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Advancements and opportunities to improve bottom–up estimates of global wetland methane emissions

Qing Zhu[1,*], Daniel J Jacob[2], Kunxiaojia Yuan[1], Fa Li[3,5], Benjamin R K Runkle[4], Min Chen[5], A Anthony Bloom[6], Benjamin Poulter[7], James D East[2], William J Riley[1], Gavin McNicol[8], John Worden[7], Christian Frankenberg[9] and Meghan Halabisky[10]

[1] Climate and Ecosystem Sciences Division, Lawrence Berkeley National Lab, Berkeley, CA 94720, United States of America
[2] School of Engineering and Applied Sciences, Harvard University, Cambridge, MA 02138, United States of America
[3] Doerr School of Sustainability, Stanford University, Stanford, CA 94305, United States of America
[4] Biological & Agricultural Engineering, University of Arkansas, Fayetteville, AR 72701, United States of America
[5] Department of Forest and Wildlife Ecology, University of Wisconsin-Madison, Madison, WI 53706, United States of America
[6] Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91107, United States of America
[7] NASA Goddard Space Flight Center, Biospheric Sciences Laboratory, Greenbelt, MD 20771, United States of America
[8] Department of Earth and Environmental Sciences, University of Illinois Chicago, Chicago, IL 60607, United States of America
[9] Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, CA, United States of America
[10] School of Environmental and Forest Sciences, University of Washington, Seattle, Washington, WA, United States of America
* Author to whom any correspondence should be addressed.

E-mail: qzhu@lbl.gov

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Abstract

Wetlands are the single largest natural source of atmospheric methane (CH_4), contributing approximately 30% of total surface CH_4 emissions, and they have been identified as the largest source of uncertainty in the global CH_4 budget based on the most recent Global Carbon Project CH_4 report. High uncertainties in the bottom–up estimates of wetland CH_4 emissions pose significant challenges for accurately understanding their spatiotemporal variations, and for the scientific community to monitor wetland CH_4 emissions from space. In fact, there are large disagreements between bottom–up estimates versus top–down estimates inferred from inversion of atmospheric CH_4 concentrations. To address these critical gaps, we review recent development, validation, and applications of bottom–up estimates of global wetland CH_4 emissions, as well as how they are used in top–down inversions. These bottom–up estimates, using (1) empirical biogeochemical modeling (e.g. WetCHARTs: 125–208 $TgCH_4\ yr^{-1}$); (2) process-based biogeochemical modeling (e.g. WETCHIMP: $190 \pm 39\ TgCH_4\ yr^{-1}$); and (3) data-driven machine learning approach (e.g. UpCH4: $146 \pm 43\ TgCH_4\ yr^{-1}$). Bottom–up estimates are subject to significant uncertainties ($\sim$80 Tg $CH_4\ yr^{-1}$), and the ranges of different estimates do not overlap, further amplifying the overall uncertainty when combining multiple data products. These substantial uncertainties highlight gaps in our understanding of wetland CH_4 biogeochemistry and wetland inundation dynamics. Major tropical and arctic wetland complexes are regional hotspots of CH_4 emissions. However, the scarcity of satellite data over the tropics and northern high latitudes offer limited information for top–down inversions to improve bottom–up estimates. Recent advances in surface measurements of CH_4 fluxes (e.g. FLUXNET-CH_4) across a wide range of ecosystems including bogs, fens, marshes, and forest swamps provide an unprecedented opportunity to improve existing bottom–up estimates of wetland CH_4 estimates. We suggest that

continuous long-term surface measurements at representative wetlands, high fidelity wetland mapping, combined with an appropriate modeling framework, will be needed to significantly improve global estimates of wetland CH_4 emissions. There is also a pressing unmet need for fine-resolution and high-precision satellite CH_4 observations directed at wetlands.

1. Introduction

Wetlands amount to approximately 30% of total global CH_4 emissions, and their emissions are on the rise, partly due to the ongoing effects of climate change (Etminan *et al* 2016, Zhang *et al* 2017, Rößger *et al* 2022, Bansal *et al* 2023). Furthermore, the increase of wetland CH_4 emissions exacerbates climate warming due to its approximately 45-fold higher global warming potential compared to carbon dioxide (CO_2) over a 100 year time frame, for a sustained emissions of CH_4 (Neubauer 2021). Global efforts (i.e. the Paris Agreement and Global Methane Pledge) (Olczak *et al* 2023) have recognized the need to reduce CH_4 emissions to mitigate the adverse impacts of climate change (Ming *et al* 2022, Malley *et al* 2023). Though natural wetlands have often been overlooked in the realm of climate policy, there is a growing body of literature discussing their potential to mitigate climate change when conserved, managed, and restored appropriately (Anderson *et al* 2016, Leifeld *et al* 2019, Zou *et al* 2022), which requires precise estimation of CH_4 emissions from natural wetlands at relevant temporal and spatial scales.

Two classes of methods have been developed to estimate global-scale wetland CH_4 emissions: 'bottom–up' and 'top–down'. Bottom–up approaches involve using parametric empirical models (Bloom *et al* 2017), land process models that incorporate wetland biogeochemistry (e.g. Riley *et al* 2011) or machine-learning models trained against observations (e.g. Yuan *et al* 2024). Top–down approaches use atmospheric CH_4 observations, atmospheric transport modeling, and initial estimates (i.e. priors) of wetland CH_4 emissions to invert for surface CH_4 fluxes (Jacob *et al* 2022). Comparisons between these two methods have shown large differences in regional and global wetland CH_4 emission estimates (i.e. 181 vs 149 $TgCH_4\ yr^{-1}$) (Saunois *et al* 2020). Attempts to use comprehensive datasets of surface flux observations (i.e. FLUXNET-CH4 Community Product) as model benchmarks have not been able to resolve these differences, leading to reduced model ensemble spread, but not uncertainty, in global CH_4 emission estimates (Chang *et al* 2023).

From a bottom–up perspective, wetland CH_4 emissions have been identified as the largest source of uncertainty in the global CH_4 budget (Saunois *et al* 2020). For example, global wetland CH_4 emissions from 2008 to 2017 are estimated to be between 102 and 182 $TgCH_4\ yr^{-1}$ with bottom–up approaches. In land surface models, such a wide range of estimates results from substantial model structural and parametric uncertainties associated with CH_4 production, oxidation, and transport processes (Poulter *et al* 2017). When the uncertainty in wetland inundation area is also considered (i.e. the model's prognostic wetland area), the uncertainty range of bottom–up estimates increases, spanning 125–218 $TgCH_4\ yr^{-1}$ (Saunois *et al* 2020). Even if global estimates converged, the relative uncertainty range expands at regional scales with, for example, northern high latitude wetlands emitting from 2 to 18 $TgCH_4\ yr^{-1}$ (Saunois *et al* 2020, Stavert *et al* 2022). Explicit wetland CH_4 uncertainty characterization efforts (Bloom *et al* 2017) demonstrate that bottom–up uncertainties in CH_4 production-temperature dependency, wetland extent, and C substrate availability together can lead to a factor of 2 uncertainty in tropical emissions and nearly an order of magnitude uncertainty in high-latitude wetland emissions. Such large uncertainties surrounding bottom–up estimates of wetland CH_4 emissions create significant challenges for the scientific community to understand the dynamics of wetland CH_4 emissions and extrapolate model predictions accurately in time and space.

Top–down inversion and attribution of surface CH_4 emissions to different sectors including natural wetlands has proven to be a valuable approach, especially for continuous global-scale monitoring of wetland CH_4 emissions (Qu *et al* 2021, Jacob *et al* 2022). However, accurate monitoring with top–down inversion is subject to uncertainties in several factors, including the spatial coverage and quality of atmospheric CH_4 concentration data (e.g. satellite or surface stations), atmospheric chemistry and transport schemes, Bayesian optimization, and prior emission estimates (Ma *et al* 2021, Chang *et al* 2023). Over poorly observed regions, such as tropical and arctic wetlands (Bloom *et al* 2016b, Palmer *et al* 2021), the success of top–down inversions relies heavily on prior estimates from bottom–up inventories with little constraint from atmospheric CH_4 concentration data (Saunois *et al* 2020, Ma *et al* 2021). Unfortunately, poorly observed tropical wetlands are global hotspots

of CH_4 emissions (Pangala *et al* 2017), and CH_4 emissions over the poorly observed arctic wetlands are highly sensitive to rapid climate change from amplified arctic warming (Rößger *et al* 2022). Therefore, the relative lack of top–down constraints over tropical and arctic wetlands hinders accurate monitoring of CH_4 emissions and highlights the important role of accurate bottom–up inventories of wetland CH_4 emissions to support effective top–down monitoring.

