Resolving the Variability of Measurements, Models, and Parameters for Global Lake and Reservoir Methane Fluxes

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Key Points:

* Global lake and reservoir methane fluxes to the atmosphere are substantial, yet highly variable
* Resolving the variability from the model and the measururements will improve future global lake and reservoir global lake methane fluxes
* Model error exhibited the largest variability, indicating that more complex models that partition uncertainty can improve global estaimtes

Abstract

Global lake and reservoir methane (CH4) fluxes to the atmosphere are substantial, and recent modeling efforts have demonstrated the magnitude and heterogeneity of these fluxes. As available CH4 flux data and models advance, however, the variability inherent to the data and models can become magnified if not explicitly addressed when upscaled. Therefore, it is critical to assess the impact of the spatiotemporal heterogeneity of empirical CH4 flux measurements and the uncertainty of CH4 models to support more robust global upscaling efforts. Specifically, evaluating the effects of variability requires investigating: 1) spatial and temporal coverage of measurements used to calibrate the model, 2) distribution of possible parameter values within the model, and 3) the model error itself. Fortunately, the availability of remotely sensed water area estimates, climate re-analysis data, and high throughput computing infrastructure creates opportunity to evaluate how uncertainty in CH4 ebullition and diffusion is distributed globally. We performed an exercise that fitted a temperature dependent reaction rate model (Arrhenius Model) for both CH4 diffusion and ebullition from lakes and reservoirs, and accounted for spatial measurement variability, temporal measurement variability, model parameter variability, and model error. We applied each equation to an extended version of the Global Lake Area, Climate, and Population database between 2002 and 2015, and compared our methane flux estimates against a baseline scenario that ignored any sources of variability. We found that estimates accounting for model error variability deviated the most from our baseline estimates. Spatial error in the measurements, followed by temporal error, produced lesser but still notable effects on the estimates, and parameter variability affected estimates the least. Our results indicate that model error is a large component of uncertainty surrounding global aquatic CH4 fluxes, and that future data collections used to calibrate models should strive for greater spatial coverage within a water body before longer durations of sampling. Ultimately, we highlight the importance of accounting for the variability in measurements and models when estimating global lake and reservoir CH4 fluxes, and we outline an approach that can be applied to partition the uncertainty across the possible sources of variability.

**Plain Language Summary**

Global lake and reservoir methane fluxes are substantial, yet uncertain. We resolved the sources of variability in the model and the measurements as a means to reduce uncertainty in future global estiamtes. Model error produced the largest uncertainty, followed next by spatial error in the measurements, then temporal error in the measurements, and finally parameter variability. This indicates that model error is a large part of the uncertainty surrounding global lake and reservoir CH4 fluxes and should be accounted for when developing new global estiamtes. Ultimately, accounting for the variability in models and measurements when estimating global lake and reservoir CH4 fluxes is important. We outline an exercise that can be applied to partition the uncertainty across the sources of variability in global estaimtes.

1 Introduction

Global lake and reservoir methane (CH4) fluxes constitute a substantial natural and anthropogenic CH4 flux from inland waters to the atmosphere ([Rosentreter et al., 2020](https://www.nature.com/articles/s41561-021-00715-2#citeas), [Johnson et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021JG006305), [Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG006793), [Harrison et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020GB006888), [Delwiche et al., 2022](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2022JG006908), [Soued et al., 2022](https://www.nature.com/articles/s41561-022-01004-2)), but remain one of the most variable, and hence uncertain, sources of CH4 fluxes globally ([Saunois et al., 2020](https://essd.copernicus.org/articles/12/1561/2020/essd-12-1561-2020.html)). Recent global emission estimates that rely on calibrated prediction models have started to incorporate sources of variability into CH4 flux estimates ([Harrison et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020GB006888), [Johnson et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021JG006305), [Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG006793), [Zhuang et al., 2023](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG007137)). Most studies, however, have not explicitly partitioned the relative contributions from the different sources of variability. These sources of variability may include the spatial and temporal variability of the CH4 flux measurements used to calibrate a model, the model performance itself (i.e., errors due to an imperfect representation of physical processes in a model; [Dietze, 2017](https://esajournals.onlinelibrary.wiley.com/doi/full/10.1002/eap.1589)), or the model parameters (i.e., distribution of potential model parameter values calibrated using *in situ* measurements). Failure to include the aforementioned sources of variability can generate overconfident global estimates, expressed as small uncertainty bounds. Explicitly partitioning the relative contribution of spatial measurement variability, temporal measurement variability, model parameter variability, and model error variability to inland water CH4 flux estimates will not only improve future estimates, but also allow us to more confidently use such estimates to navigate solutions for reducing CH4 emissions.

Partitioning sources of variability has improved predictive modeling for other processes ([Jian et al., 2018](https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.14301), [Heilman et al., 2022](https://doi.org/10.1016/j.ecolmodel.2015.03.017), [Thomas et al., 2018](https://doi.org/10.1002/eap.1761)). For example, Jian et al. ([2018](https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.14301)) tested the variability that is associated with different temporal aggregations of observed data and model performance for soil carbon (C) respiration rates by calibrating, validating, and predicting global soil C rates across different timescales, driver variables, and model types. Importantly, Jian et al. ([2018](https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.14301)) showed that temperature dependent reaction rate models that relied on measurements at sub-annual timescales exhibited less variability for globally upscaled soil respiration rates compared to data that were aggregated to annual rates ([Jian et al., 2018](https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.14301)). Like global soil C respiration, some global lake and reservoir CH4 flux and production estimates have also relied on temperature dependent reaction rate models ([Johnson et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021JG006305), [Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG006793), [Aben et al., 2017](https://www.nature.com/articles/s41467-017-01535-y), [Jansen et al., 2023](https://onlinelibrary.wiley.com/doi/full/10.1111/gcb.16298)). The successful use of such temperature models for CH4 fluxes and production (i.e., rates of methanogenesis) in lakes and reservoirs provides the basis for resolving sources of variability in emission estimates, similarly to Jian et al. ([2018](https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.14301)). Exploring the sources of variability of temperature dependent models provides a basis for updating and improving future global estimates based on the variability associated with current estimates.

The variability associated with the measurements and calibration of a temperature dependent model can be examined by isolating the spatial and temporal measurement variability from model derived variability ([Dietze, 2017](https://esajournals.onlinelibrary.wiley.com/doi/full/10.1002/eap.1589)). Isolating the different sources of variability associated with model calibration and then comparing the outcome of the global estimates that independently use each source of variability against a baseline prediction that excludes any sources of variability can identify which source of variability contributesd most to uncertainty in the global estiamtes. The sources of variability we isolated include spatial measurement, temporal measurement, model performance, and model parameters. We describe all four sources of variability in more detail in the following paragraphs.

