Second Revision of

Satellite constraints on the latitudinal distribution and temperature sensitivity of wetland methane emissions

Shuang Ma1, John R Worden1, A. Anthony Bloom1, Yuzhong Zhang2,3, Benjamin Poulter4, Daniel H. Cusworth1, Yi Yin5, Sudhanshu Pandey6, Joannes D. Maasakkers6, Xiao Lu7, Lu Shen7, Jianxiong Sheng8, Christian Frankenberg5, Charles E. Miller1, Daniel J. Jacob7

1 Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA
2 Key Laboratory of Coastal Environment and Resources of Zhejiang Province, School of Engineering, Westlake University, Hangzhou, Zhejiang Province, China
3 Institute of Advanced Technology, Westlake Institute for Advanced Study, Hangzhou, Zhejiang Province, China
4 NASA Goddard Space Flight Center, Biospheric Science Laboratory, Greenbelt, MD, USA
5 Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, CA, USA
6 SRON Netherlands Institute for Space Research, Utrecht, The Netherlands
7 School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, USA
8 Center for Global Change Science, Massachusetts Institute of Technology, Cambridge, MA, USA
Satellite constraints on the latitudinal distribution and temperature sensitivity of wetland CH$_4$ emissions

Shuang Ma$^1$, John R Worden$^1$, A. Anthony Bloom$^1$, Yuzhong Zhang$^{2,3}$, Benjamin Poulter$^4$, Daniel H. Cusworth$^1$, Yi Yin$^5$, Sudhanshu Pandey$^6$, Joannes D. Maasakkers$^6$, Xiao Lu$^7$, Lu Shen$^7$, Jianxiong Sheng$^8$, Christian Frankenberg$^5$, Charles E. Miller$^1$, Daniel J. Jacob$^7$

1. Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA
2. Key Laboratory of Coastal Environment and Resources of Zhejiang Province, School of Engineering, Westlake University, Hangzhou, Zhejiang Province, China.
3. Institute of Advanced Technology, Westlake Institute for Advanced Study, Hangzhou, Zhejiang Province, China
4. NASA Goddard Space Flight Center, Biospheric Science Laboratory, Greenbelt, MD, USA
5. Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, CA, USA.
6. SRON Netherlands Institute for Space Research, Utrecht, The Netherlands
7. School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, USA
8. Center for Global Change Science, Massachusetts Institute of Technology, Cambridge, MA, USA
Key points

1. We use a novel Bayesian approach to account for cross-correlations and spatial uncertainties in top-down flux estimates

2. We validate and refine bottom-up wetland CH$_4$ estimates with satellite-informed CH$_4$ flux estimates

3. We find ~25% less global emissions from best-fit models and a lower-than-expected sensitivity of global wetland CH$_4$ emissions to temperature

Plain language summary:

Wetland methane (CH$_4$) emissions represent about 30% of the global CH$_4$ budget and remain its most uncertain component. To test and refine bottom-up wetland models using satellite-informed top-down CH$_4$ fluxes, we present an approach that comprehensively accounts for prior flux assumptions, posterior cross-correlations, and spatial uncertainties in top-down flux estimates. Our results place new constraints on the latitudinal distribution of wetland emissions for bottom-up estimates: we find that tropical wetland emissions contribute 72% (63-85%) to the global wetland total. We also find that for bottom-up model estimates, a lower-than-expected temperature sensitivity agrees better with atmospheric CH$_4$ measurements. Overall, our approach demonstrates the potential for using satellite-inferred CH$_4$ flux estimates to quantitatively refine bottom-up estimates and their sensitivity to climate.
Abstract

