Landkildehus, F., Lauridsen, T. L., Søndergaard, M., & Syväranta, J. (2018). Synergy between nutrients and warming enhances methane ebullition from experimental lakes. *Nature Climate Change*, 8(2), 156–160. https://doi.org/10.1038/s41558-017-0063-z

Deemer, B. R., Harrison, J. A., Li, S., Beaulieu, J. J., DelSontro, T., Barros, N., et al. (2016). Greenhouse gas emissions from reservoir water surfaces: a new global synthesis. *BioScience*, *66*(11), 949–964. https://doi.org/10.1093/biosci/biw117

DelSontro, T., Kunz, M. J., Kempter, T., Wüest, A., Wehrli, B., & Senn, D. B. (2011). Spatial Heterogeneity of Methane Ebullition in a Large Tropical Reservoir. *Environmental Science & Technology*, *45*(23), 9866–9873. https://doi.org/10.1021/es2005545

DelSontro, T., Boutet, L., St-Pierre, A., del Giorgio, P. A., & Prairie, Y. T. (2016). Methane ebullition and diffusion from northern ponds and lakes regulated by the interaction between temperature and system productivity: Productivity regulates methane lake flux. *Limnology and Oceanography*, *61*(S1), S62–S77. https://doi.org/10.1002/lno.10335

DelSontro, T., Beaulieu, J. J., & Downing, J. A. (2018). Greenhouse gas emissions from lakes and impoundments: Upscaling in the face of global change: GHG emissions from lakes and impoundments. *Limnology and Oceanography Letters*, *3*(3), 64–75. https://doi.org/10.1002/lol2.10073

Denfeld, B. A., Baulch, H. M., del Giorgio, P. A., Hampton, S. E., & Karlsson, J. (2018). A synthesis of carbon dioxide and methane dynamics during the ice-covered period of northern lakes: Under-ice CO ₂ and CH ₄ dynamics. *Limnology and Oceanography Letters*, *3*(3), 117–131. https://doi.org/10.1002/lol2.10079

Dillon, P. J., & Rigler, F. H. (1974). The phosphorus-chlorophyll relationship in lakes. *Limnology and Oceanography*, *19*(5), 767–773.

Doubek, J. P., & Carey, C. C. (2017). Catchment, morphometric, and water quality characteristics differ between reservoirs and naturally formed lakes on a latitudinal gradient in the conterminous United States. *Inland Waters*, 7(2), 171–180. https://doi.org/10.1080/20442041.2017.1293317

Downing, J. (2010). Emerging global role of small lakes and ponds: little things mean a lot. *Limnetica*, 29, 9–24.

Downing, J. A., Prairie, Y. T., Cole, J. J., Duarte, C. M., Tranvik, L. J., Striegl, R. G., et al. (2006). The global abundance and size distribution of lakes, ponds, and impoundments. *Limnology and Oceanography*, *51*(5), 2388–2397.

Fairchild, G. W., Robinson, C., Brainard, A. S., & Coutu, G. W. (2013). Historical changes in the distribution and abundance of constructed ponds in response to changing population density and land use. *Landscape Research*, *38*, 593–606. https://doi.org/10.1080/01426397.2012.672640

Gorsky, A. L., Racanelli, G. A., Belvin, A. C., & Chambers, R. M. (2019). Greenhouse gas flux from stormwater ponds in southeastern Virginia (USA). *Anthropocene*, *28*, 100218. https://doi.org/10.1016/j.ancene.2019.100218

Grasset, C., Mendonça, R., Villamor Saucedo, 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: Methanogenic potential of different OC types. *Limnology and Oceanography*, *63*(4), 1488–1501. https://doi.org/10.1002/lno.10786

Grinham, A., Albert, S., Deering, N., Dunbabin, M., Bastviken, D., Sherman, B., et al. (2018). The importance of small artificial water bodies as sources of methane emissions in Queensland, Australia. *Hydrology and Earth System Sciences Discussions*, 1–27. https://doi.org/10.5194/hess-2018-294

Guérin, F., Abril, G., Richard, S., Burban, B., Reynouard, C., Seyler, P., & Delmas, R. (2006). Methane and carbon dioxide emissions from tropical reservoirs: Significance of downstream rivers. *Geophysical Research Letters*, *33*(21). https://doi.org/10.1029/2006GL027929