1.1 Spatial and temporal measurement variability

The range of potential CH4 fluxes from waterbodies depends on the duration of sampling or the total of number sampling sites on a waterbody ([Wik et al., 2016](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2015GL066501), [Jansen et al., 2020](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020GL088647)). CH4 fluxes from lakes and reservoirs come from two predominant pathways - ebullition (bubbles with high CH4 fractions directly from sediments) and diffusion (dissolved CH4 that accumulates in the water-column and passes across the air-water interface). Both flux pathways are highly variable over space and time. Temporally, diffusion can exhibit diel ([Sieczko et al., 2020](https://www.pnas.org/doi/full/10.1073/pnas.2006024117), [Xiao et al., 2013](https://www.sciencedirect.com/science/article/abs/pii/S1001074212602691?via%3Dihub)), seasonal ([McClure et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JG005205), [Natchimuthu et al., 2016](https://aslopubs.onlinelibrary.wiley.com/doi/epdf/10.1002/lno.10222)), and interannual temporal variability ([Ragg et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2021JG006388), [Prairie et al., 2018](https://link.springer.com/article/10.1007/s10021-017-0198-9)), while ebullition can also exhibit large temporal variability depending on the waterbody’s geographic location (e.g., temperate ([Beaulieu et al., 2016](https://aslopubs.onlinelibrary.wiley.com/doi/10.1002/lno.10284), [McClure et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JG005205), [Matthews et al., 2020](https://www.nature.com/articles/s41598-020-68246-1)) vs. equatorial ([Linkhorst et al., 2020](https://aslopubs.onlinelibrary.wiley.com/doi/10.1002/lno.11410))). Spatially, diffusion generally exhibits less variability within a lake ([Natchimuthu et al., 2016](https://aslopubs.onlinelibrary.wiley.com/doi/epdf/10.1002/lno.10222)) or reservoir ([McClure et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JG005205)), while ebullition can exhibit substantial spatial variation in both lakes ([Walter-Anthony & Anthony 2013](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/jgrg.20087)) and reservoirs ([Beaulieu et al., 2016](https://aslopubs.onlinelibrary.wiley.com/doi/10.1002/lno.10284)). Altogether, the spatiotemporal variability of diffusion and ebullition in lakes and reservoirs can lead to multiple orders of magnitude in reported fluxes depending on the number of sites sampled or the duration of sampling ([Wik et al., 2016](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2015GL066501)).

While individual waterbody fluxes can vary by orders of magnitude, properly accounting for this variability from different spatial and temporal coverages of CH4 flux measurements has not been fully resolved in global upscaling. Typically, empirical measurements used in global estimates are aggregated into single values of lake- or reservoir-wide mean fluxes, even though the measurements used to derive individual waterbody mean fluxes come from varying sampling durations and spatial extents. Consequently, global lake and reservoir CH4 flux efforts have yet to isolate the spatial and temporal variability associated with the measurements or quantify how that variability contributes to global estimate variability.

1.2 Model process error

Many global lake and reservoir CH4 flux estimates rely on temperature-dependent relationships to represent reactions that form the basis for aquatic CH4 emissions ([Yvon-Durocher et al., 2014](https://www.nature.com/articles/nature13164), [Johnson et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021JG006305), [Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG006793), [Aben et al., 2017](https://www.nature.com/articles/s41467-017-01535-y)). As temperature is a significant driver of microbial CH4 production ([Marotta et al., 2014](https://www.nature.com/articles/nclimate2222), [Zeikus and Winfrey 1976](https://journals.asm.org/doi/abs/10.1128/aem.37.2.244-253.1979?casa_token=zArQGMJ-IMYAAAAA:XRtUh4olofiO_rZiOTEZzHyn-VB3puzyIw9gppqQVIPH9B-elXsTtJnCnuyhK9TNeK1R5rvVzXWgaA)), temperature alone has been considered an adequate predictor of CH4 ebullition (e.g., [Aben et al., 2017](https://www.nature.com/articles/s41467-017-01535-y)) and diffusion (e.g., [Rasilo et al., 2015](https://onlinelibrary.wiley.com/doi/full/10.1111/gcb.12741?casa_token=aLob9dTSH50AAAAA%3ACCRExtEU2qX8mKl-BHYUCDhxCshwgMLTSGgDTHTiJVhAl9tGwmXG13-DENdCnRf7U_1zooP7nqMDB1M)) rates. Temperature dependent models, however, may poorly reflect CH4 dynamics because alternative mechanisms can control CH4 production (e.g., organic matter type ([Kelly and Chynoweth 1981](https://aslopubs.onlinelibrary.wiley.com/doi/abs/10.4319/lo.1981.26.5.0891), [Grasset et al., 2018](https://aslopubs.onlinelibrary.wiley.com/doi/full/10.1002/lno.10786))) and emission from the water surface (e.g., air pressure ([Casper et al., 2000](https://link.springer.com/article/10.1023/A:1006269900174)), wind speed ([Joyce and Jewell 2003](https://pubs.geoscienceworld.org/aeg/eeg/article/9/2/167/60671/Physical-Controls-on-Methane-Ebullition-from?casa_token=hEA54319BTsAAAAA:C7L2gNpzMl850h9Oks_N01vbcqTgLWUyTz7rZhZ96_-EZRGi3Wt49zl7_35gu43IF3wEkqY)), water level ([Harrison et al., 2017](https://pubs.acs.org/doi/full/10.1021/acs.est.6b03185)), and sedimentation rate ([Maeck et al., 2014](https://pubs.acs.org/doi/full/10.1021/es4003907?casa_token=dfBKPO-vW8MAAAAA%3Av2E3Tl2BUDif4q4cinbO_HTfUPuJubuyqzHT7MsUFvJBL19-vqpOWDEXomLWYQLt1cZGXvL5oCmYPko))). However, empirical data for these mechanisms are frequently limited, such that their effect is likely captured only as unexplained variation.

Temperature dependent reaction rate models are likely to exhibit high model error (exhibited by the standard deviation of the residuals) when fitted to observed data. Yet, this model error has rarely been added to prior global CH4 flux estimates. If a global flux estimate is generated that includes model error and does not deviate far from a baseline estimate that does not include model error, then it is considered a valid model to generate global flux estimates. Otherwise, newer, more complex models that account for more mechanisms may be more robust for global estimates. Investigating how the model error that is associated with a temperature dependent model propagates to the resulting global CH4 diffusion and ebullition estimates is necessary to determine the validity of using these models for future global estimates.