Wetland methane (CH$_4$) emissions comprise about one-third of the global CH$_4$ budget. The latitudinal distribution and climate sensitivity of wetland CH$_4$ fluxes are the key determinants of the global CH$_4$-climate feedback. However, large differences exist between bottom-up estimates, informed by ground-based flux measurements, and top-down estimates derived from spaceborne total column CH$_4$. Despite the extensive coverage of satellite CH$_4$ concentration observations, challenges remain with using top-down estimates to test and refine bottom-up models, mainly because of the uncertainties in the satellite retrievals, the model representation errors, the variable prior emissions, and the confounding role of the posterior error covariance structures. Here, we use satellite-based top-down CH$_4$ flux estimates (2010-2012) to test and refine a range of bottom-up wetland CH$_4$ emission models that use a range of hypothesized wetland extents and process controls. Our comparison between bottom-up models and satellite-based fluxes innovatively accounts for cross-correlations and spatial uncertainties typically found in top-down inverse estimates, such that only the information from satellite observations and the atmospheric transport model is kept as a constraint. We present a satellite-constrained wetland CH$_4$ ensemble product derived from assembling the highest-performance bottom-up models, which estimates global wetland CH$_4$ emissions of 148 (117-189, 5th-95th percentile) Tg CH$_4$ yr$^{-1}$. Our study places new constraints on the latitudinal distribution of wetland emissions: based on the highest-performing models, we find that tropical wetland emissions contribute 72% (63-85%) to the global wetland total. We also find that for bottom-up model estimates, a lower-than-expected temperature sensitivity agrees better with atmospheric CH$_4$ measurements. Overall, our approach demonstrates the potential for using satellites to quantitatively refine bottom-up wetland CH$_4$ emission estimates and their sensitivity to climate.
Keywords: wetland CH₄, top-down constraints, terrestrial ecosystem models, climate sensitivity, global budget, latitudinal distribution
1 Introduction

Methane (CH$_4$) has 28 times the global warming potential of CO$_2$ on a 100-year time scale (Myhre et al., 2013). Atmospheric CH$_4$ concentrations have increased by more than 150% since the pre-industrial age, and are directly responsible for approximately 20% of the anthropogenic radiative forcing (IPCC, 2013; Kirschke et al., 2013). Wetland CH$_4$ emissions represent about 30% of the total CH$_4$ source, and remain the most uncertain component of the atmospheric CH$_4$ budget (Saunois et al., 2020). The global wetland CH$_4$ budget differs substantially within and between top-down and bottom-up approaches. For example, bottom-up modeling estimates range from 117 to 203 Tg CH$_4$ yr$^{-1}$ and top-down atmospheric inversion estimates range from 111 to 167 Tg CH$_4$ yr$^{-1}$ from wetlands (Tian et al., 2016). The largest uncertainties in bottom-up modeling approaches stem from wetland inundation extent (driver data), biogeochemical process description (model structure), and responses to climatic variability (parameter uncertainty) (Bloom et al., 2017; Melton et al., 2013; Pandey et al., 2020; Poulter et al., 2017; Zhang et al., 2018). For top-down inversions, the uncertainties are due to concentration data retrieval, atmospheric chemistry, model errors related to atmospheric transport, and bottom-up information in the distribution of emissions (Maasakkers et al., 2021). Reconciling bottom-up and top-down emissions estimates is key to understanding the spatiotemporal distribution of wetland CH$_4$ fluxes and reducing uncertainty on global CH$_4$-climate feedbacks in the coming decades.

Atmospheric inversions use space-borne observations of atmospheric column CH$_4$ to provide a constraint on the global scale spatial and temporal variability of wetland CH$_4$ emissions (Lu et al., 2021; Turner et al., 2019; Zhang et al., 2021). Attempts have been made to evaluate the performance of bottom-up models with CH$_4$ flux estimates from atmospheric inversions (Hayman et al., 2014; Spahni et al., 2011). However, top-down inversion results can
be difficult to compare directly to bottom-up models because of their inherent uncertainty from
model transport and chemistry, a coarser spatial resolution, and absence of process-level
emission controls (e.g., soil C decomposition and water table). Atmospheric inversion solutions
at specific locations are often correlated spatially with solutions in other regions, due to limited
observational constraints. When observational constraints are relatively weak—for example, due
to atmospheric transport patterns or limited observational coverage—the inversion solution
depends strongly on the prior CH$_4$ flux estimates. As a result, much of the interpretation of
emissions processes is confounded by prior CH$_4$ flux assumptions that are required to constrain
the atmospheric inversion solution.

Here, we employ a Bayesian methodology to evaluate the skill of a range of bottom-up
biogeochemical wetland CH$_4$ models that incorporate different biogeochemical structures,
wetland extent, and parametrizations by comparing them to satellite-based atmospheric inversion
estimates of wetland CH$_4$ emissions. Our study does not produce top-down or bottom-up
estimates, but makes the two comparable by accurately accounting for the error characteristics of
the inversion estimates, namely the limited spatial resolution, cross-correlations, and
uncertainties in top-down atmospheric inversions estimates (section 2.3). We then compare
common process-level drivers among models to assess which climatic drivers best explain the
spatial and temporal variability of wetland CH$_4$ emissions (section 2.4). The Bayesian evaluation
of bottom-up models with top-down inversions allows us to reduce the large uncertainty on
estimates of the distribution and temperature sensitivity of wetland CH$_4$ emissions. We
summarize the datasets used in this methodology and the steps for testing and updating wetland
biogeochemistry models with top-down measurements in Figure 1.
2 Data and methods