Because wetland CH_4 emissions are both important and uncertain, and monitoring is a critical part of understanding their contributions to global warming, we aim to identify key gaps in bottom–up estimates and guide improvements to top–down modeling. We review recent efforts to develop, validate, and apply global and regional wetland CH_4 emission estimates. After decades of development of a surface wetland observational network (FLUXNET-CH_4; (Knox *et al* 2019, Delwiche *et al* 2021)) across a wide range of ecosystems (e.g. bogs, fens, marshes, swamps), *in situ* observations of wetland CH_4 emissions provide a unique opportunity to improve bottom–up emission estimates when paired with appropriate modeling frameworks. We therefore provide suggestions on reducing uncertainties in existing estimates by combining recent advances of *in situ* wetland CH_4 flux measurements and bottom–up process-based and machine-learning models.

2. Bottom–up approaches

Existing bottom–up estimates of wetland CH_4 emissions have primarily been generated with one of three different modeling approaches: (1) empirical biogeochemical modeling; (2) process-based biogeochemical modeling; (3) data-driven machine learning approach (table 1, figure 1). The key difference between empirical biogeochemical modeling versus process-based biogeochemical modeling is that empirical biogeochemical modeling does not prognostically provide global estimates. It first combines biogeochemical relationships between wetland CH_4 emissions and environmental variables (temperature, wetland extent, hydrological proxy, substrate proxy) to generate the temporal and spatial variations of CH_4 emissions. Then it requires information regarding global total wetland CH_4 emissions to enable the distribution of emissions in space and time across prescribed wetland regions. Process-based biogeochemical modeling, in contrast, draws on domain knowledge of wetland biogeochemistry to represent CH_4 production, consumption, and transport processes and prognostically simulate wetland CH_4 emissions. Lastly, the machine learning approach is mostly trained on *in-situ* CH_4 observations and environmental predictors (McNicol *et al* 2023), with little biogeochemistry considerations, although physical knowledge can also be used as an important constraint (Yuan *et al* 2022, 2024).

2.1. Empirical modeling

Empirical biogeochemical modeling takes advantage of theoretical understanding of first-order constraints on wetland CH_4 emissions and therefore bypasses explicit model representation of detailed CH_4 biogeochemical processes (e.g. production, oxidation, and transport). For example, wetland CH_4 production is a anaerobic and microbial mediated chemical reaction, which means that production rates are strongly regulated both by redox thermodynamics and reaction kinetics (Le Mer and Pierre 2001). As a result, the first-order constraints on wetland CH_4 emissions are soil hydrology (e.g. water table level), which regulates redox thermodynamics, and temperature, which regulates reaction kinetics. Bloom *et al* (2010) used this theoretical basis to predict wetland CH_4 emissions at a global scale by relating satellite observations of groundwater volume and surface skin temperature to the CH_4 emissions:

$$F_{CH_4} = k \cdot [D + \alpha\Gamma] \cdot Q_{10}^{\frac{T-T_0}{10}} \quad (1)$$

where k is a scaling parameter to link environmental variables to CH_4 emission. D and Γ are initial volume and temporal changes of groundwater volumes. α represents the fractional influence of Γ on total wetland groundwater volume. Q_{10} is the temperature response factor referring to the change of methanogenesis rate under a 10 K temperature change (Inglett *et al* 2012). T and T_0 are surface skin temperature and reference temperature (273 K). The parameterization of k implicitly includes other environmental factors, such as pH control.

In a more recent version of this model, Bloom *et al* (2017) implicitly considered carbon substrate availability as an additional kinetic constraint on land surface CH_4 production and emission, and replaced the volumetric groundwater constraint with a prescribed wetland extent:

$$F_{CH_4} = s \cdot A \cdot R \cdot Q_{10}^{\frac{T-T_0}{10}} \quad (2)$$

where R is the heterotrophic respiration (RH) rate that serves as a proxy of carbon substrate availability. In this case, the soil organic matter is assumed to decompose uniformly under aerobic and anaerobic conditions; and there are no time delays between fermentation and CH_4 production (Riley *et al* 2011). A is wetland extent. s is a global scaling factor to match prescribed global annual flux.

Table 1. Bottom–up inventories of wetland CH_4 emissions.

Method	Product name	Critical processes	Temporal range	Spatial coverage and resolution	Estimates range ($TgCH_4\ yr^{-1}$)	Validation	References
Empirical BGC modeling	Bloom2010	Temperature control, groundwater storage.	2003–2007	Global, $3^\circ \times 3^\circ$	170 ± 15	GEOS-Chem modeled CH_4 concentration	(Bloom *et al* 2010)
	WetCHARTs	Carbon substrate availability, temperature control, wetland extent.	2009–2010[a]	Global, $0.5^\circ \times 0.5^\circ$	124.5–207.5	GEOS-Chem modeled CH_4 concentration	(Bloom *et al* 2017)
Process based BGC modeling	WETCHIMP	10 biogeochemistry models that resolved wetland methane production, oxidation, and transport. Models either used prescribed or prognostically simulated wetland extent.	1993–2004	Global, variable resolutions from $2.5^\circ \times 1.9^\circ$ to $0.5^\circ \times 0.5^\circ$	190 ± 39	Evaluated against top–down inversed CH_4 flux.	(Melton *et al* 2013)
	GCP-CH_4v1	11 biogeochemistry models. Models either used prescribed or prognostically simulated wetland extent.	2000–2012	Global, $0.5^\circ \times 0.5^\circ$	151–222	Evaluated against top–down inversed CH_4 flux.	(Saunois *et al* 2016)
	GCP-CH_4v2	13 biogeochemistry models with prescribed wetland extend.	2008–2017	Global, $0.5^\circ \times 0.5^\circ$	102–182	Evaluated against top–down inversed CH_4 flux; Also, directly validated at 42 FLUXNET sites[b]	(Saunois *et al* 2020)

(Continued.)

Table 1. (Continued.)

	Kaplan	Based on LPJ-DGVM model, labile carbon substrate, temperature control, water table depth	1991–2000	Global, 0.5° × 0.5°	174.6 ± 19.4	—	(Bergamaschi *et al* 2007)
	GISS	Emission factor, temperature and precipitation control	—	Global	110	—	(Fung *et al* 1991)
Machine learning	UpCH$_4$v1	Implicit process representation learned by training Random Forest with observed wetland CH$_4$ emission.	2001–2018	Global, 0.25° × 0.25°	146 ± 43	Cross-validated at 43 FLUXNET sites.	(McNicol*et al* 2023)
	RF-PEATMAP RF-DYPTOP RF-GLWD	Implicit process representation learned by training random forest.	2013–2014	>45° North, 0.5° × 0.5° or 1° × 1°	22–41; 21–40; 26–50[c]	Cross-validated at 25 FLUXNET sites.	(Peltola *et al* 2019)
	Zhu2013	Implicit process representation learned by training artificial neural network.	1990–2009	>45° North, 0.5° × 0.5°	44–54	Validated with 25% samples randomly selected from 34 chamber sites.	(Zhu *et al* 2013)
	CMS-CH4-BA	Explicit constraint from physical knowledge; process representation learned by training artificial neural network.	2002–2021	Boreal Arctic region defined by BAWLD (Olefeldt *et al* 2021)	20.3 ± 0.9	Cross-validated at 36 Eddy Covariance sites and 84 chamber sites.	(Yuan *et al* 2024)

[a] Full ensemble version that considers 4 wetland extent parameterizations, 9 terrestrial biosphere models of heterotrophic respiration and 3 temperature parameterizations.

[b] Validated by an independent study (Chang *et al* 2023).

[c] Three uncertainty ranges correspond to estimates using different wetland maps: PEATMAP, DYPTOP, GLWD.

[d] BGC means biogeochemical.