1.3 Model parameter variability

Parameter values in models are important components for introducing variability in global lake and reservoir CH4 flux estimates. For example, variation in the parameters has been used to explore the sensitivity of global reservoir CH4 fluxes to temperature and littoral area with the G-Res tool ([Harrison et al 2020](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2020GB006888)). Model parameters in higher complexity lake biogeochemical models have also been calibrated using Monte-Carlo Markov Chain approaches, which generate distributions of possible model parameter values. These distributions can then be applied to represent variation in global flux estimates that results from uncertainty in calibrated model parameters ([Zhuang et al., 2023](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG007137)). However, the variability in the model parameter values in recently applied temperature dependent models are typically excluded in global estimates. Aben et al., ([2017](https://www.nature.com/articles/s41467-017-01535-y)) calibrated a temperature dependent model on observed ebullition fluxes that exhibited large ranges in parameter values, and more recent global ebullition estimates ([Johnson et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021JG006305), [Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG006793)) have relied on the averaged parameter values when generating global estimates. Therefore, the overall effects of model parameter variability on overall variability in global lake and reservoir CH4 fluxes are still unclear.

1.4 Quantifying sources of variability

To determine the dominant sources of variability among spatial and temporal measurements, model parameters, and model error, we created a new global time series of CH4 diffusion and ebullition rates among lakes and reservoirs. From these data, we generated new flux estimates to account for spatiotemporal measurement variability around the original observations. Next, we fitted a temperature dependent model from Aben et al. ([2017](https://www.nature.com/articles/s41467-017-01535-y)) across both diffusion and ebullition fluxes in lakes and reservoirs to generate four equations that represented a baseline scenario without any sources of variability, followed by eight separate equations, each representing the high and low variability associated with spatial measurement heterogeneity, temporal measurement heterogeneity, model parameters, and model error. We then applied all 36 of these equations to an extended version of the Global Lake Area, Climate, and Population (GLCP) data product ([Labou et al. 2020](https://portal.edirepository.org/nis/mapbrowse?packageid=edi.394.4)., [Meyer et al., 2020](https://www.nature.com/articles/s41597-020-0517-4)) and calculated global area-corrected CH4 fluxes. Finally, we compared the 32 global estimates representing potential variability scenarios against the four baseline global estimates to determine what source of variability contributed most to overall global estimate variance. The aim of this study was to address two questions. First, how did our baseline global flux estimate and subsequent variability scenario estimates compare to previous global lake and reservoir CH4 fluxes? Second, across the different sources of variability we tested, does spatial measurement variability, temporal measurement variability, model parameter variability, or model error contribute the most to overall global estimate uncertainty?

**2 Materials and Methods**

2.1 Workflow design

We developed a model exercise to explore the sources of variability in global lake and reservoir CH4 flux estimates (Fig. 1). First, we combined the latest published global compilations of lake and reservoir CH4 diffusion and ebullition measurements, extended the data product to a monthly time step when possible, and determined the total number of sampling sites and duration (i.e., number of months) of sampling as a means to resolve spatial and temporal measurement variability (Fig. 1A). We then calibrated a temperature dependent model from Aben et al., ([2017](https://www.nature.com/articles/s41467-017-01535-y)) (see Model section below) on the observed diffusion and ebullition flux in lakes and reservoirs to establish our four baseline equations, as well as eight equations to represent high and low spatial variability of the measurements, eight equations to represent high and low temporal variability of the measurements, eight equations to represent high and low model parameter variability, and eight equations to represent high and low model error (Fig. 1B). Next, we applied the different model scenarios to an extended version of the GLCP data product ([Labou et al. 2020](https://portal.edirepository.org/nis/mapbrowse?packageid=edi.394.4)., [Meyer et al., 2020](https://www.nature.com/articles/s41597-020-0517-4)) and generated nine separate global CH4 flux estimates for approximately 1.42 million lakes (Fig. 1C). Finally, we compared the different model scenario global estimates against the baseline calibration that included no sources of variability (Fig. 1D).

2.2 Building a new global flux database (Fig. 1A)

2.2.1 Appending and extending the newest observed data product

We obtained lake and reservoir CH4 fluxes from Johnson et al., ([2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021JG006305)) and Johnson et al., ([2022](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG006793)) (links to data: [Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1029%2F2022JG006793&file=2022JG006793-sup-0002-Data+Set+SI-S01.xlsx), [Johnson et al., 2021](https://agupubs.onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1029%2F2021JG006305&file=2021JG006305-sup-0002-Supporting+Information+SI-S02.xlsx))) via their comprehensive data products that include a wide size range of reservoirs and lakes. We combined these products and used them as the base of our newly derived data product (Fig. 2). We then expanded the combined [Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1029%2F2022JG006793&file=2022JG006793-sup-0002-Data+Set+SI-S01.xlsx) and [Johnson et al., 2021](https://agupubs.onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1029%2F2021JG006305&file=2021JG006305-sup-0002-Supporting+Information+SI-S02.xlsx)) data product to a monthly temporal resolution by accessing each original research study cited by Johnson et al., ([2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021JG006305)) and ([2022](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG006793)), and then located the fluxes within the text, table, or figure(s) in the manuscript. If the reported fluxes were in a figure, we used WebPlotDigitizer (<http://arohatgi.info/WebPlotDigitizer>), a tool that estimates numerical data from plots, to determine the monthly CH4 diffusion and ebullition fluxes.

Some flux values in the original data sets were derived from wetlands, beaver ponds, rivers, or estuaries. Because our aim was to generate global flux estimates with quantified variability for lakes and reservoirs only, we removed these studies from our extended data product but recognize that these waterbody types also contribute to global CH4 flux estimates ([Smufer et al., 2023,](https://link.springer.com/article/10.1007/s10021-023-00835-3) [Holgerson and Raymond 2016](https://www.nature.com/articles/ngeo2654)).

2.2.2 Assigning spatial and temporal measurement variability

We generated new high and low representative flux values based on the total number of sampling locations and sampled months across all lakes and reservoirs within our combined data product (Fig. 1C, Fig. 3) to resolve how the spatial and temporal variability in CH4 fluxes translated to variability in global estimates. We plotted the range of potential ebullition and diffusive fluxes against the total number of months sampled and the total number of sampling sites on the lake or reservoirs from our newly derived data product (Fig. 3; *sensu* Wik et al. (2016)). Next, we found the maximum and minimum flux values that corresponded with the total number of months and sites sampled on the waterbody (circles, Fig. 3) and then attributed these to each waterbody in the data product according to their true sampling resolution. This approach generated eight additional columns in our data product, including the low potential flux estimates for (1) diffusion and (2) ebullition based on the number of sampling sites, high potential flux estimates for (3) diffusion and (4) ebullition based on the number of sampling sites, low potential flux estimates for (5) diffusion and (6) ebullition based on the number of months of sampling, and the high potential flux estimates for (7) diffusion and (8) ebullition based on the duration of sampling. Each new flux estimate column was subsequently used in our spatial and temporal measurement variability calibration scenarios (see below).