2.1 Inverse analysis of GOSAT observations

Atmospheric CH$_4$ inverse problems estimate fluxes on a geospatial grid using observed concentrations of CH$_4$. The TANSO-FTS instrument onboard the Greenhouse Gases Observing Satellite (GOSAT; Kuze et al., 2009) provides global column-averaged dry mixing ratios of CH$_4$ ($X_{\text{CH}_4}$; Parker et al., 2020). These observations are related to fluxes through an atmospheric transport and chemistry model. The posterior wetland CH$_4$ emission in our analysis is from a global flux inversion using GOSAT observations from 2010-2018 (Zhang et al., 2021). In addition to wetland emissions (resolved at 14 subcontinental regions and for individual months), the inversion by Zhang et al. (2021) also simultaneously optimizes anthropogenic CH$_4$ emissions (2010-2018 mean and trend on a $4^\circ \times 5^\circ$ grid) and tropospheric OH concentration (the main sink of CH$_4$, hemispheric averages estimated annually) (Zhang et al., 2021). The inversion used WetCHARTs v1.0 Extended Ensemble (2010-2018) (Bloom et al. 2017) as the prior estimates for wetland emissions (Zhang et al., 2021). For more details on the atmospheric inversion, readers are referred to Zhang et al. (2021) and a discussion on the quasi-linearity of the inverse problem can be found in Text S2.

The Zhang et al. (2021) global flux inversion analytically solves the inverse problem assuming Gaussian errors with a Bayesian optimal estimation (OE) approach (Maasakkers et al. 2019; Maasakkers et al., 2021). A feature of this inversion approach is that it provides an averaging kernel matrix ($A$) and a posterior error covariance matrix ($\hat{S}$) for the posterior estimates ($\hat{x}$) of wetland emissions. The posterior covariance for the wetlands automatically includes the cross-state error from the other emission sectors and therefore they are accounted for in our error analysis (Worden, 2004). These inversion diagnostics allow for an explicit
representation of the impact of the prior estimates (including spatial uncertainties and cross-correlations) for the inversion-based estimates of wetland CH$_4$ emissions (Rodgers, 2000). In the Appendix, we demonstrate in detail why we need to account for uncertainties and cross-correlations before using inversion results to constrain land models (Equations A1-A3) and show how elements in $A$ relate to uncertainties and cross-correlations of regional CH$_4$ emissions (Figure A1). In Section 2.3, we introduce the approach to account for the prior estimates and spatial resolution with diagnostic quantities from the Bayesian inversion.

2.2 Biogeochemical bottom-up models

We evaluated 42 global wetland biogeochemical model simulated emissions with the satellite-based inversion product. These bottom-up models represent the state-of-the-science ability to simulate large-scale wetland CH$_4$ emissions, which cover different biogeochemical structures, wetland extent, and parametrizations, including 18 members from WetCHARTs v1.3.1 Extended Ensembles (2001-2019; Bloom et al., 2017), 11 members from Global Carbon Project version 1 (GCPv1, 2000-2012; Poulter et al., 2017; Saunois et al., 2016), and 13 members from GCPv2 (2000-2017; Saunois et al., 2020). Both GCP versions are chosen because they are driven by different wetland extent maps with different spatiotemporal variabilities. We use only the 2010-2012 data for comparison because GCPv1 simulations end in 2012. To examine the effect of using only a three-year overlap period in scoring model performance, a longer period ranking (2010-2017) is done with WetCHARTs and GCPv2. We discuss the effect of using different periods on evaluating model performance in section 3.1.