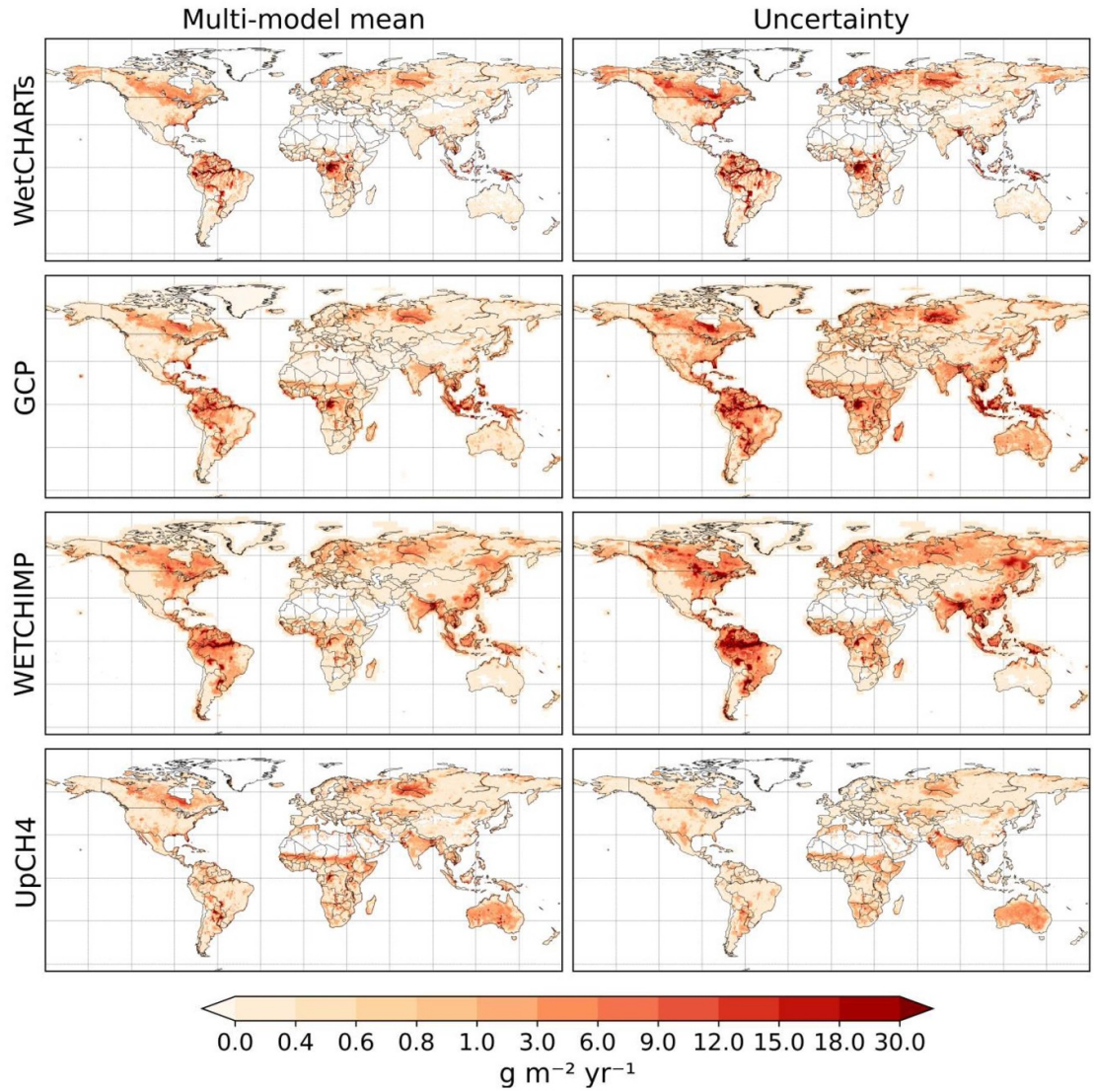

Figure 1. Spatial distributions of bottom–up estimates of global wetland CH_4 emissions, in terms of mean and uncertainty. These estimates were selected to exemplify three different methodologies: (1) empirical biogeochemistry modeling (WetCHARTs: 125–208 $TgCH_4\ yr^{-1}$); (2) process-based biogeochemistry modeling (GCP 108–182 $TgCH_4\ yr^{-1}$, WETCHIMP: 151–229 $TgCH_4\ yr^{-1}$); and (3) data-driven machine learning model (UpCH4: 103–189 $TgCH_4\ yr^{-1}$). More details can be found in table 1. We used all ensemble members from each bottom–up estimate to derive mean and uncertainty ranges.

Recently, the use of a constant temperature sensitivity factor (e.g. Q_{10} or activation energy) has been shown to lead to large biases in inferred wetland CH_4 emissions across global FLUXNET-CH4 dataset (Chang *et al* 2021). These biases emerge from known mechanisms not directly related to the current air or soil temperature, including substrate availability, microbial biomass and activity, hydrology, and plant aerenchyma. The emergent hysteretic relationships between air (or soil) temperatures and CH_4 emissions imply the need to either update the functional form of the temperature relationships used in simple regression models, apply more sophisticated machine learning techniques (Yuan *et al* 2022), or develop more complete process representations in process-based wetland models (Grant *et al* 2017).

2.2. Biogeochemical modeling

The second major approach uses process-based models to prognostically derive large-scale wetland CH_4 emissions (table 1, figure 1). Process-based biogeochemical models combine wetland inundation extent and CH_4 emission flux per unit wetland area to calculate the total emission flux. The inundation extent could be: (1) prescribed with observationally-constrained static or dynamic wetland maps, (2) inferred from simple parameterizations calibrated against satellite observations of wetland inundation, or (3) prognostically simulated with a wetland hydrology model. For example, the Dynamic Land Ecosystem Model used a maximal wetland dataset to inform wetland extent and internally simulated intra-annual variability (Tian *et al* 2010). In CLM4Me

(Riley *et al* 2011), the wetland model integrated in CLM and ELM, simulated water table depth and wetland extend. The Global Inundation Extent from Multi-Satellites (GIEMSs) (Prigent *et al* 2007) are used to develop a simple parameterization for wetland extent, which is then used prognostically in the land model.

To calculate CH_4 emissions, models explicitly resolve major processes including production, oxidation, diffusion, ebullition, and aerenchyma transport (Melton *et al* 2013, Wania *et al* 2013) with various levels of complexities. The two dominant CH_4 production pathways in most wetlands are acetotrophic and hydrogenotrophic methanogenesis. Acetotrophic methanogens use acetate as their substrate and hydrogenotrophic methanogens use carbon dioxide as a substrate with hydrogen serving as the electron donor (Le Mer and Pierre 2001). Process-based biogeochemical models either (1) use labile carbon concentration as a proxy for carbon substrate availability (Tian *et al* 2010, Ringeval *et al* 2012); (2) use soil RH flux as a surrogate for carbon substrate availability without distinguishing the production pathway (Wania *et al* 2010, Riley *et al* 2011) or (3) resolve the multiple microbial functional groups (including fermenters, anaerobic and aerobic decomposers), substrates, and production pathways (Grant *et al* 2017, Chang *et al* 2021). The consumption of CH_4 via oxidation represents a microbial metabolic reaction wherein methanotrophs generate energy and assimilate carbon from CH_4. The CH_4 oxidation rate is typically modeled as a function of CH_4 concentration in the inundated soil, mediated by environmental factors such as temperature and pH (Tian *et al* 2010, Ringeval *et al* 2012). Other models further consider oxygen availability that drives CH_4 oxidation (Wania *et al* 2010, Riley *et al* 2011). More mechanistic models, e.g. *ecosys* (Grant *et al* 2017), explicitly represent microbial biomass, activity, and dependencies on competition with other functional groups, nutrient constraints and dynamics, pH, oxygen availability, etc. CH_4 is transported from its production site to the atmosphere via diffusion, ebullition, and plant aerenchyma, driven by concentration gradients, pressure, and resistance parameters of each conducting media. A comparable range of model complexities in representing these processes exist as described for CH_4 production and oxidation described above.

In particular, not all process-based biogeochemical models explicitly consider CH_4 oxidation and transport. For example, the Sheffield dynamic global vegetation model (SDGVM) (Cao *et al* 1996) considers only CH_4 production and oxidation, thus, its net emission is equal to the difference between production and oxidation rates. Without transport dynamics and lags, the model assumes immediate release of available CH_4 within the soil column. Some other process-based biogeochemical models ignore both oxidation and transport, and assume gross production is equal to net emission. For example, the Lund–Potsdam–Jena dynamic global vegetation models (LPJ-Bern and LPJ-WSL) (Hodson *et al* 2011, Spahni *et al* 2011) that participated in WETCHIMP did not explicitly consider CH_4 oxidation and transport, which made their representations of emissions almost identical to the empirical biogeochemical modeling approach described in Bloom *et al* (2010), (Bloom *et al* 2017). In summary, current process-based biogeochemical models resolve wetland CH_4 emissions with different levels of process details, thus presenting significant structural uncertainty in model simulations.