2.3 Generating model scenarios (Fig. 1B)

2.3.1 Arrhenius model

We used our extended flux database to calibrate a temperature dependent Arrhenius model (Eqn. 1) to estimate lake and reservoir CH4 ebullition and diffusion following Aben et al. ([2017](https://www.nature.com/articles/s41467-017-01535-y)), Johnson et al. ([2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021JG006305)), and Johnson et al. ([2022](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG006793)) (Fig. 1B):

Eqn 1.

where is the ebullitive or diffusive flux at 20°C (), (theta) is the system temperature parameter, T is the surface air temperature at 2 m (°C), and stands for the Residual Standard Deviation, which was used to represent model error in those scenarios (Fig. 1). is bracketed in Eqn 1 because it was only used in our model error scenarios and not represented in the baseline, spatial, temporal, and parameter variability equation scenarios (Table 1). Previous mean estimates for and used for ebullition global upscaling were 100 and 1.1, respectively ([Aben et al., 2017](https://www.nature.com/articles/s41467-017-01535-y), [Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1029%2F2022JG006793&file=2022JG006793-sup-0002-Data+Set+SI-S01.xlsx), [Johnson et al., 2021](https://agupubs.onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1029%2F2021JG006305&file=2021JG006305-sup-0002-Supporting+Information+SI-S02.xlsx))). Instead of using previously reported values, we refitted Eqn. 1 using the newest lake and reservoir diffusion and ebullition observations from our extended database to generate the baseline estimate scenario for each combination of waterbody type and flux (Fig. 1, Table 1) and then assessed the model performance based on the significance level of and θ (p<0.05) (Table 1). The derived high and low diffusive and ebullitive fluxes based on the duration of sampling and the total number of sampling sites were also applied to the model to generate the equations that represented spatial and temporal variability. Parameter variability was accounted for by adding or subtracting the standard deviation of parameters estimated during model calibration from the calibrated parameter value. Model error was accounted for by either adding or subtracting the term from the baseline calibrated equations (Fig. 1B, Table 1). See more details of the calibration scenarios in the following paragraphs.

2.3.2 Model calibration scenarios

Once our four baseline scenario equations were derived (Table 1), we refitted Eqn. 1 a total of 16 more times to characterize the variability associated with duration of sampling and number of sample sites for ebullitive and diffusive fluxes from lakes and reservoirs: eight equations for the high and low potential diffusive fluxes due to spatial and temporal variability in lakes and reservoirs and eight equations for high and low potential ebullition from spatial and temporal variability in lakes and reservoirs. We then used the standard deviation of the parameters from the baseline scenario equations to generate eight more equations that represented high and low parameter estimates for ebullition and diffusion from lakes and reservoirs. The variability associated with model parameter estimates was represented by replacing the mean parameter estimates in the baseline scenarios with the mean parameter estimate ± 1 standard deviation (SD). This exercise resulted in four equations with -1 SD Mean of and between diffusion and ebullition from lakes and reservoirs, and four equations with +1 SD mean of and between diffusion and ebullition from lakes and reservoirs. Finally, we used the from the baseline scenario equations to generate eight equations that represented high and low model error for ebullition and diffusion from lakes and reservoirs. The variability associated with model error was represented by adding or subtracting the standard deviation of the residuals from the flux estimates made by the baseline scenario models. This exercise resulted in four equations that subtracted 1 SD the residuals from the baseline scenario between diffusion and ebullition from lakes and reservoirs, and four equations that added 1 SD residuals from the baseline between diffusion and ebullition from lakes and reservoirs.

2.4 Application of equations on GLCP (Fig. 1C)

2.4.1 GLCP data product

We applied all derived equations (Fig. 1B, Table 1) to the extended GLCP data product to estimate monthly global CH4 ebullition and diffusion from lakes and reservoirs (Fig. 1C). The GLCP dataset is a compilation of lake surface area for approximately 1.42  million lakes and reservoirs of at least 10 ha in area with co-located basin-level air temperature and ice cover data ([Labou et al. 2020](https://portal.edirepository.org/nis/mapbrowse?packageid=edi.394.4)., [Meyer et al., 2020](https://www.nature.com/articles/s41597-020-0517-4)). Using original codes from GLCP v1.4 ([Labou et al. 2020](https://portal.edirepository.org/nis/mapbrowse?packageid=edi.394.4)), we were able to include monthly ice area derived from MODIS Snow and Ice data products. Together, this extended version of the GLCP included seasonal lake surface area (km2), 2 m air temperature, and mean monthly percent ice cover. The resulting data product is ~40 GB in size and can be accessed from [Meyer et al., 2020](https://www.nature.com/articles/s41597-020-0517-4), which contains a complete description of the GLCP.

2.4.2 Applying Arrhenius equations to GLCP

We applied the baseline and variability scenario Arrhenius equations (Eqn. 1) separately to each of the 1.42 million lakes. First, we determined the waterbody type (i.e., lake or reservoir) to distinguish which models were to be applied (i.e., 18 equations for lakes and 18 for reservoirs). This exercise generated a 166 month time series from 2002 to 2015 of estimated CH4 diffusion and ebullition across all 1.42 million waterbodies. These initial estimates, however, had not accounted for ice cover, which can significantly suppress fluxes in lakes and reservoirs. We accounted for ice-cover suppression of CH4 diffusion and ebullition by including a percent ice-cover threshold for all applied equations. If the percent ice cover for a specific lake or reservoir exceeded 100%, we assumed that all fluxes were zero for that estimated month. Importantly, including an ice-cover flux suppression reduces the chance of overestimating fluxes during winter months in higher and lower latitudes, but can also underestimate fluxes in the spring months where fluxes of stored gas in the ice and water column can be substantial relative to annual CH4 fluxes ([Denfeld et al. 2018](https://aslopubs.onlinelibrary.wiley.com/doi/full/10.1002/lol2.10079)). Finally, we combined and standardized our flux estimates to be comparable to global flux estimates recently represented from Lauerwald et al ([2023a](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022GB007658?casa_token=eFwE0ZmTR-MAAAAA%3AACB_zG60meSSgC9f6hhnJ2fxAeJIv8nsUJSg2M8fevsf7nqGEzwuf7Bg-zQwWnx7HJ2j2gSyVgah99Q), [2023b](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022GB007657?casa_token=p9dKO_ZB9RsAAAAA%3A3iiLhVg0edb_1p87Yy000sB26F_eFZhI0J_ikcR9zAOcZt9C1SpZYUj8FttXLQfmpBCm6udXL6SaYsc)) by summing the monthly flux rates for ebullition and diffusion for each of the 1.42 million waterbodies and then dividing by the total lake and reservoir area.