Halabisky, M. (2011). Object-based classification of semi-arid wetlands. *Journal of Applied Remote Sensing*, 5(1), 053511. https://doi.org/10.1117/1.3563569

Harrison, J. A., Deemer, B. R., Birchfield, M. K., & O'Malley, M. T. (2017). Reservoir waterlevel drawdowns accelerate and amplify methane emission. *Environmental Science & Technology*, *51*(3), 1267–1277. https://doi.org/10.1021/acs.est.6b03185

Hayes, N. M., Deemer, B. R., Corman, J. R., Razavi, N. R., & Strock, K. E. (2017). Key differences between lakes and reservoirs modify climate signals: A case for a new conceptual model: Lakes and reservoirs modify climate signals. *Limnology and Oceanography Letters*, 2(2), 47–62. https://doi.org/10.1002/lol2.10036

Holgerson, M. A. (2015). Drivers of carbon dioxide and methane supersaturation in small, temporary ponds. *Biogeochemistry*, *124*(1–3), 305–318. https://doi.org/10.1007/s10533-015-0099-y

Holgerson, M. A., & Raymond, P. A. (2016). Large contribution to inland water CO₂ and CH₄ emissions from very small ponds. *Nature Geoscience*, *9*(3), 222–226. https://doi.org/10.1038/ngeo2654

Jammet, M., Crill, P., Dengel, S., & Friborg, T. (2015). Large methane emissions from a subarctic lake during spring thaw: mechanisms and landscape significance. *Journal of Geophysical Research: Biogeosciences*, *120*(11), 2289–2305. https://doi.org/10.1002/2015JG003137

Jansen, J., Thornton, B. F., Wik, M., MacIntyre, S., & Crill, P. M. (2020). Temperature proxies as a solution to biased sampling of lake methane emissions. *Geophysical Research Letters*. https://doi.org/10.1029/2020GL088647

Juutinen, S., Rantakari, M., Kortelainen, P., Huttunen, J. T., Larmola, T., Alm, J., et al. (2009). Methane dynamics in different boreal lake types. *Biogeosciences*, *6*(2), 209–223. https://doi.org/10.5194/bg-6-209-2009

Kankaala, P., Huotari, J., Tulonen, T., & Ojala, A. (2013). Lake-size dependent physical forcing drives carbon dioxide and methane effluxes from lakes in a boreal landscape. *Limnology and Oceanography*, *58*(6), 1915–1930. https://doi.org/10.4319/lo.2013.58.6.1915

Kirschke, S., Bousquet, P., Ciais, P., Saunois, M., Canadell, J. G., Dlugokencky, E. J., et al. (2013). Three decades of global methane sources and sinks. *Nature Geoscience*, *6*(10), 813–823. https://doi.org/10.1038/ngeo1955

Kyzivat, E. D., Smith, L. C., Pitcher, L. H., Fayne, J. V., Cooley, S. W., Cooper, M. G., et al. (2019). A high-resolution airborne color-infrared camera water mask for the NASA ABoVE campaign. *Remote Sensing*, *11*(18), 2163. https://doi.org/10.3390/rs11182163

Lehner, B., Liermann, C. R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., et al. (2011). High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. *Frontiers in Ecology and the Environment*, 9(9), 494–502. https://doi.org/10.1890/100125

Maeck, A., DelSontro, T., McGinnis, D. F., Fischer, H., Flury, S., Schmidt, M., et al. (2013). Sediment trapping by dams creates methane emission hot spots. *Environmental Science & Technology*, 47(15), 8130–8137. https://doi.org/10.1021/es4003907

Maeck, A., Hofmann, H., & Lorke, A. (2014). Pumping methane out of aquatic sedimentsebullition forcing mechanisms in an impounded river. *Biogeosciences*, *11*(11), 2925–2938. https://doi.org/10.5194/bg-11-2925-2014

McGinnis, D. F., Greinert, J., Artemov, Y., Beaubien, S. E., & Wüest, A. (2006). Fate of rising methane bubbles in stratified waters: How much methane reaches the atmosphere? *Journal of Geophysical Research*, *111*(C9), 1–15. https://doi.org/10.1029/2005JC003183