2.3. Machine learning approach

Unlike empirical or process-based biogeochemical modeling, a third emerging method to derive bottom–up estimates of wetland CH_4 emissions is data-driven modeling, with some or no constraints from first-order biogeochemical processes (table 1, figure 1). This approach trains machine learning models to accurately predict site level (from meter to kilometer scales) observations of wetland CH_4 emissions, allowing algorithms to learn complex, non-linear, and multivariate relationships, between observed CH_4 emissions and environmental predictors (e.g. temperature, precipitation, air pressure). High-quality and extensive measurements of wetland CH_4 emissions are required for robust model training, validation, and testing, which are increasingly available from eddy covariance tower networks (Knox *et al* 2019, Delwiche *et al* 2021) or chambers (Bao *et al* 2021, Bansal *et al* 2023). Previous efforts have shown some success in capturing global and regional dynamics of wetland CH_4 emissions with machine learning approaches. For example, random forest models have been used to upscale FLUXNET-CH_4 *in situ* measurements for both regional (Peltola *et al* 2019) and global (McNicol *et al* 2023) emission estimates. Besides upscaling, machine learning models also provide insights into feature importance (Yuan *et al* 2022, 2024), revealing which environmental predictors exert the most control on emissions. Thus, the trained model can be used not only for prediction and upscaling, but it also offers a powerful tool to describe and interpret the spatial and temporal dynamics of wetland CH_4 emissions.

Nonetheless, a major hurdle in constructing machine learning-based bottom–up estimates lies in ensuring the representativeness of data across a wide range of wetland ecosystems. One of the key sources of uncertainty stems from the limited spatial coverage of ground observations, particularly over critical wetland ecosystems like tropical flooded forests (McNicol *et al* 2023). Process-based models are used

to assess the needed spatial and wetland-type coverage to achieve a specified level of accuracy. For example, Shirley *et al* (2023) performed an analogous analysis for eddy covariance-derived CO_2 emissions across Alaska, and showed that more than ten times the existing EC towers would be required to halve the estimated emission biases. Continuous development of an observational network over tropical and other representative wetlands (Griffis *et al* 2020, Soosaar *et al* 2022), and technical advances on machine learning approaches by adding realistic physical constraints (Yuan *et al* 2022), could play a major role in reducing uncertainties in machine learning based wetland CH_4 emission estimates.

3. Uncertainties and future opportunities to improve existing bottom–up estimates

In this section we focus our attention on global bottom–up estimates of wetland CH_4 emissions listed in table 1 and figure 1. These global products have been developed in the most recent decade. We aim to discuss existing uncertainties and opportunities for future improvements. Uncertainties are discussed in the context of (1) wetland extent and (2) emission intensity (per unit area of wetland).

3.1. WetCHARTS

WetCHARTS estimates used empirical biogeochemical modeling driven by remotely sensed inundation, model-derived RH flux, and a temperature sensitivity factor (Q_{10}) (Bloom *et al* 2017). Overall, uncertainty of wetland CH_4 emissions in WetCHARTS is of a similar magnitude to its mean estimate (e.g. high emission hot spots (e.g. tropical, boreal arctic regions) exhibit high uncertainties (figure 1)).

The uncertainties in wetland extent came from the Global Lakes and Wetlands Database (GLWD) (Lehner and Döll 2004) for spatial variation and the Surface Water Microwave Product Series (SWAMPS) (Schroeder *et al* 2015) for temporal variation. Besides the wetland areas, SWAMPS datasets also include rivers, lakes, and reservoirs that represent about 20% of total terrestrial surface water (Lehner and Döll 2004). Therefore, WetCHARTS implicitly estimated CH_4 emissions from both wetland and non-wetland waters. Recent development of gridded wetland extent products that explicitly exclude non-wetland water bodies, i.e. WAD2M (Zhang *et al* 2021) could reduce uncertainties of WetCHARTS estimates by improving estimates of the spatial variation of wetland extent. Besides coarse resolution global wetland mapping (25–50 km) (Zhang *et al* 2021, Fluet-Chouinard *et al* 2023), new opportunities exist for high resolution wetland extent mapping (<100 m spatial resolution) especially to account for small wetlands omitted in coarse resolution wetland mapping by blending multiple satellite remote sensing products and high resolution land cover classification data (Lane *et al* 2023). Uncertainties in wetland CH_4 emission intensity also stem from their parameterizations of RH and the temperature sensitivity factor. WetCHARTS derived RH estimates from the Multi-scale Synthesis and Terrestrial Model Intercomparison Project (Huntzinger *et al* 2013) multi-model ensemble and from the carbon data model framework (Bloom *et al* 2016a) data assimilation analysis, both of which were subject to large structural and parametric uncertainties. The global datasets of respiration were either for total non-wetland ecosystem respiration (i.e. both autotrophic and heterotrophic) (Jung *et al* 2020) or total soil respiration (i.e. autotrophic and heterotrophic) due to limited direct observations of soil RH. Although separation of the RH from total ecosystem respiration is technically challenging at a global scale, a recent effort estimated the global soil RH flux to be 38.6–56.3 PgC yr^{-1}, using 455 data points from the Global Soil Respiration Database (Yao *et al* 2021). Further, despite potential advances in estimating global RH rates, the CH_4:CO_2 respiration ratio and its temperature dependence under anaerobic (oxygen-depleted) soil conditions remains considerably uncertain (Chang *et al* 2021, Ma *et al* 2021), and is expected to continue dominating the C-mediated uncertainty in bottom–up wetland CH_4 emission rate estimates. It is important to note that WetCHARTS's global total emissions were scaled to 124.5, 166, or 207.5 $TgCH_4$ yr^{-1} to match Global Carbon Project (GCP)-CH4v1 top–down estimates of global wetland emissions. Therefore, by design, WetCHARTS's uncertainties in wetland extent and CH_4 emission intensity was partly obscured by forcing wetland CH_4 emissions to match existing estimates of global wetland emissions.

WetCHARTS has been extensively validated against atmospheric CH_4 concentration data including surface measurements from World Data Centre for Greenhouse Gases (Bloom *et al* 2017) and the Greenhouse Gases Observing Satellite (GOSAT) remote sensing product (Palmer *et al* 2021). WetCHARTS has been evaluated at 104 surface CH_4 concentration measurement sites with the GEOS-Chem chemistry transport model (Bey *et al* 2001), in which the latitudinal profile of simulated CH_4 anomalies reasonably matched the observations (Bloom *et al* 2017). Across all ensemble members, the WetCHARTS-driven TOMCAT atmospheric chemistry transport model (Chipperfield 2006) also reasonably reproduced the global seasonality of atmospheric CH_4 concentrations. However, using WetCHARTS significantly underestimated the seasonal-cycle amplitude by −7.4 ppb (parts per

billion). Particularly, over the northern tropical wetland region, such bias could be as high as −11.9 ppb (Parker *et al* 2020), highlighting the need for uncertainty reduction over tropical wetlands. Significant differences among WetCHARTS ensemble members have been revealed in a similar study that used WetCHARTS to drive GEOS-Chem and were then validated with inversion of GOSAT data (Ma *et al* 2021). Ensemble members with a low Q_{10} temperature factor and a low global total emission scaling factor (equation (2)) performed much better than others (Ma *et al* 2021). Future efforts are needed to better represent temperature sensitivity of wetland CH_4 emission using *in situ* measurements across a diverse range of wetlands.

3.2. WETCHIMP

WETCHIMP used ten biogeochemical models to generate bottom–up estimates of global wetland CH_4 emissions (Melton *et al* 2013). These models determine wetland extents with either prognostic simulation, partially prognostic simulation, or prescribed datasets. To reduce inter-model discrepancies, WETCHIMP used the GIEMSs (Prigent *et al* 2007) to scale each model's wetland extent. For example, wetland extent simulated by ORCHIDEE was scaled towards GIEMS; CLM4Me directly used GIEMS data to parameterize inundation fraction of land surface; DELM limited the simulated annual maximal wetland extent to GIEMS; and LJP-WSL prescribed wetland extent based on GIEMS. In such a way, uncertainty stemming from wetland extent was thereby imposed to be the same across all the models, although it did not eliminate the uncertainty.