2.5 Quantifying the sources of variability (Fig. 1D)

We compared the output of the global flux estimates from all variability scenarios against our baseline scenarios to determine which sources of variability contributed the most to overall global prediction variance (Fig. 1D). We calculated the absolute value of the difference of the standardized global CH4 fluxes between the high and low bounds of our variability sources and compared those to the standardized global flux of our baseline scenario equations.

3 Results

3.1 Newly derived observation data product

The newly derived data product consisted of 496 waterbodies (361 lakes and 135 reservoirs) and a total of 1343 measured observations (Fig. 2). The data include 385 ebullition measurements, and 958 diffusion measurements.

3.2 Ranges of potential flux variability from direct observations

We found that among the 496 lakes and reservoirs, CH4 diffusion was more variable than ebullition (Fig. 3). For those waterbodies with the fewest sampling sites and lowest number of months sampled, diffusion ranged from 10-3 to 104 mg CH4 m-2 d-1 both spatially and temporally in lakes and reservoirs, whereas ebullition only ranged from 10-2 to 103 mg CH4 m-2 d-1 spatially and temporally in lakes and reservoirs (Fig. 3). As the number of sample sites and total number of months increased, the range of potential flux variability decreased, more so for diffusion than ebullition, despite ebullition having a larger initial range of fluxes at the lowest spatial and temporal extents. Diffusive fluxes decreased from a range of 7 orders of magnitude to ~2 (10-0.5 to 101.5 mg CH4 m-2 d-1) when increasing temporal coverage from one monthly sampling to 48 months, while an increase in sampling sites from one to 80 decreased diffusive flux variability from a range of 7 orders of magnitude to ~1 (10-1 to 100 mg CH4 m-2 d-1). The range of ebullitive flux decreased from 6 orders of magnitude to ~3 (10-1 to 102 mg CH4 m-2 d-1) with an increase in temporal coverage of one month of sampling to 15 months, while an increase in sampling sites from 1 to 50 resulted in an ebullitive flux range decrease from 6 order of magnitude to ~1 (10-1 to 100 mg CH4 m-2 d-1).

3.3 Global CH4 flux estaimtes among model scenarios

The standardized global CH4 flux estimates among our baseline estaimtes and variability scenario estiamtes ranged from 0 to 1250 g CH4 m-2 yr-1 across all lakes and reservoirs and across all variability scenarios (Fig. 4). The combined baseline estimates (global ebullition + diffusion in individual lakes and reservoirs) exhibited a median global flux of 67 g CH4 m-2 yr-1 with lower and upper 75% confidence interval bounds (hereafter referred to as 75% CI) of 34 and 115 g CH4 m-2 yr-1, respectively. The median for the low temporal estimates were 49 g CH4 m-2 yr-1 (75% CI of 26 and 132 g CH4 m-2 yr-1), whereas the median high temporal estimates were more than double the low temporal estimates (117 g CH4 m-2 yr-1, 75% CI of 45 and 310 g CH4 m-2 yr-1). The low spatial flux estimates exhibited a median global flux of 3 g CH4 m-2 yr-1 (75% CI of 0.2 and 5 g CH4 m-2 yr-1) with the high spatial flux estimates being almost two orders of magnitude higher (181 g CH4 m-2 yr-1, 75% CI of 70 and 475 g CH4 m-2 yr-1). For our parameter variability scenarios, the low and high estimates were similar (60 g CH4 m-2 yr-1 with 75% CI of 30 and 180 g CH4 m-2 yr-1 for low versus 75 g CH4 m-2 yr-1 with 75% CI of 35 and 210 g CH4 m-2 yr-1 for high). Finally, the low and high model error estimates exhibited the largest difference with a median global flux of 2 g CH4 m-2 yr-1 (75% CI of 0.1 and 3 g CH4 m-2 yr-1) for low and 286 g CH4 m-2 yr-1 (75% CI of 114 and 736 g CH4 m-2 yr-1) for high.

3.4 Comparisons to baseline equation estiamtes

Our baseline scenario closely matched the median, as well as the upper and lower 75% CI, of the global lake and reservoir CH4 flux estimates reported in Lauerwald et al. (2023a and 2023b), with our globally aggregated baseline estimate only 4 g CH4 m-2 yr-1 higher (Fig. 5). The fact that our baseline estimate is closely aligned with previous estimates provides confidence that our approach is valid, supports the comparison of our variability scenarios against our baseline estimates, and indicates that the discussion of the variability analysis of our baseline estimates extends also to previous global model exercises that used temperature dependent reaction rate models (e.g., [Lauerwald et al 2023b](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022GB007658?casa_token=XnQThTemYPwAAAAA%3AcU1uGunHwZjhsN3dunhVTWNJEWWQIffyjk6hEjUkZgoWN3dn8MbYebQcbEKHPVlU8MFuEnAiXjXMIU8)).

Among the sources of variability (Fig. 5), we found that model error exhibited the highest overall difference compared to our baseline scenario. Median area-corrected global methane flux for the low model error scenario was 65 g CH4 m-2 yr-1 lower than the mean baseline estimate, while the median for the high model error scenario was 219 g CH4 m-2 yr-1 higher than baseline, resulting in a difference of 284 g CH4 m-2 yr-1 between scenarios (range, 0 g to 736 g CH4 m-2 yr-1). The next largest source of variability was from spatial measurement error (absolute difference between scenarios of 178 g CH4 m-2 yr-1 and range from 0.2 to 475 g CH4 m-2 yr-1), followed by temporal measurement variability (absolute difference of 68 g CH4 m-2 yr-1 and range from 26 to 310 g CH4 m-2 yr-1). The lowest source of variability among global estimates was from the variation associated with the parameters (absolute difference between scenarios of 15 g CH4 m-2 yr-1 and range from 30 to 210 g CH4 m-2 yr-1).

4 Discussion

We successfully conducted an exercise (Fig. 1) that developed a new global empirical data product (Fig. 2) and explored the sources of variability contributing to global CH4 flux estimates from lakes and reservoirs. Our exercise accounted for spatial and temporal variability in the measurements (Fig. 3), parameter variability, and model error to generate eight global individual lake and reservoir CH4 flux estimates (Fig. 4), which were then aggregated to global estimates and compared to previous estimates as well as our baseline estimate that did not account for any underlying variability (Fig. 5). The combination of a new data product and a first principles approach to partitioning sources of variability ([Dietze, 2017](https://esajournals.onlinelibrary.wiley.com/doi/full/10.1002/eap.1589)) helps depict the variability in the measurements and models associated with global lake and reservoir CH4 flux estimates and robustly attribute them to global estimate uncertainty.