Messager, M. L., Lehner, B., Grill, G., Nedeva, I., & Schmitt, O. (2016). Estimating the volume and age of water stored in global lakes using a geo-statistical approach. *Nature Communications*, 7, 13603. https://doi.org/10.1038/ncomms13603

Miller, B. L., Chen, H., He, Y., Yuan, X., & Holtgrieve, G. W. (2019). Magnitudes and drivers of greenhouse gas fluxes in floodplain ponds during drawdown and inundation by the Three Gorges Reservoir. *Journal of Geophysical Research: Biogeosciences*, 2018JG004701. https://doi.org/10.1029/2018JG004701

Ollivier, Q. R., Maher, D. T., Pitfield, C., & Macreadie, P. I. (2018). Punching above their weight: Large release of greenhouse gases from small agricultural dams. *Global Change Biology*. https://doi.org/10.1111/gcb.14477

Peacock, M., Audet, J., Jordan, S., Smeds, J., & Wallin, M. B. (2019). Greenhouse gas emissions from urban ponds are driven by nutrient status and hydrology. *Ecosphere*, *10*(3), e02643. https://doi.org/10.1002/ecs2.2643

Podgrajsek, E., Sahlée, E., & Rutgersson, A. (2014). Diurnal cycle of lake methane flux. *Journal of Geophysical Research: Biogeosciences*, *119*(3), 236–248. https://doi.org/10.1002/2013JG002327

Prather, M. J., Holmes, C. D., & Hsu, J. (2012). Reactive greenhouse gas scenarios: Systematic exploration of uncertainties and the role of atmospheric chemistry. *Geophysical Research Letters*, *39*(9), n/a-n/a. https://doi.org/10.1029/2012GL051440

R Core Team. (2020). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Rasilo, T., Prairie, Y. T., & del Giorgio, P. A. (2015). Large-scale patterns in summer diffusive CH₄ fluxes across boreal lakes, and contribution to diffusive C emissions. *Global Change Biology*, *21*(3), 1124–1139. https://doi.org/10.1111/gcb.12741

Reed, D. C., Deemer, B. R., van Grinsven, S., & Harrison, J. A. (2017). Are elusive anaerobic pathways key methane sinks in eutrophic lakes and reservoirs? *Biogeochemistry*, *134*(1–2), 29–39. https://doi.org/10.1007/s10533-017-0356-3

Rosentreter, J. A., Borges, A. V., Deemer, B. R., Holgerson, M. A., Liu, S., Duarte, C. A., et al. (In Press). Half of global methane emissions come from highly variable aquatic ecosystem sources. *Nature Geoscience*.

Salas, H. J., & Martino, P. (1991). A simplified phosphorus trophic state model for warm-water tropical lakes. *Water Research*, 25(3), 341–350.

Saunois, M., Bousquet, P., Poulter, B., Peregon, A., Ciais, P., Canadell, J. G., et al. (2016). The global methane budget 2000–2012. *Earth System Science Data*, 8(2), 697–751. https://doi.org/10.5194/essd-8-697-2016

Saunois, M., Stavert, A. R., Poulter, B., Bousquet, P., Canadell, J. G., Jackson, R. B., et al. (2019). The Global Methane Budget 2000-2017. *Earth System Science Data Discussions*, 1–138. https://doi.org/10.5194/essd-2019-128

Sayers, M. J., Grimm, A. G., Shuchman, R. A., Deines, A. M., Bunnell, D. B., Raymer, Z. B., et al. (2015). A new method to generate a high-resolution global distribution map of lake chlorophyll. *International Journal of Remote Sensing*, *36*(7), 1942–1964. https://doi.org/10.1080/01431161.2015.1029099

Schmadel, N. M., Harvey, J. W., Schwarz, G. E., Alexander, R. B., Gomez Velez, J. D., Scott, D., & Ator, S. W. (2019). Small ponds in headwater catchments are a dominant influence on regional nutrient and sediment budgets. *Geophysical Research Letters*, *46*(16), 9669–9677. https://doi.org/10.1029/2019GL083937