WetCHARTs is a process-informed wetland CH$_4$ emission dataset for atmospheric chemistry and transport modeling, representing a probability distribution of biogeochemical process control uncertainties (Bloom et al., 2017). The WetCHARTs Extended Ensemble (EE)
was derived by combining a range of CH$_4$:C temperature sensitivities ($Q_{10}$ CH$_4$:C), three global wetland emissions scaling factors, and two dynamic wetland extent maps. $Q_{10}$ CH$_4$:C is the temperature dependence of the ratio of C respired as CH$_4$ (equals the change of the respiration rate for a 10 °C increase). A $Q_{10}$ CH$_4$:C value larger than 1 indicates CH$_4$ respiration is more sensitive to the temperature than CO$_2$ respiration. Global wetland emissions scaling factors are used to calibrate models with three prescribed global CH$_4$ emission rates: low (124.5 Tg CH$_4$ yr$^{-1}$), medium (166 Tg CH$_4$ yr$^{-1}$), and high (207.5 Tg CH$_4$ yr$^{-1}$) from 2000–2009 top-down wetland CH$_4$ emission estimates (Saunois et al. 2016). Two wetland extent inventories are used to represent wetland extent fraction, including GLOBCOVER (Bontemps et al., 2011) and Global Lakes and Wetlands Database (GLWD, Lehner & Döll, 2004). GLOBCOVER is a global land-cover map using the fine resolution (300m) mode data from the MERIS sensor on-board ENVISAT satellite. GLWD is an inventory-based product that synthesizes a number of best available sources for lakes and wetlands on a global scale. Monthly ERA-Interim precipitation is used to represent the seasonal variation in hydrology. Hereafter, we use WC_GLOBCOVER_PREC and WC_GLWD_PREC to refer to the two wetland extent datasets.

GCP models are land biosphere models: their CH$_4$ modules represent various formulations of model structure, parameterization, and initialization (Poulter et al., 2017; Saunois et al., 2020). The models were simulated following a common protocol for model spin-up and transient runs, using standardized climate and atmospheric CO$_2$. Wetland inventories are used to set the long-term annual mean wetland area, and seasonal cycles are added from fractional surface water using data from the Surface Water Microwave Product Series (SWAMPS). GCPv1 uses GLWD (Global Lakes and Wetlands Dataset; Lehner & Döll, 2004) coupled with SWAMPSv2 (Schroeder et al., 2015), for clarity in this paper we refer it as
One of the improvements in GCPv2 is decreased high-latitude emissions due to decreased wetland area after correction for the “double counting” of wetland extent (Saunois et al., 2020). We use our approach here to see if the GCPv2 model simulations better agree with satellite observations than GCPv1. CH$_4$ emissions from rice paddies are excluded in both WetCHARTs and GCP simulations. WetCHARTs implicitly includes emission from non-wetland freshwater bodies. GCPv1 and v2 exclude non-wetland freshwater based on satellite observations. We discuss the different ways of treating non-wetland freshwater and its potential impact on our analysis in section 3.5. More details on model simulations and wetland extent can be found in Bloom et al., (2017), Poulter et al., (2017), and Saunois et al., (2020).

2.3 Accounting for the prior estimates and spatial resolution

The comparison between a gridded inverse solution and an independent wetland model is complicated by the fact that the inverse solution contains cross-correlated information (Worden et al., 2004) and corresponding varying spatial resolution, as discussed in Section 2.1 and the Appendix. Therefore, for an appropriate comparison between model and estimate, a wetland model needs to be projected through an observation operator first (Rodgers, 2000). This takes the form of the following:

$$\tilde{x}_{model} = x_a + A(x_{model} - x_a)$$

where $\tilde{x}_{model}$ is projected model emissions, $x_{model}$ is the estimated CH$_4$ emission from the biogeochemical model of interest, and $x_a$ is the prior estimates used in inversion. $A$ is averaging
kernel matrix, the diagonal terms in $A$ describe the sensitivity of inversion results to the variability of the “true” emissions, and the cross-terms describe the sensitivity of the wetland estimate to emissions from other regions. The approach here allows the modeled estimates ($\hat{x}_{\text{model}}$) to be "viewed" in a consistent way ($\hat{\mathbf{X}}_{\text{model}}$) with the inversion and essentially removes the impact of the prior estimates. Figure S1 shows the difference before and after the projection of the model through Equation 1. The inversion-model mismatch is enlarged during the information-rich period and reduced for the poor signal period. We then compare these projected model emissions to posterior fluxes to rank bottom-up wetland models.

2.4 Evaluating biogeochemistry model performance

We evaluate the weighted Root Mean Square Error (wRMSE) between projected biogeochemistry model emissions ($\hat{\mathbf{X}}_{\text{model}}$, see section 2.3) and inversion-based estimates of wetland CH$_4$ emissions ($\hat{x}$). Specifically, the wRMSE use the posterior covariance matrix ($\hat{S}$) to account for spatial uncertainties and cross-correlations between regions from the inversion:

$$\text{wRMSE} = \left[ \frac{(\hat{x} - \hat{x}_{\text{model}})\hat{S}^{-1}(\hat{x} - \hat{x}_{\text{model}})^T}{N} \right] #(2)$$

where N is the number of elements in $\hat{x}$. The wRMSE metric represents the overall model performance across the globe (14 regions by 36 monthly emissions). Based on the wRMSE ranking of each biogeochemical model, we group the top one-third as the ‘Highest-Performance model ensemble (HP)’ and the bottom one-third as the ‘Lowest-Performance model ensemble (LP)’.