4.1 Comparison to previous estiamtes

Our baseline equation estimates were closely aligned with previous global estimates (Fig. 5), which allowed us to further explore the sources of variability associated with the measurements, the parameters, and the model. We found that incorporating variability associated with the range of fluxes associated with spatial and temporal variation, the model parameters, and model error produced substantial deviations from previous global estimates (Fig. 5). Our results suggest a need for caution in using CH4 flux estimates without explicitly accounting for their potential variation ([Drake et al. 2018](https://aslopubs.onlinelibrary.wiley.com/doi/full/10.1002/lol2.10055)). More specifically, the global equation estimates that accounted for temporal and spatial measurement variability and model error variability exhibited an exceptionally wide range of estimated global CH4 flux rates compared to previous global estimates (Fig. 5). These results highlight that previous estimates, including our own baseline scenario, can generate overconfident global flux estimates when sources of variability within the measurements and models have not been completely resolved.

4.2 Model error is the greatest source of variability in global estiamtes

The Arrhenius model (Eqn. 1) we used to estimate global CH4 fluxes is a useful model for this exercise because it is relatively simple to calibrate ([Aben et al., 2017](https://www.nature.com/articles/s41467-017-01535-y)), can account for monthly seasonal changes in higher and lower latitudes ([Jansen et al., 2023](https://onlinelibrary.wiley.com/doi/full/10.1111/gcb.16298)), and is easily transferable to global data bases compared to other models. However, we still saw that the highest deviation from our baseline estimate was associated with our model error global estimates (Fig. 5). This result could be due to the fact that, despite its ease of transferability, a modified Arrhenius model is still a relatively simple process-based model with only one driver variable (e.g., 2 m surface air temperature). The simplicity and lack of additional drivers in an Arrhenius model has the potential to introduce more model uncertainty compared to more complex models that are better able to capture additional processes that control diffusion or ebullition. For this reason, our results are not entirely unexpected considering model error is generally considered to be a substantial contributor in ecological prediction uncertainty ([Diniz-Filho et al., 2009](https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1600-0587.2009.06196.x), [Massoud et al., 2017](https://onlinelibrary.wiley.com/doi/10.1111/ele.12876), [Page et al., 2017](https://www.sciencedirect.com/science/article/abs/pii/S0043135418300605), [Thomas et al., 2018](https://esajournals.onlinelibrary.wiley.com/doi/10.1002/eap.1761), [Watling et al., 2015](https://www.sciencedirect.com/science/article/abs/pii/S0304380015001283), [Valle et al., 2009](https://www.jstor.org/stable/40346281)). Regardless, the Arrhenius model serves as an ideal example for examining the influence of measurement and parameter variability on CH4 emission models because of its widespread use across previous publications ([Aben et al., 2017](https://www.nature.com/articles/s41467-017-01535-y), [Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1029%2F2022JG006793&file=2022JG006793-sup-0002-Data+Set+SI-S01.xlsx), [Johnson et al., 2021](https://agupubs.onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1029%2F2021JG006305&file=2021JG006305-sup-0002-Supporting+Information+SI-S02.xlsx))). Arrhenius models demand less data than more complex models, which is an advantage over more complex models, and accounting for model error and other sources of variation will increase their usefulness in deriving global lake and reservoir CH4 flux estimates.

We chose a simple model to demonstrate how sources of variability can propagate to large variability in global CH4 flux estimates. As a result, our exercise paves the way to apply this approach to more complex models that have been used to derive global estimates. For example, the Arctic Lake Biogeochemical Model (ALBM, [Zhuang et al., 2023](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG007137)) and ResME (REServoir for ME, [Delwiche et al., 2022](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2022JG006908)) are both high-order process-based models that have shown promise for their transferability to global lake and reservoir data products. Explicitly resolving the sources of variability with global estimates derived from these models will further provide important context on how to improve future global estimates. More specifically, comparing how partitioned sources of variability from the ALBM and ResME models differ from the variability associated with an Arrhenius model can provide useful insight into whether more complex models are more robust for global estimates. More complex models may generate estimates with lower ranges in potential global flux estimates and may reduce model error variability, but could still exhibit high variability associated with measurements used to calibrate the models. Such a result would indicate that CH4 flux models are more robust but that our measurement techniques require attention in order to further improve estimates. This iterative approach of resolving variability with the newest models is critical for constraining current and future globally reported CH4 lake and reservoir flux estimates (Sanouis et al 2020).

An enticing opportunity for future global upscaling is to generate estimates with an ensemble modeling approach, which is common in global climate models and more recently in lake modeling ([Moore et al., 2021).](https://www.sciencedirect.com/science/article/pii/S1364815221001444) For example, the ResME and ALBM models, Arrhenius models, simple linear regression models ([Deemer and Holgerson 2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JG005600)), or the G-res tool ([Prairie et al., 2021](https://www.sciencedirect.com/science/article/pii/S1364815221001602)) are all adequate candidates to estimate global fluxes through a model ensemble, before building new models to compare. A global estimate resulting from a model ensemble may allow the most effective partitioning of variability associated with model error, rather than relying on each model’s residual standard deviation like we did in our exercise. Importantly, developing a middle ground between using models that are oversimplified and have high model error, using complex models that are data and computationally intensive, and using an ensemble of models that may generate accurate estimates but are computationally difficult to execute will greatly expand future CH4 flux estimates for lakes and reservoirs, similar to those developed for wetlands ([Chang et al., 2023](https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.16755)).

4.3 Measurement variability remains a large contributor to global estimate variability

The variability associated with CH4 diffusion and ebullition measurements within and across lakes and reservoirs is high ([Wik et al., 2016](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2015GL066501), [Bastviken et al., 2004).](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2004GB002238) Translating this variability to global estimates, however, remains a challenge. Our model exercise evaluated the variability associated with empirically derived ebullition and diffusion measurements. Previous upscaling estimates from models have either relied on single values associated with multiple waterbodies in a database (e.g., [Rosentreter et al., 2020](https://www.nature.com/articles/s41561-021-00715-2#citeas)) or have been calibrated with numerous measurements from one or two waterbodies (e.g. [Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG006793)). Our data product contained a highly variable set of CH4 flux measurements, which was mostly due to limited temporal extent of sampling and/or limited number of sample sites on a waterbody. We demonstrated that including the potential minimum and maximum CH4 fluxes from the entire empirical data set in our global estimates exhibited high deviation from our baseline estimates and ranged widely (Fig. 5). Therefore, adopting ranges of potential flux values following Wik et al. ([2016](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2015GL066501)), and then calibrating the Arrhenius model with these high and low potential values was a successful method to resolve variability associated with the measurements.