Significant uncertainties also exist in the parameterization of wetland CH_4 emission intensity across WETCHIMP models. First, methanogens relied on carbon substrates (e.g. CO_2 or acetate) to produce CH_4. Although none of the models explicitly account for complex interactions between substrates and acetoclastic or hydrogenotrophic methanogens, they all scale CH_4 production to other variables as a proxy. Such scaling significantly differed across WETCHIMP models. For example, the majority of models (e.g. CLM4Me, LPJ-Bern, SDGVM) used non-wetland RH to derive wetland CH_4 production rate, while UW-VIC used non-wetland net primary productivity. Second, oxidative loss of CH_4 during transport from production in the soil to the atmosphere was explicitly represented in 7 out of 10 models. The multi-model ensemble mean of global wetland CH_4 emission was 190 Tg CH_4 yr^{-1} with an uncertainty of 39 Tg CH_4 yr^{-1}. Although it is not clear what the appropriate level of BGC process complexity should be considered in process-based models, opportunities exist to improve the parameterization of critical parameters in existing models using long-term high-frequency measurements from eddy covariance flux sites (Chang *et al* 2023).

3.3. GCP-CH_4

Both GCP-CH4v1 and GCP-CH4v2 bottom–up products estimated global wetland CH_4 emissions with multiple process-based biogeochemistry models (table 1). Overall, GCP-CH4v1 encompassed uncertainties from both wetland emission intensity and wetland extent, while GCP-CH4v2 harmonized wetland extent uncertainty by using the same wetland dataset (Zhang *et al* 2021) in a diagnostic mode for all biogeochemical models (Saunois *et al* 2020). Although GCP-CH4v2 harmonized its models' wetland inundation uncertainty, the uncertainty ranges (102–179 $TgCH_4$ yr^{-1}) of global total emissions did not significantly change compared with GCP-CH4v1 (151–222 $TgCH_4$ yr^{-1}), indicating significant structural and parametric uncertainties in representing key CH_4 production, oxidation, and transport processes.

GCP-CH4 estimates have been validated against surface flux measurements from FLUXNET-CH4 as well as CH_4 concentrations products from GOSAT (Ma *et al* 2021, Chang *et al* 2023, Ito *et al* 2023). FLUXNET-CH4 provided a direct comparison between simulations from biogeochemical models and observed wetland emission intensity. Evaluated at 42 FLUXNET-CH4 sites, GCP-CH4 v2 on average overestimated emission intensity by 63 $mgCH_4$ m^{-2} d^{-1}. Promisingly, selecting the top 20% high-performance GCP-CH4 bottom–up model estimates reduced the uncertainty range by 62% (Chang *et al* 2023), but, unfortunately, increased global differences with the top 20% high-performance top–down approaches. However, due to the spatial coverage of the existing FLUXNET-CH4 monitoring network (figure S1), such *in-situ* validation with FLUXNET-CH4 observations is biased towards northern high latitudes. A further validation of GCP-CH4 estimates over boreal arctic sites (>60°N) found that GCP-CH4 estimated summer emission ensemble mean matched the ML-upscaled and top–down estimates well, but there were large differences between the individual models, indicating substantial model uncertainty (Ito *et al* 2023).

3.4. Machine learning estimates

In the past two decades, wetland CH_4 emissions have been increasingly measured at the surface using various techniques, i.e. eddy covariance and automated and manual chambers. A recent synthesis of eddy covariance measurements (FLUXNET-CH4) covered major wetland ecosystems including wet tundra, bogs, fens, marshes, rice paddies, and swamps, as well as upland and waterbody sites (Knox *et al*

2019). Such high-frequency, multi-year, and multi-ecosystem datasets provide a promising opportunity for biogeochemical models to calibrate and to reduce parametric uncertainty. Although tropical wetlands are under-represented in the current version of FLUXNET-CH4 (Delwiche *et al* 2021), development is ongoing to include more tropical wetland sites (Griffis *et al* 2020). Recently, a multi-decadal gridded product of wetland CH_4 emissions has been developed by upscaling *in situ* eddy covariance measurements to global-scale. UpCH4v1 is the first of this kind of product that covers global wetlands (McNicol *et al* 2023) and it provides a critical benchmark opportunity for evaluating extra-tropical estimates from biogeochemical models as well as a model intercomparison opportunity for tropical estimates, where training sites are fewer. Machine learning approaches, such as UpCH4v1, enable the propagation of emission uncertainties from simulated site training data via model ensembles to globally upscaled estimates. Similarly, some regional gridded products of wetland CH_4 emissions upscaled either eddy covariance or chamber measurements to boreal arctic regions and provide critical constraints for biogeochemical models over specific regions of interest (Zhu *et al* 2013, Peltola *et al* 2019, Yuan *et al* 2024).

Machine learning estimates (1) will benefit from using representative training data across spatial, temporal, and predictor space; (2) can define regions of model applicability; and (3) can estimate extrapolation errors (Meyer and Pebesma 2022). The scale mis-match between site level emission measurements (1 m^2–1 km^2) and global emission product grid-cell area (10–1000 km^2) likely introduce upscaling biases that could be reduced with intermediate, landscape-scale understanding of wetland emissions, hydrogeomorphic position and connectivity, and methane processes.

Emerging techniques of physically-guided machine learning could significantly benefit the generalization of machine learning models and improve model robustness given limited training data. Known physical constraints (e.g. process interactions) are especially important for extrapolating the machine learning model to less representative sites (Yuan *et al* 2022, Liu *et al* 2024). For example, the lack of site representativeness over tropical wetlands in the FLUXNET-CH4 dataset might be partially resolved with physical knowledge guidance during the training of machine learning models. In the context of upscaling wetland CH_4 emissions, traditional ML models often suffer from overfitting, especially when data is sparse or unbalanced across diverse wetland ecosystems. Traditional ML models lack robustness when extrapolating to underrepresented regions or climate conditions. Physically-guided ML approaches substantially resolve these issues by considering physical constraints derived from known biogeochemical processes, such as the temperature sensitivity of CH_4 production, hydrological controls on wetland inundation, substrate availability, etc (Liu *et al* 2024, Yuan *et al* 2024). These constraints benefit model predictions and ensure a more realistic response of CH_4 emissions to changes in environmental conditions, even in data-scarce regions. For example, incorporating causal relationships (e.g. between CH_4 emissions and potential predictors) into machine learning frameworks can improve model accuracy, generalization, and interpretability (Yuan *et al* 2022). By combining the strengths of both data-driven and physical constraints, physically-guided machine learning provides a more robust and reliable tool for upscaling global wetland CH_4 emissions.

4. Role of bottom–up estimates in top–down inversion of wetland CH_4 emission

Top–down inversions use a chemical transport model (CTM) that simulates the transport and chemical reactions of atmospheric CH_4 (Jacob *et al* 2022). With an optimization algorithm, CTM can be used to update the priori estimates of CH_4 emissions (bottom–up estimates) and find the posterior CH_4 emissions that best match the observed CH_4 concentrations. In this case, bottom–up emission estimates provide key knowledge about the magnitude, seasonality, and spatial distribution of surface CH_4 fluxes. We reviewed three major intercomparison efforts on CH_4 top–down inversions during the recent decade (figure 2, table S1), including Kirschke *et al* (2013) (9 models), GCP-CH_4v1 (8 models) (Saunois *et al* 2016), and GCP-CH_4v2 (9 models) (Saunois *et al* 2020). Each effort involved multiple state-of-the-art inversion systems. If a top–down inversion system has been involved in multiple studies, the latest configuration is discussed and shown in figure 2. We focus on major differences in the use of bottom–up wetland CH_4 emissions (prior). We also reviewed atmospheric CH_4 concentration datasets used by each individual top–down inversion because satellite remote sensing data could potentially supplement surface observations to provide a more complete understanding of atmospheric CH_4 (Palmer *et al* 2021).