To highlight the significance of removing the impact of the prior assumptions from atmospheric inversion estimates, we show the relative differences in model performance before and after accounting for cross-correlations and spatial uncertainties (Table S4).
To further assess whether satellite-based flux estimates provide insights on biogeochemical processes, we use the factorial WetCHARTs configurations to evaluate the relationships between key process configurations (temperature sensitivity of CH$_4$ production, global wetland emissions scaling factors, wetland extent maps), and corresponding model performance (wRMSE). For each process $p$, we calculate the marginal performance of each model $m$, $\Delta$wRMSE$(m,p)$, as follows:

$\Delta$wRMSE$(m,p) = \text{wRMSE}_{\text{MM}(m,p)} - \text{wRMSE}(m)$(3)

where wRMSE$_{\text{MM}(m,p)}$ is the reference mean wRMSE for all configurations of $p$ for the reference model subset which share the same process configurations other than $p$ (see Table S1). For example, for all three WetCHARTs models that use the same wetland extent map (GLOBCOVER) and global wetland CH$_4$ emissions scaling factor (124.5 Tg CH$_4$ yr$^{-1}$), their reference mean performance wRMSE$_{\text{MM}(m,p)}$ will be the average of all three wRMSE values, and their marginal performance $\Delta$wRMSE$(m,p)$ will depend on their $Q_{10}$CH$_4$:C value ($Q_{10}$CH$_4$:C = 1, 2, or 3). Larger $\Delta$wRMSE values indicate a better model agreement with atmospheric estimates (relative to the reference model subset).

3 Results and discussion

3.1 Global, latitudinal, regional CH$_4$ emission and seasonal variation

Median global CH$_4$ emissions (2010-2012) from the Highest-Performance model ensemble (HP) is 148 Tg CH$_4$ yr$^{-1}$ (117-189, 5$^{\text{th}}$-95$^{\text{th}}$ percentiles), about 25% lower than the median (201 Tg CH$_4$ yr$^{-1}$) of the Lowest-Performance model ensemble (LP) models (160-218, 5$^{\text{th}}$-95$^{\text{th}}$ percentiles; Figure 2, Table 1). The global wetland emission from HP generally agrees with independent top-down estimates of 149-159 Tg CH$_4$ yr$^{-1}$ (Ghosh et al., 2015) and 111-167 Tg CH$_4$ yr$^{-1}$ (Tian et al.,
2016), whereas LP exhibits higher values in general agreement in line with a range of bottom-up estimates of 141-264 Tg CH\(_4\) yr\(^{-1}\) (Melton et al., 2013), 153-227 Tg CH\(_4\) yr\(^{-1}\) (Saunois et al., 2016), and 160-206 Tg CH\(_4\) yr\(^{-1}\) (Poulter et al., 2017).

The total tropical wetland emissions (south of 23°N) are similar between HP and LP ensembles (median values are 111 and 114 Tg CH\(_4\) yr\(^{-1}\), respectively), but with contrasting spatial distributions. Amazon wetland emissions account for the largest tropical emission source in both ensembles, albeit with lower emissions across HP models (median = 34, range =17-42 Tg CH\(_4\) yr\(^{-1}\)) relative to the LP ensemble (median = 40 Tg CH\(_4\) yr\(^{-1}\), range = 20-66 Tg CH\(_4\) yr\(^{-1}\)) (Table S2). Across non-tropical wetlands (north of 23°N) LP emissions are 1.5 times more than those of HP (64 and 43 Tg CH\(_4\) yr\(^{-1}\), respectively), where about two-thirds of excess CH\(_4\) emissions from the LP ensemble are in high-latitude regions (Table 1). In particular, median emissions from Alaska, Boreal North America, and Temperate North America are larger by a factor of two in the LP ensemble. We found larger seasonal emissions rates in LP in all cold regions and two temperate regions in East Asia and North America, which is mainly due to larger seasonal amplitudes in LP model wetland extent dynamics (Figures S2 S3, Table S2). Overall, HP models have a higher contribution from the tropics to the global budget (72%) than LP models (62%).