Our exercise also showed that spatial measurement variability contributed more than temporal variability (Fig. 4 and 5). This result suggests that increasing the number of sampling sites within each water body can produce an estimate more representative of a water body (or multiple water bodies) than extending the number of sampling months. It is important to note, however, that our exercise does not resolve how spatial or temporal measurement variability changes with latitude, which was exhibited in our globally depicted individual lake and reservoir estimates (Fig. 4). Parsing variability over space and time may show that equatorial lakes and reservoirs are generally dominated by spatial variability due to a lack of seasonality in the fluxes ([Linkhorst et al., 2020](https://aslopubs.onlinelibrary.wiley.com/doi/10.1002/lno.11410)), while higher and lower latitude lakes and reservoirs may be dominated by temporal measurement variability because they experience greater seasonal controls on the fluxes ([McClure et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JG005205)). Here we illustrate the importance of spatial and temporal variability surrounding the measurements that are used to calibrate a model, and that these decisions warrant inclusion in future global lake and reservoir CH4 estimates.

4.4 Resolving parameter values beyond Arrhenius models

Our analysis showed that variability in the and parameters in the Arrhenius model did not cause large deviation from our baseline equation estimates or have a wide range in total variation between the -1 SD and +1 SD scenarios (Fig. 5). This result also suggests that the parameter values associated with our baseline equations and parameter scenarios (Fig. 2, Table 1) had lower bounds of variability and closely matched the and parameters used from previous studies.

The low contribution to variability from the parameter values does not, however, imply that the evaluation of parameter variability should be excluded in future global CH4 flux estimates. New models that rely on more driver variables and biogeochemical processes will result in more model parameters. Evaluating how the variability of parameter values from new models change can provide important insight as to what driver variables are most important for generating global flux estimates. As the number of parameters in a model increases, the model is able to better fit the data, which causes the model residual error, the largest source of variability in our estimates, to decrease ([Dietze, 2017](https://esajournals.onlinelibrary.wiley.com/doi/full/10.1002/eap.1589)). However, as the number of parameters in a model grows, the uncertainty in them also increases and obfuscates the decrease in model residual error, thus reinforcing the notion that the ideal model is one of intermediate complexity that minimizes the total uncertainty between both the parameters and the model error ([Dietze, 2017](https://esajournals.onlinelibrary.wiley.com/doi/full/10.1002/eap.1589), [Gelfand and Ghosh 1998](https://academic.oup.com/biomet/article-abstract/85/1/1/238416?redirectedFrom=fulltext)).

4.5 Overlooked sources ov variability

Our exercise specifically focused on global flux estimate variability associated with CH4 flux measurements and our chosen model. Other components of variability in global estimates have been explored previously and could be considered in future assessments. The first and most commonly mentioned source of variability is the lack of certainty in global lake and reservoir area. We chose to exclude this component in our analysis because it has recently been resolved by Johnson et al. ([2021](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022JG006793)). Additionally, new approaches to detecting, extracting, and monitoring surface water extent have been developed in the last two decades which has substantially improved the detection of the number of waterbodies ([Hang et al., 2018](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2018RG000598)). Altogether, expanding established waterbody derived data products similar to the GLCP would significantly improve our ability to apply CH4 flux models to lakes and reservoirs globally.

Next, our estimates did not assign any uncertainty associated with the driver data (i.e., a variable(s) present in a model). Here, the Arrhenius model’s driver variable was represented from a climate re-analysis product estimate 2 m over the waterbody ([Meyer et al., 2020](https://www.nature.com/articles/s41597-020-0517-4)). Similar to variability in the measurements of the target variable itself that were used to calibrate the model (i.e., diffusion and ebullition), variability also occurs in the drivers (i.e., temperature). Therefore, generating an ensemble of climate re-analysis products that represent 2 m air temperature, and then linking them with a global lake data product, would be appropriate to account for this variability.

Other sources of uncertainty need to be considered in future research. Ice cover can substantially inhibit diffusive and ebullitive CH4 fluxes in temperate regions ([Denfeld et al. 2018](https://aslopubs.onlinelibrary.wiley.com/doi/full/10.1002/lol2.10079)). Another variable of potential importance is littoral area, which can control ebullition from the water surface. For example, we assigned a littoral area to each GLCP lake or reservoir with 3 m as the littoral area depth cutoff following ([Bastviken et al., 2004](https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2004GB002238), Supplemental Info). However, the 3 m depth does not imply that ebullition is completely suppressed below this depth, as there is evidence of ebullition occurring at depths deeper than 3 m across water bodies, particularly reservoirs ([DelSontro et al., 2011](https://pubs.acs.org/doi/10.1021/es2005545), [2015](https://pubs.acs.org/doi/10.1021/es5054286), [Linkhorst et al., 2021](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020GB006717)). Finally, diel variability in ebullition and diffusion can have significant impact on global estimates ([Johnson et al., 2022](https://agupubs.onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1029%2F2022JG006793&file=2022JG006793-sup-0002-Data+Set+SI-S01.xlsx)). It is important to note, however, that our scenarios were calibrated from monthly values, which likely resolved any diel variability. Thus, future estimates need to consider the time step of their driver and target data and the impact that would have on the results.

Finally, building hierarchical models that partition the sources of uncertainty probabilistically will further advance resolution of variability in future estimates. Our exercise tested the sources of variability by comparing global estimates from different high and low scenarios associated with a variability source against a baseline scenario, following an approach similar to Jian et al., ([2018](https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.14301)) for global soil respiration. Adapting the Arrhenius model into a Bayesian hierarchical model is common in fields like ecological forecasting, which typically resolves the sources of variability in the measurements and models between spatial and temporal estimates. For example, Zhuang et al., ([2023](file:///Users/ryanmcclure/Documents/Zhuang%20et%20al.,%202023)) adopted a Bayesian framework when estimating their model parameters for the ALBM model that was applied to the HydroLakes data product ([Messenger et al., 2016](https://www.nature.com/articles/ncomms13603)) to make global lake CH4 flux projections. This is a critical step to both introduce larger variation in the estimates and to integrate sensitivity analyses into the model workflow to resolve uncertainty before generating a new global lake and reservoir CH4 emission estimate.

5 Conclusions

Our exercise indicated that the variability associated with measurements and model components cannot be ignored when generating new global lake and reservoir CH4 flux estimates. We showed that model error variability was the largest contributor to global flux variability, highlighting that more complex models could better resolve variability of global flux estimates. The next largest source of variability came from spatial variation in the measurements followed closely by temporal variation in the measurements, suggesting that future data products will be more robust by collating empirical data from sites with ample spatial and temporal coverage. Reducing the variability associated with the measurements is also a collective community effort that will only improve with FAIR data practices ([Wilkinson et al., 2016](https://www.nature.com/articles/sdata201618), [Lin et al., 2020](https://www.nature.com/articles/s41597-020-0486-7)). Finally, we found that model parameterization was the lowest source of variability in our exercise. However, parameter variability could increase when more complex models are applied, indicating that there is likely an intermediate model complexity that minimizes the total variation contributed between the parameters and the model residual error. Altogether, our exercise emphasized that accounting for the variability associated with CH4 flux measurements and models is critical to avoid overconfidence in global CH4 emissions estimates from lakes and reservoirs. Ultimately, by highlighting the importance of model error, parameter variability, and within-waterbody spatial and temporal variability to global CH4 emissions estimates, our work provides a roadmap for subsequent efforts to reduce variability in estimates of greenhouse gas fluxes from freshwater bodies, thereby helping to resolve a highly uncertain component of the global carbon budget.