Schubert, C. J., Diem, T., & Eugster, W. (2012). Methane emissions from a small wind shielded lake determined by eddy covariance, flux chambers, anchored funnels, and boundary model calculations: a comparison. *Environmental Science & Technology*, *46*(8), 4515–4522. https://doi.org/10.1021/es203465x

Stanley, E. H., Collins, S. M., Lottig, N. R., Oliver, S. K., Webster, K. E., Cheruvelil, K. S., & Soranno, P. A. (2019). Biases in lake water quality sampling and implications for macroscale research: Biases in studying and monitoring lakes. *Limnology and Oceanography*, 64(4), 1572–1585. https://doi.org/10.1002/lno.11136

Taiyun Wei and Viliam Simko (2017). R package "corrplot": Visualization of a Correlation Matrix (Version 0.84). Available from https://github.com/taiyun/corrplot

Toming, K., Kotta, J., Uuemaa, E., Sobek, S., Kutser, T., & Tranvik, L. J. (2020). Predicting lake dissolved organic carbon at a global scale. *Scientific Reports*, *10*(1), 8471. https://doi.org/10.1038/s41598-020-65010-3

Van Meter, R., Bailey, L., & Campbell Grant, E. (2008). Methods for estimating the amount of vernal pool habitat in the Northeastern United States. *Wetlands*, *28*(3), 585–593.

Verpoorter, C., Kutser, T., Seekell, D. A., & Tranvik, L. J. (2014). A global inventory of lakes based on high-resolution satellite imagery. *Geophysical Research Letters*, *41*(18), 6396–6402. https://doi.org/10.1002/2014GL060641

Webb, J. R., Leavitt, P. R., Simpson, G. L., Baulch, H. M., Haig, H. A., Hodder, K. R., & Finlay, K. (2019). Regulation of carbon dioxide and methane in small agricultural reservoirs: optimizing potential for greenhouse gas uptake. *Biogeosciences*, *16*(21), 4211–4227. https://doi.org/10.5194/bg-16-4211-2019

West, W. E., Coloso, J. J., & Jones, S. E. (2012). Effects of algal and terrestrial carbon on methane production rates and methanogen community structure in a temperate lake sediment: Methanogen response to trophic change. *Freshwater Biology*, *57*(5), 949–955. https://doi.org/10.1111/j.1365-2427.2012.02755.x

West, W. E., McCarthy, S. M., & Jones, S. E. (2015). Phytoplankton lipid content influences freshwater lake methanogenesis. *Freshwater Biology*, *60*(11), 2261–2269. https://doi.org/10.1111/fwb.12652

West, W. E., Creamer, K. P., & Jones, S. E. (2015). Productivity and depth regulate lake contributions to atmospheric methane: Lake productivity fuels methane emissions. *Limnology and Oceanography*, 1–11. https://doi.org/10.1002/lno.10247

Whiting, G. J., & Chanton, J. P. (1993). Primary production control of methane emission from wetlands. *Nature*, *364*, 794–795.

Wik, M., Thornton, B. F., Bastviken, D., Uhlbäck, J., & Crill, P. M. (2016). Biased sampling of methane release from northern lakes: A problem for extrapolation. *Geophysical Research Letters*, *43*(3), 1256–1262. https://doi.org/10.1002/2015GL066501

Wu, Q., Lane, C., & Liu, H. (2014). An Effective Method for Detecting Potential Woodland Vernal Pools Using High-Resolution LiDAR Data and Aerial Imagery. *Remote Sensing*, 6(11), 11444–11467. https://doi.org/10.3390/rs61111444

Yvon-Durocher, G., Allen, A. P., Bastviken, D., Conrad, R., Gudasz, C., St-Pierre, A., et al. (2014). Methane fluxes show consistent temperature dependence across microbial to ecosystem scales. *Nature*, *507*(7493), 488–491. https://doi.org/10.1038/nature13164

Zohary, T., & Ostrovsky, I. (2011). Ecological impacts of excessive water level fluctuations in stratified freshwater lakes. *Inland Waters*, *1*(1), 47–59. https://doi.org/10.5268/IW-1.1.406

Table Legends

Table 1. Results of multivariate linear regression predicting total methane flux in 167 waterbodies (n=134 lakes, n=31 reservoirs). The global model included was fit as LN(CH4+1) ~ waterbody_type*latitude_absolute + waterbody_type*area_ln + waterbody_type*chlorophylla_modeled_ln. Dashes indicate that variable was not included in that particular model. Top models within 2 AICc of the best model are reported.