We find that HP model emissions are consistent with the annual and month-to-month seasonality of independent aircraft-based wetland CH\(_4\) emission in the Alaska region (Carbon in Arctic Reservoirs Vulnerability Experiment, CARVE campaign) (Miller et al., 2016), where May-Oct 2012 emissions amount to 1.66±0.95 and 1.80±0.45 Tg CH\(_4\), respectively. Although both HP and the CARVE all datasets have notable uncertainties (Figure 3a), LP emissions and
uncertainties during the same period (4.2±3.7 Tg CH₄) substantially exceed the CARVE and HP emission estimates (Figure 3b).

<table>
<thead>
<tr>
<th></th>
<th>Highest-performance model ensemble (HP)</th>
<th>Lowest-performance model ensemble (LP)</th>
<th>Prior estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>CH₄ emission (Tg C year^⁻¹, 2010-2012)</td>
<td>148.1 (116.5-189.0)</td>
<td>201.0 (160.7-217.8)</td>
<td>164.4 (122.6-206.8)</td>
</tr>
<tr>
<td>Globe</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-tropics</td>
<td>42.7 (20.0-60.5)</td>
<td>63.5 (24.6-109.1)</td>
<td>37.4 (20.5-73.5)</td>
</tr>
<tr>
<td>Tropics</td>
<td>111.0 (71.1-139.3)</td>
<td>113.7 (90.6-172.7)</td>
<td>119.7 (82.8-171.2)</td>
</tr>
<tr>
<td>High-latitude</td>
<td>28.5 (12.4-41.4)</td>
<td>44.1 (13.6-79.0)</td>
<td>22.6 (11.7-55.2)</td>
</tr>
<tr>
<td>Temperate</td>
<td>12.8 (7.9-25.2)</td>
<td>20.5 (9.2-41.9)</td>
<td>12.4 (7.3-20.9)</td>
</tr>
<tr>
<td>Latitudinal contribution to CH₄ emission</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-tropics/globe ratio</td>
<td>28% (15%-37%)</td>
<td>38% (13%-52%)</td>
<td>23% (13%-43%)</td>
</tr>
<tr>
<td>Tropics/globe ratio</td>
<td>72% (63%-85%)</td>
<td>62% (48%-87%)</td>
<td>77% (57%-87%)</td>
</tr>
<tr>
<td>High-latitude/globe ratio</td>
<td>17% (9%-27%)</td>
<td>26% (7%-36%)</td>
<td>14% (7%-32%)</td>
</tr>
<tr>
<td>Temperate/globe ratio</td>
<td>9% (6%-15%)</td>
<td>10% (5%-24%)</td>
<td>9% (6%-11%)</td>
</tr>
</tbody>
</table>

Table 1. Wetland CH₄ emissions (2010-2012) for the globe, non-tropics, tropics, high-latitude, and temperate regions, and the relative contribution of each region to global emissions. The prior estimates represent the WetCHARTs models that were used as prior fluxes in the inversion. The values represent median and the 5th - 95th percentile ranges are shown in the brackets.

3.2 Atmospheric CH₄ constraints on land model processes

We compare the parameter values and wetland extent maps against the model performance (wRMSE) within the WetCHARTs members (Figure 4) and find that 1) models using a Q₁₀ CH₄:C equals 1 have significantly higher performance than the ones using larger Q₁₀ CH₄:C.
values; 2) models with the smallest global wetland CH$_4$ emission scaling factor perform better than those with larger scaling factors; and 3) models using the GLOBCOVER derived wetland extent maps outperform those using the GLWD map. Relative to the median WetCHARTs configurations, atmospheric constraints indicate lower temperature sensitivity and a lower-than-expected mean global wetland emissions, and satellite-based wetland extent (GLOBCOVER) generally leads to better agreement with atmospheric CH$_4$ measurements.

Despite the lack of parameter information from GCP models, we find most GCPv2 simulations perform better than GCPv1 (Table S1). Since 10 out of 11 GCPv1 land-surface models also participated in GCPv2 (13 models), we compared their performance and find the same land surface models agree better with satellite CH$_4$ observation when using a Mix_SWAMP extent map rather than GLWD_SWAMP (eg. TRIPLEX-GHG). Of all the land models compared, a majority of low-ranked simulations use a GLWD-based annual extent map (9 out of 14), and most high-ranked simulations use a non-GLWD-based map (10 out of 14).

In both GCP v1 and GCP v2 simulations, LPX-Bern (Land surface Processes and eXchanges model of the University of Bern; (Spahni et al., 2013)) and JULES (the Joint UK Land Earth Simulator; (Hayman et al., 2014)) have the best agreement with satellite data (Table S1). This may be due to their more realistic model structures or better choice of parameter values in representing the seasonality of CH$_4$ emissions, which awaits further investigation.