Top–down inversions utilize multiple bottom–up inventories to provide prior knowledge of surface CH_4 fluxes. Because of the need for spatially and temporally resolved information, they tend to use bottom–up inventories from the Emissions Database for Global Atmospheric Research for fossil fuels, agriculture, waste, and biofuels (Janssens-Maenhout *et al* 2019), and the bottom–up inventory from the Global Fire Emissions Database for global biomass burning (Giglio *et al* 2013). Remarkably,

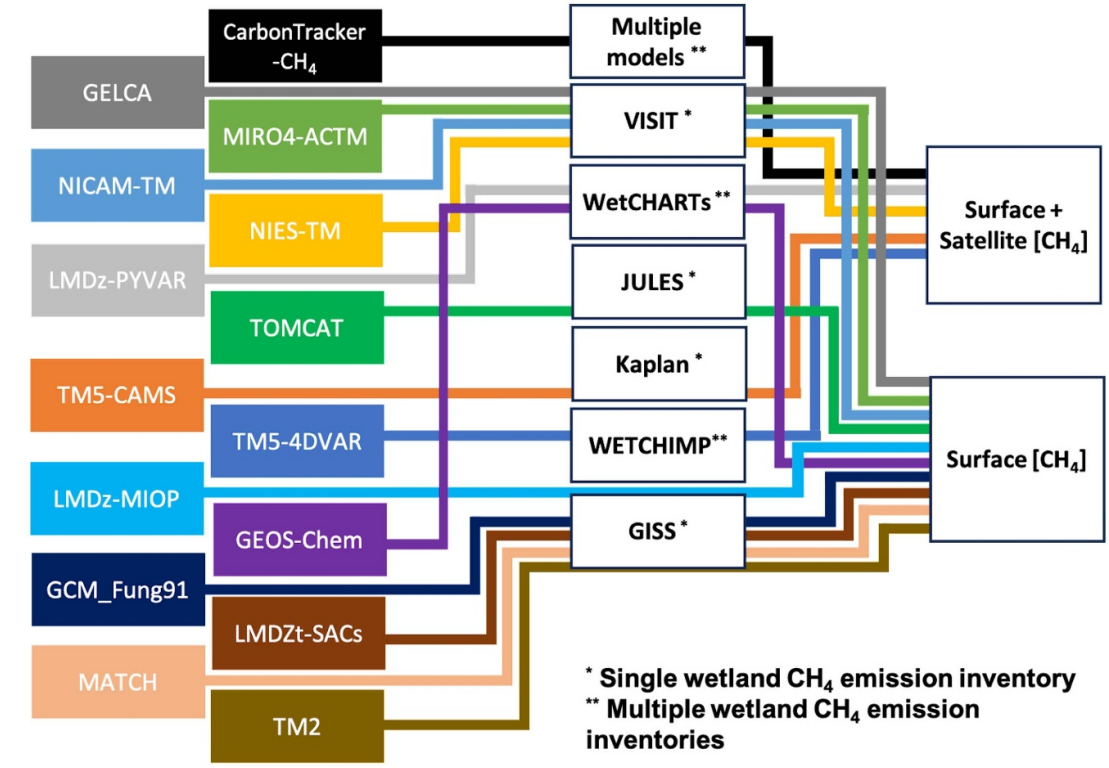

Figure 2. Overview of major top–down inversion systems using different bottom–up inventories of wetland CH_4 emission (priors) and atmospheric CH_4 concentration data (constraints). We include fifteen top–down systems from three major intercomparison efforts on CH_4 top–down inversions in the recent decade (Kirschke *et al* 2013 (9 inversions), GCP-CH_4v1 (8 inversions) (Saunois *et al* 2016), and GCP-CH_4v2 (9 inversions) (Saunois *et al* 2020)). For those top–down inversion systems that participated in multiple intercomparison efforts, we only showed the most recent version. The colored boxes denote different top–down inversions and the colored lines connect top–down inversion systems to their corresponding prior wetland CH_4 emission and atmospheric CH_4 concentration data. 11 out of 15 top–down inversion systems used wetland CH_4 emission prior from a single biogeochemistry model (i.e. VISIT, JULES, Kaplan, GISS), which were highly subject to that biogeochemistry model structure and parametric uncertainties. 10 out of 15 top–down systems used only surface CH_4 concentration data as constraint.

a significant inconsistency persists in bottom–up inventories for wetland CH_4 emissions, despite wetlands being the primary natural source of natural CH_4 emissions. Here we show that, within the three major intercomparison efforts on CH_4 top–down inversions, fifteen top–down inversion systems used seven different wetland inventories, mainly from process-based biogeochemical models and two used empirical biogeochemical modeling estimates from WetCHARTs (figure 2).

Surprisingly, most of the top–down inversions (11 out of 15) relied on wetland inventories from a single biogeochemistry model, such as VISIT (Ito and Inatomi 2012) or GISS (Fung *et al* 1991). The use of a single biogeochemical model might be favorable if the model is appropriately structured and parameterized. However, using a single model also tends to bias the seasonality and spatial distribution of fluxes due to its representation of biogeochemical processes and its original parameter optimization. A recent analysis of GCP-CH4v2 bottom–up models indicated that the multi-model ensemble mean best matched the observed seasonal cycle over high latitudes, while an individual model could significantly overestimate growing season wetland CH_4 emissions (Ito *et al* 2023). For the spatial distribution of wetland CH_4 emissions, individual models were significantly biased when benchmarked using ILAMB (Collier *et al* 2018) with surface eddy covariance measurements of wetland CH_4 flux (Chang *et al* 2023). For example, TEM-MDM best captured tropical (<30°) wetland emissions, while BRTSim-BAMS4 had the highest performance score over arctic tundra wetlands. Such spatial-temporal inconsistencies in wetland bottom–up inventories contributes to large uncertainty in the top–down posterior estimates of surface CH_4 emissions.

Most top–down inversion systems (of 9 out of 15) relied on the surface observational network of CH_4 concentrations (figure 2), whose spatial coverage

is sparse, especially over Eurasia and Africa (figure S1). In the earlier intercomparison effort (Kirschke *et al* 2013), the usage of atmospheric CH_4 data was very different between inversion systems. Seven out of 9 top–down inversions used a subset of surface sites (from 23 to 88 sites) and the other 2 used SCIAMACHY CH_4 retrievals (Frankenberg *et al* 2011) and surface observations. In recent efforts (Saunois *et al* 2020), more top–down inversions (5 out of 9) combined surface data with GOSAT retrievals (Yoshida *et al* 2013) to provide a higher spatial coverage of atmospheric CH_4 concentrations. The enhanced capacity of top–down inversion systems to incorporate multiple sources of CH_4 concentration data has promoted a more robust modeling protocol, thereby potentially improving comparability of results and facilitating interpretation. Given that atmospheric CH_4 concentrations offer valuable spatial-temporal constraints on CH_4 emissions, there remains a clear need for harmonizing the utilization of this data in the future.

Mid-latitude CH_4 concentrations have been relatively well observed by satellite remote sensing, however, observations over tropical and arctic wetlands are still highly limited (Jacob *et al* 2022). Tropical wetland regions tend to have higher cloud coverage than mid-latitudes and obstruct the remote sensing of CH_4 concentrations. Over the boreal and arctic wetland regions, seasonal darkness, cloudiness, and low sun angles make remote sensing during the non-growing season particularly challenging, even though the cold season may contribute over 50% of annual CH_4 emissions over arctic wetlands (Zona *et al* 2016). Tropical and arctic wetlands play important roles as spatial and temporal hotspots for global wetland CH_4 emissions. However, the limited remote sensing capabilities over tropical wetlands and the boreal Arctic during cold seasons present a formidable challenge to the global monitoring of CH_4 emissions. Future satellite instruments should meet the growing demands of investigating humid tropical and boreal-arctic wetland regions, to achieve higher accuracy retrievals, expand spatial coverage, and improve temporal coverage.

5. Impacts of bottom–up estimates of wetland emission on atmospheric CH_4

To further demonstrate the large impacts of bottom–up estimates of wetland CH_4 emission on top–down CH_4 monitoring, we simulate 2019 atmospheric CH_4 using wetland emissions from a wide selection of bottom–up inventories including an empirical biogeochemical model, a process-based biogeochemical model, and a machine learning model to drive with the GEOS-Chem global atmospheric chemistry model version 14.1.0 (doi.org/10.5281/zenodo.7600404). Simulations are compared to TROPOMI satellite observations of dry-air mole fractions, bias-corrected against GOSAT using machine learning (Balasus *et al* 2023).