Table 2. Individual linear least squares regression models predicting total methane flux for all data (n=313 waterbodies), lakes (n=227), and reservoirs (n=86). Boxes are shaded to emphasize significant variables (p<0.05) with $R^2>0.10$. Note that chlorophyll a represents measured values and modeled values from TP (see text).

Table 3. Recommendations for future research to increase certainty in upscaling global methane emissions from inland waters.

Table 1. Results of multivariate linear regression predicting total methane flux in 167 waterbodies (n=134 lakes, n=31 reservoirs). The global model included was fit as LN(CH4+1) ~ waterbody_type*latitude_absolute + waterbody_type*area_ln + waterbody_type*chlorophylla_modeled_ln. Dashes indicate that variable was not included in that particular model. Top models within 2 AICc of the best model are reported.

Acc

Model	AICc	Delta AICc	Adj R ²	Intercept estimate	Waterbody Type Est (Res)	Abs. Latitude Est	Area Est	Chla Est	Waterbody *lat	Waterbody* area	Waterbody *chla
Null	642.96			3.36							
latitude + area + watertype*chla	555.36	0	0.43	3.16	1.30	-0.03	-0.27	0.36			0.33
watertype*latitude + area + watertype*chla	555.46	0.56	0.44	3.49	0.02	-0.03	-0.26	0.35	0.03		0.42
watertype + latitude + area + chla	556.69	1.25	0.42	3.02	1.94	-0.03	-0.28	0.43			
latitude + watertype*area + watertype*chla	556.87	1.41	0.43	3.07	1.12	-0.03	-0.28	0.36		0.08	0.36
watertype*latitude + watertype*area + watertype*chla	557.09	1.51	0.43	3.40	-0.12	-0.04	-0.28	0.35	0.03	0.08	0.44

Table 2. Individual linear least squares regression models predicting total methane flux for all data (n=313 waterbodies), lakes (n=227), and reservoirs (n=86). Boxes are shaded to emphasize significant variables (p<0.05) with $R^2 \ge 0.15$. Note that chlorophyll a represents measured values and modeled values from TP (see text).

	All data (n=317)				Lakes (n=227)				Reservoirs (n=86)			
•	n	R ²	р	sign	n	\mathbb{R}^2	р	sign	n	R ²	р	sign
Water temperature	173	0.03	0.02	+	137	0.08	< 0.001	+	36	0.00	0.33	-
Latitude (absolute)	294	0.02	0.006	-	210	0.05	< 0.001	-	84	0.01	0.22	-
Surface area (LN)	276	0.04	< 0.001	-	198	0.15	<0.001	-	78	0.00	0.52	+
Maximum depth (LN)	147	0.18	< 0.001	-	138	0.19	<0.001	-	9	0.15	0.17	+
Mean depth (LN)	104	0.00	0.66	-	51	0.03	0.13	-	53	0.00	0.75	-
DOC (LN)	89	0.07	0.006	+	73	0.19	< 0.001	+	16	0.00	0.98	-
Chlorophyll a (LN)	178	0.13	< 0.001	+	147	0.08	< 0.001	+	31	0.43	< 0.001	+

Acce

Table 3.

Table 3. Recommendations for future research to increase certainty in upscaling global

 methane emissions from inland waters

Across site sampling:

- Increased effort sampling large lakes (> 1 km²), small reservoirs (< 1 km²), and very small lakes (< 0.01 km²) to reduce uncertainty
- Randomized samples to determine true distribution of methane flux

Within site sampling:

- Measure DOC, chlorophyll a, and report surface area
- Sample both ebullition and diffusion
- More sampling during ice off and fall turnover
- More spatial and temporal coverage at individual study sites

Global database needs:

- Create database for global lake nutrient concentrations
- Expand global chlorophyll and DOC databases to small lakes and for increased temporal coverage
- Expand global surface area database to small lakes
- Improve mapping of lake vs. reservoir surface areas