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**Open Research**

An example of the analysis workflow for the country of Belgium can be accessed and run at [the following GitHub link](https://github.com/ryanmclake/RV-GLME). Upon acceptance of publication, all datasets analyzed in this manuscript will be cited therein and available through the Environmental Data Initiative online repository. The code and methods to develop the Global Lake Climate and Population data product used in this study can be accessed at the following links:

[https://doi.org/10.6073/pasta/834e2d4e8ee7eb2fa9a5a5b32d759683](https://portal.edirepository.org/nis/mapbrowse?packageid=edi.394.4),

[https://doi.org/10.1038/s41597-020-0517-4](https://www.nature.com/articles/s41597-020-0517-4#citeas),

<https://code.earthengine.google.com/a7836db97270082811ea354735c82963>.

Additional information on the percent ice cover and littoral area calcualtions can be found in the Supplemental Information documents.

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**Figure 1**. Our workflow was designed to go from (A) empirical measurements to (B) different model variability scenarios to (C) global estimates based on the variability scenarios, and finally (D) a comparison of the different variability scenarios against a baseline scenario that represented no variability. Section A of the graphic depicts development of the empirical data product and the derivation of high and low potential CH4 fluxes for diffusion and ebullition separately and for lakes and reservoirs separately based on the duration of sampling and the number of sampling sites from the original studies. Section B depicts the different variability scenarios (and modified Arrhenius equations) we developed and applied across diffusion and ebullition from lakes and reservoirs separately, thereby generating a total of 36 separate equations for our global estimates (four baseline scenarios and four for each of the eight variability scenarios). Section C depicts our application of the 36 equations to an extended version of the GLCP data product. Section D shows how we compared the global estimates derived from our chosen variability scenarios against a baseline scenario that did not represent any sources of variability.

A diagram of a large scale of a large scale

Description automatically generated with medium confidence

**Figure 2.** Lake and reservoir locations and type of fluxes that are in the newly accrued global CH4 flux data product. References that link to the measurements for each site are found in the new data product (XXX).

A map of the world with blue and orange dots

Description automatically generated

**Figure 3.** The newly developed data product’s range of potential fluxes for diffusion (four left panels) and ebullition (four right panels) depending on the total number of months sampled (top panels) and total number of sampling sites used (bottom panels). The small symbols represent all flux values for lakes (dots) and reservoirs (triangles), whereas the outer bounded large circles indicate the maximum (darker shades) and minimum (lighter shades) potential flux values that were applied for the spatial and temporal measurement variability equation scenarios in Table 1. Note that the X and Y axes differ among the embedded plots.

Several different colored graphs

Description automatically generated with medium confidence

**Figure 4.** Global representations of the individual lake and reservoir CH4 flux estimates (diffusion + ebullition) generated for the baseline and all variability scenarios. See section 2.4.2 for details on the method of this approach. Corrected CH4 flux is the sum of the monthly flux rates for ebullition and diffusion for each of the 1.42 million waterbodies divided by the respective total lake or reservoir area.

A map of the world

Description automatically generated

**Figure 5.** Global flux estimates derived across all of our variability scenarios, which were compared against the global baseline estimates (green) and previously reported global flux estimates from Lauerwald et al., ([2023a](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022GB007658?casa_token=eFwE0ZmTR-MAAAAA%3AACB_zG60meSSgC9f6hhnJ2fxAeJIv8nsUJSg2M8fevsf7nqGEzwuf7Bg-zQwWnx7HJ2j2gSyVgah99Q), [2023b](https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022GB007657?casa_token=p9dKO_ZB9RsAAAAA%3A3iiLhVg0edb_1p87Yy000sB26F_eFZhI0J_ikcR9zAOcZt9C1SpZYUj8FttXLQfmpBCm6udXL6SaYsc)).

A diagram of different colors

Description automatically generated

**Table 1.** Assessment of the baseline scenario model fits across ebullition and diffusion in lakes and reservoirs (top row) and the corresponding parameter values derived from the baseline and variability scenarios that were used to generate global flux estimates (remaining rows). The model variability scenarios have the model residual standard deviation added and subtracted from the equation to represent the upper and lower bounds of potential model error. : ebullitive or diffusive flux at 20°C (mg CH4 m-2 d-1), (theta): system temperature parameter

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Assessment** | **Lake Diffusion**  **p-val., p-val., df** | **Lake Ebullition**  **p-val., p-val., df** | **Reservoir Diffusion**  **p-val., p-val., df** | **Reservoir Ebullition**  **p-val., p-val., df** |
| Baseline | <0.001, <0.001, 400 | <0.001, <0.001, 145 | 0.02, <0.001, 94 | 0.38, <0.001, 40 |
| **Scenario** | **Lake Diffusion**  **,** | **Lake Ebullition**  **,** | **Reservoir Diffusion**  **,** | **Reservoir Ebullition**  **,** |
| Baseline | 25.6, 1.06 | 79.5, 1.05 | 24.8, 1.02 | 70.8, 1.38 |
| Temporal Low | 13.0, 1.14 | 53.9, 1.06 | 18.8, 1.01 | 25.6, 1.37 |
| Temporal High | 41.9, 0.99 | 142, 1.04 | 30.9, 1.04 | 123, 1.46 |
| Spatial Low | 11.8, 1.15 | 51.7, 1.07 | 20.4, 1.02 | 5.88, 1.69 |
| Spatial High | 45.6, 0.99 | 143, 1.04 | 30.5, 1.03 | 164, 1.39 |
| Parameter Low | 21.8, 1.05 | 69.4, 1.03 | 13.5, 0.96 | 0.15, 1.19 |
| Parameter High | 29.4, 1.08 | 89.6, 1.06 | 36.1, 1.09 | 145, 1.58 |
| Model low | (25.6, 1.06) - 69.1 | (79.5, 1.05) - 116 | (24.8, 1.02) - 95.6 | (70.8, 1.38) - 425 |
| Model high | (25.6, 1.06) + 69.1 | (79.5, 1.05) + 116 | (24.8, 1.02) + 95.6 | (70.8, 1.38) + 425 |