These 1 year simulations of 2019 use the same inventories for all anthropogenic and natural CH_4 emissions sources besides wetlands (e.g. fossil fuels, agriculture, waste, and biofuels, fire). For wetland emissions, we use LPJ-wsl (Zhang *et al* 2016), a process-based biogeochemical model, WetCHARTs (Bloom *et al* 2017) with its nine best-performing ensemble members identified in Ma *et al* (2021), and UpCH4 v1.0 (McNicol *et al* 2023), a machine learning estimate of wetland CH_4 emissions. GEOS-Chem is initialized using CH_4 concentrations biased corrected against zonal mean XCH_4 observations from TROPOMI. These simulations (figure 3) demonstrate how different bottom–up wetland inventories lead to vastly different atmospheric CH_4 concentrations and seasonality.

Significant errors in CH_4 emissions seasonality are evident for most of the estimates used and such errors will bias top–down inverse estimates. An accumulating bias during the year is expected due to an imbalance in GEOS-Chem's methane budget with default emission and loss terms, but seasonally varying bias is due primarily to the representation of wetland emissions (East *et al* 2024). When present in priors used for surface CH_4 flux inversions, errors in seasonality propagate to the final inverse estimates (Maasakkers *et al* 2019). Differences in seasonality result from different parameterizations of biogeochemical processes. For example, for boreal wetlands, freeze-thaw cycles, snow cover effects, and soil temperature all affect high-latitude wetland emissions seasonality (Olefeldt *et al* 2013, Bao *et al* 2021), but model parameterizations may not include all these processes, leading to spatial and seasonal biases compared to atmospheric measurements. Therefore, the results highlight the urgent need to harmonize and improve bottom–up wetland inventories with better error characterization including spatial and temporal covariances.

6. Moving forward

6.1. Improve the mapping of wetland inundation area

Bottom–up estimates of wetland CH_4 emissions (empirical, process-based, or machine-learning) rely heavily on inputs of wetland inundation maps to calculate regional and global emissions. Besides the difference in size and distribution, wetlands ecosystems are also diverse (e.g. bogs, fens, marshes, swamps) (Lehner and Döll 2004). However, prevailing long-term global datasets of wetland inundation area (i.e. GIEMS-2, WAD2M, SWAMPv3.2) do not agree on

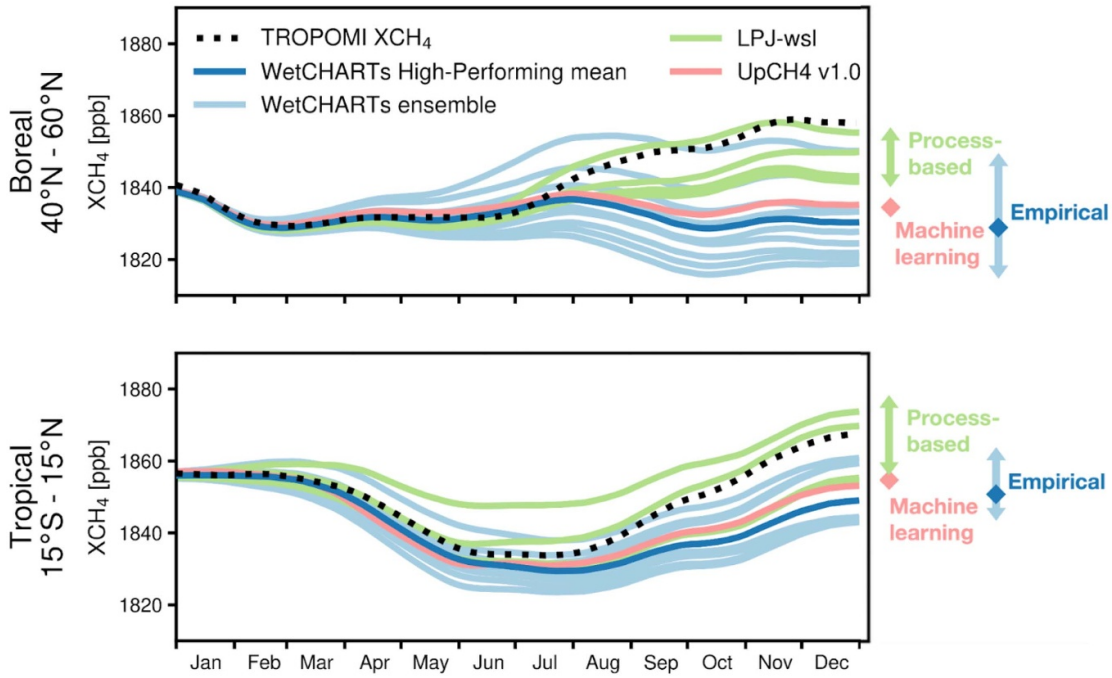

Figure 3. Atmospheric methane dry-air mole fraction (XCH_4) from blended TROPOMI + GOSAT satellite observations (Balasus *et al* 2023) and from GEOS-Chem using different bottom–up wetland emissions. The GEOS-Chem atmosphere is sampled to match the satellite observations and lines are daily, area-weighted means with two passes of a 30 d moving average filter applied. Simulations are for the year 2019. GEOS-Chem XCH_4 is bias-corrected to match zonal mean observed XCH_4 at the simulation start. Observations and modeled methane north of 60°N are not included due to the data not being reliable and available throughout the year.

the size of global wetland area and have no explicit information on wetland types. Furthermore, those coarse spatial resolution (e.g. 0.25°) wetland datasets have limited capability to capture fine-scale details of small wetlands.

There are many reasons why wetland maps may not agree. Wetlands are typically defined by their inundation depth and duration, which can vary significantly. Some wetlands are permanently wet, while others are only wet during certain seasons or periods of the year. This variability makes it challenging to establish clear boundaries for what constitutes a wetland, what is a meadow or grassland, and what is a waterbody. Wetlands are difficult to define as they often occur at the interface between terrestrial and aquatic environments. The boundaries of these transition zones can be both ambiguous and dynamic, further complicating the definition of wetlands. Different disciplines have their own definitions of wetlands, based on specific criteria such as soil type, vegetation, or hydrology. These definitions can overlap with other landcover datasets such as forests or waterbodies. Wetland inundation maps each have a certain degree of error and bias towards or against specific wetland types or regions which is largely driven by the limitations of the sensor used to create the wetland map and the wetland types found in particular regions. For example, forested wetlands in the Pacific Northwest of the USA often are missing from wetland inventories as they are difficult to detect under forest canopy in spectral imagery (Halabisky *et al* 2023). Additionally, the temporal resolution of the sensor used to create a wetland map may omit wetlands that may have large fluctuations in water extent. For example, wetlands in central Australia may be dry for decades and then full of water only for a few years, which could easily be missed depending on the timing of the sensor acquisition.

Wetlands encompass a wide range of ecosystems, including bogs, fens, marshes, and swamps, each with distinct characteristics that influence CH_4 emissions. However, distinguishing different wetland ecosystems is still challenging when mapping global wetland inundation. Recent efforts combined soil properties, vegetation indices, inundation duration, and climatic information to provide fine-scale classification of wetland ecosystem maps (Lehner *et al* 2024). For example, information on seasonality could be used to distinguish permanent, intermittent, or ephemeral wetlands. Such information is critical for estimating CH_4 emissions, which requires continuous inundation to develop microbial biomass and activities. Also, ombrotrophic bogs dramatically differ from minerotrophic fens in terms of substrates, nutrient supply, and pH, which all significantly impact wetland CH_4 emissions. Mapping and modeling the variability in

CH_4 dynamics across these wetland types is crucial for reducing uncertainties in bottom–up estimates.

High-resolution mapping of wetland extent has improved in recent years. Using Landsat reflectance time-series products and Sentinel-1 synthetic aperture radar imagery, Zhang *et al* (2023) developed the first global 30 m wetland map, with explicit wetland type information. Combining automatic sample extraction, satellite time-series images, and local adaptive random forest models, the 30 m data provided a better estimate of the spatial distribution of wetlands and wetland types including small wetlands that may be overlooked by existing global wetland products (Zhang *et al* 2024). However, the high resolution wetland maps only recorded the annual maximum of wetland area and thus ignored temporal variations, which are important for seasonally flooded wetlands. While high resolution maps may identify wetlands missing from coarser resolution datasets, they have face many of the challenges mentioned above such as, wetland definition limitations, sensor bias, and temporal mismatches.