3.3 Sensitivity of CH$_4$ to climatic, physical, and biological drivers

We find wetland extent and precipitation have the highest correlation with CH$_4$ emission over tropical regions in both HP and LP (Figure S6). This finding is in line with previous studies that find declining wetland area to be the dominant control of decreased tropical CH$_4$ emissions over 1993-2004 (Papa et al., 2010; Poulter et al., 2017), and that rain-fed pulses of CH$_4$ from East
Africa in 2018-2019 contribute to the atmospheric growth rate (Lunt et al., 2021). Much lower correlations between temperature/carbon (C) availability and CH$_4$ emissions are found in both the HP (0.31 and 0.13) and LP (0.29 and 0.28) ensembles in tropical regions, which implies that temperature and C availability are not the limiting factors in tropical wetland CH$_4$ emission (C availability is represented by heterotrophic respiration rate in biogeochemical models, data only available for WetCHARTs simulations).

In contrast to the tropics, non-tropical wetland CH$_4$ emissions exhibit a higher correlation with C availability and temperature in all models (Figure S6, 0.93 and 0.90 in HP, 0.91 and 0.88 in LP), followed by wetland extent and precipitation (0.75 and 0.79 in HP, 0.75 and 0.76 in LP). Our results indicate that C availability and temperature are highly correlated with CH$_4$ emissions in high-latitude and temperate regions, consistent with previous studies that found temperature and decomposing substrate supply to be the dominant controls on non-tropical wetland CH$_4$ emissions (Chen et al., 2015; Ma et al., 2017; Schuur et al., 2015; Yvon-Durocher et al., 2014).

3.4 Implications for the global and regional CH$_4$ budget

Altogether, we find that lower total emissions, lower temperature sensitivity, and wetland extent are the primary factors driving biogeochemical model performance against the global inverse flux estimates (Figure 2b, 4). In addition, the highest-performance models estimate a higher fraction of CH$_4$ emissions from the tropics (72%) than the process-based modeling results of 66% (Melton et al. 2013), 55% (Bloom et al., 2010), and 48% from GCPv1 (Poulter et al., 2017), and the inverse modeling results of 63% (Bousquet et al., 2011), but are comparable to 76% from WetCHARTs v1 extended ensemble (Bloom et al., 2017) and 74% from GCPv2 (Saunois et al., 2020). Our results, therefore, imply a larger role of tropical CH$_4$ emissions in the global wetland emission budget.
The large uncertainties in predicting wetland CH₄ emission come from 1) climate and wetland extent predictions (drivers) (Andresen et al., 2020; Zhang et al., 2017); 2) process controls (model structures); and 3) climatic sensitivities of CH₄ productions (parameter values) (Poulter et al., 2017; Riley et al., 2011). Our approach enables the evaluation of terrestrial biosphere models with satellite-informed estimates and places constraints for land model predictions by telling which wetland extent maps, biogeochemical processes, and parameters values used in the models are more realistic, as discussed in section 3.2 (Cox et al., 2013; Wenzel et al., 2016).

The high correlation to precipitation and wetland extent in both HP and LP models indicates increasing CH₄ emission in response to climate change, as wet areas in the tropics are likely to get wetter, have increased anoxic soil area, and become saturated for longer periods (Chou et al., 2009; Neelin et al., 2003). In line with our findings, shifting precipitation patterns have been found to drive long-term simulated CH₄ emission changes in the tropics (Zhang et al., 2017). Our analysis reveals how wetlands across the globe respond to variations in temperature, precipitation, inundation, and carbon availability. However, with 3 years of data (2010-2012), we cannot refute the possibility that, on decadal-centennial timescales, temperature is the primary control on tropical wetland emissions. With longer-term results, our analysis can be used as constraints on terrestrial biosphere model CH₄ simulations.

A poor understanding of tropical wetland biogeochemistry and associated spatial heterogeneity lead to large inter-model discrepancies in tropical wetland CH₄ emissions (Poulter et al., 2017; Riley et al., 2011). The lack of ground-based CH₄ emission observations (Bridgham et al., 2013; Melton et al., 2013) further limits the evaluation of process-based model performance in the tropics. Satellite-based observations with improved accuracy and finer
spatiotemporal resolutions, such as TROPOMI and GeoCarb, are expected to offer additional information for process-based model validation, especially for data-scarce regions (Bloom et al., 2016). With our Bayesian methodology, we showcase the large differences in model performance before and after considering cross-correlations and spatial uncertainties, emphasizing the importance of removing the prior error from atmospheric inversion estimates (Table S4). Our findings, and approach for accounting for these correlations, prior estimates, and spatial resolutions, show how space-borne measurements of total column CH$_4$ can evaluate and ultimately place constraints on global wetland biogeochemistry.