One of the key limitations of existing wetland maps stems from the characteristics of the sensors they use to generate global datasets. Optical sensors such as Landsat, while providing high spatial resolution, often miss small or seasonally inundated wetlands due to infrequent temporal coverage and interference from cloud cover, especially in tropical regions. Additionally, forested wetlands, particularly in tropical and boreal zones, are underrepresented because of the difficulty for Landsat to detect inundation under dense vegetation canopies. In contrast, microwave sensors (e.g. the sensor used for the SWAMPS) are less affected by cloud contamination and can detect wetlands under vegetation cover. However, their low spatial resolution is insufficient for accurately mapping small or fragmented wetlands. Capturing the temporal dynamics of small wetlands therefore remains a significant challenge for both types of sensors. Importantly all wetland maps are constrained by the lack of high quality training and validation data necessary to develop improved unbiased maps. Therefore, it is critical that regardless of the wetland dataset used the limitations and bias are well known.

Significant opportunities exist to (1) bias correct long-term coarse resolution datasets based on high resolution wetland maps; or (2) aggregate the high resolution maps of maximum wetland area to coarse resolution grid cells and impose seasonal patterns based on existing datasets that consider seasonal variations in wetland area, e.g. WAD2M, GIEMS-2; 3.) continue to improve development of high resolution global wetland inundation maps that also contain seasonal information. Specifically, high-resolution remote sensing datasets, such as Sentinel-1 and Sentinel-2, can provide insights into the dynamics of small wetlands that are often missed in large-scale datasets. Applying bias correction could better align large-scale coarse-resolution datasets (e.g. WAD2M, GIMES) with finer-scale datasets through statistical calibration or machine learning techniques. Also, combining optical sensor data (e.g. Landsat, Sentinel) with microwave sensor data (e.g. SSM/I, SSMIS) allows for the detection of inundation under varying conditions, including vegetative cover, cloud contamination, and seasonal flood timing and duration, all of which are essential for wetland mapping in regions with strong hydrological seasonality, such as tropical and semi-arid environments.

6.2. Reduce parametric uncertainty in bottom–up estimates

The FLUXNET-CH4 synthesis activities deliver high-quality, standardized measurements of CH_4 emissions from wetlands at a 30 min frequency (Knox *et al* 2019, Delwiche *et al* 2021). These datasets are crucial for tuning CH_4 parameters in process-based biogeochemistry models, such as those involved in the WETCHIMP and GCP-CH4 projects (Melton *et al* 2013, Saunois *et al* 2020). However, calibrating model parameters across diverse wetland types through a large ensemble parameter perturbation experiment poses significant challenges.

Advances in the machine learning surrogate modeling technique offer a promising solution for efficiently and effectively optimizing model parameters with a small number of parameter perturbations (Dagon *et al* 2020, Li *et al* 2023b). Machine learning models could be used to identify predictive relationships between parameter variations and discrepancies between model predictions and observed data. Thus, this approach will enable the determination of optimal parameter sets that minimize model errors. For instance, feed-forward neural network models have successfully acted as surrogates for CLM5 physical model simulations, which successfully identified optimal parameter values related to carbon and energy fluxes (Dagon *et al* 2020). This approach, with its low computational demands and high accuracy in parameter optimization, holds great potential for application in CH_4 biogeochemistry models. More importantly, recent advances in machine learning techniques could further improve the physical consistency of the machine learning surrogate model to capture not only the emergent pools and fluxes simulated by process-based models but also consistently represent the underlying functional responses between environmental drivers and biogeochemical fluxes (Zhu *et al* 2022, Li *et al* 2023a, Liu *et al* 2024), thus enhancing parameter optimization robustness.

A globally distributed observational network is essential for reducing uncertainties in bottom–up modeling of wetland CH_4 emissions by providing representative and high-quality data across diverse wetland ecosystems. Current observational networks, such as FLUXNET-CH_4, are biased toward northern high latitudes and temperate regions, leaving critical gaps in underrepresented areas, such as tropical wetlands (Zhu *et al* 2024), which are hotspots for CH_4 emissions. A comprehensive observational network would capture the spatial and temporal variability of wetland CH_4 emissions, allowing bottom–up models to be calibrated and validated across a wide range of environmental gradients. Future efforts and support are needed to expand the coverage of observational networks.

Besides reducing parametric uncertainty, process-based biogeochemistry models also suffer from structural uncertainty due to incomplete representation of CH_4 biogeochemical processes. For example, the differential equations used in those models were often derived from empirical knowledge and limited amounts of data. Equation Discovery, an emerging AI method (Song *et al* 2024), can offer insights into process representations using existing datasets. Unlike data-driven machine learning models that attempt to approximate the relationship between predictors and CH_4 emissions, equation discovery AI would uncover governing equations that control CH_4 emissions, thus directly reducing structural uncertainty within process-based biogeochemistry models. With a more accurate process-level representation, such an approach would also enhance out-of-sample extrapolation, which is critically important for the long-term projection of wetland CH_4 emissions under changing climate.

6.3. Enhance satellite remote sensing capability over humid wetlands to constrain bottom–up estimation

Satellite remote sensing of atmospheric CH_4 concentrations provide additional constraints on bottom–up inventories of CH_4 fluxes (Jacob *et al* 2022). As an important source of prior information, atmospheric transport inversions need to adopt a more consistent protocol on the usage of prior wetland CH_4 inventory (figure 2). Harmonizing existing bottom–up estimates of wetland CH_4 emissions and having appropriate error statistics is an important step moving forward.

Furthermore, current transport inversions often rely on large-scale CH_4 flux mappers including GOSAT (2009–present) and TROPOMI (2018–present) (Parker *et al* 2020, Palmer *et al* 2021, Helfter *et al* 2022). Although GOSAT and TROPOMI provide long-term continuous data to quantify emissions on regional scales, coarse spatial resolution and data scarcity and uncertainty over humid wetlands remain big challenges. The geostationary GEO-CAPE instrument (Moore *et al* 2018) would have enabled higher-frequency observations over the Americas but was canceled by NASA in 2022. The MERLIN lidar instrument scheduled for launch in 2027 (Ehret *et al* 2017) will be enable effective cloud clearing and nighttime observations for tropical and boreal wetlands but the data will be sparse. The recently launched MethaneSAT instrument and soon to be launched Global Observing SATellite for Greenhouse gases and Water cycle instrument would provide the combination of 0.1–1 km pixels and high precision needed to effectively observe wetland emissions but are directed at anthropogenic emissions (Jacob *et al* 2022). There is the need to expand the concept of high-resolution, high-precision satellite observations to focus on wetlands and provide opportunities to improve inversions of surface wetland CH_4 emissions, particularly over wetland hotspot regions.

7. Conclusions

In this study, we review the major methodologies employed for the development of bottom–up estimates of wetland methane (CH_4) emissions. Existing wetland CH_4 emission estimates primarily stem from three distinct approaches: empirical biogeochemical modeling, process-based biogeochemical modeling, and machine learning approaches, each susceptible to many sources of uncertainty. We also delve into the critical challenges that need to be tackled to reduce uncertainty in these bottom–up estimates. The ongoing progress in wetland mapping and the refinement of surface measurements of wetland CH_4 emissions intensity provide great potential for enhancing the accuracy of existing wetland CH_4 emission estimates. As wetland CH_4 emissions constitute the largest and most uncertain component of natural CH_4 sources, we further explore the pivotal role they play in influencing top–down CH_4 inversions. Our results demonstrate the pressing need to enhance bottom–up estimates to bolster top–down modeling of wetland CH_4 emissions. At the same time, there is a pressing need for fine-resolution high-precision satellite observations directed at wetlands. We encourage collaborative efforts between the bottom–up and top–down modeling communities to address the uncertainties surrounding wetland CH_4 emission estimates, thereby facilitating more precise monitoring and effective management of these emissions.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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ORCID iDs

Qing Zhu https://orcid.org/0000-0003-2441-944X
Kunxiaojia Yuan https://orcid.org/0000-0002-1336-5768
Benjamin R K Runkle https://orcid.org/0000-0002-2583-1199
Benjamin Poulter https://orcid.org/0000-0002-9493-8600
James D East https://orcid.org/0000-0001-7199-6229
William J Riley https://orcid.org/0000-0002-4615-2304

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