4. Remaining uncertainties, future directions, and summary

While our estimates account for the spatial resolution and error associated with the inversion of observations to fluxes, we do not explicitly account for errors in model transport and chemistry, such as interhemispheric mixing time, vertical mixing, tropopause height, and stratospheric gradient. These errors are important and can be accounted for if the corresponding posterior covariance is provided, possibly through multi-model comparisons (e.g., Schuh et al. 2010) or by integrating measurements with different sensitivities to the profile of CH$_4$ (e.g., Jiang et al. 2013, 2017). We thus advocate studies that either characterize or mitigate these errors to offer better constraints for bottom-up estimates. We note that the methodology presented in this study can only apply to atmospheric CH$_4$ inversions that calculate prior and posterior covariances (Turner et al., 2015). The methodology can also be approximated with other inversion methods (e.g., 4D-Var methods) if these can generate posterior covariance estimates (Liu et al., 2014; Chevallier et al., 2010)

Non-wetland freshwater bodies (lakes, rivers, and ponds) are potentially a significant CH$_4$ source and have uncertainties larger than that of wetland fluxes (Bridgham et al., 2013;
Saunois et al., 2020). WetCHARTs includes emissions from non-wetland freshwater bodies and
WetCHARTS is used as the prior for the GEOS-Chem inversion so that we expect the
corresponding flux estimates to include their effects in the inversion. GCPv1 excludes permanent
water bodies, rivers, snow, and ice with satellite-based Land-cover data MOD12Q1 V004 (Friedl
et al., 2010). GCPv2 removes permanent non-wetland freshwater using the Global Surface Water
dataset (Pekel et al., 2016), with the assumed criteria that permanent waters are present for more
than half of the 32-year observing period. Quantitatively differentiating wetland and non-wetland
emissions is therefore important but challenging due to the current spatiotemporal resolution of
data on surface inundation (Pekel et al., 2016; Schroeder et al., 2015). Our results indicate that
aquatic emissions are much lower than those recently reported using bottom-up methods
(Saunois et al. 2020; Rosentreter et al. 2021) highlighting an important topic that needs
reconciling by the scientific community.

Overall, our approach provides a quantitative and comprehensive means to test global-
scale biogeochemical models using satellite CH\textsubscript{4} measurements—and associated hypotheses
relating to CH\textsubscript{4} emissions—thereby providing a much-needed constraint on the uncertain role of
wetlands in the global atmospheric CH\textsubscript{4} budget.

Acknowledgments

Part of this research was carried out at the Jet Propulsion Laboratory, California Institute of
Technology, under a contract with the National Aeronautics and Space Administration. Funding
for this study was provided through (NASA CMS 80NM0018F0583). Y. Zhang acknowledges
funding by NSFC (Project 42007198) and Westlake University. The authors declare that they
have no conflict of interest. The dataset for the 2010–2012 posterior wetland fluxes and the
averaging kernel of the transport model is available at an open-access repository (https://doi.org/10.5281/zenodo.4052518; Zhang et al., 2021). The WetCHARTs v1.0 is available at the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC, https://daac.ornl.gov/CMS/guides/CMS_Global_Monthly_Wetland_methane.html). The WetCHARTs v1.3.1 is available at the ORNL DAAC, https://doi.org/10.3334/ORNLDAAC/1915. ERA-Interim temperature and precipitation datasets were obtained from http://apps.ecmwf.int/datasets/data/interim-full-mnth. CARDAMOM 2001–2010 heterotrophic respiration outputs are available at http://datashare.is.ed.ac.uk/handle/10283/875; Global Carbon Project v1 and v2 are available at https://doi.org/10.18160/GCP-CH4-2019 and from the Global Carbon Project (https://www.globalcarbonproject.org/methanebudget/)
References


IPCC. (2013). *Climate change 2013: the physical science basis Contribution of WorkingGroup I to the Fifth Assessment Report ofthe Intergovernmental Panel on Climate Change.* Cambridge: Cambridge University Press.


Global methane budget and trend, 2010-2017: Complementarity of inverse analyses using in-situ (globalviewplus obspack) and satellite (gosat) observations. *Atmospheric Chemistry and Physics*, 21(6), 4637–4657. https://doi.org/10.5194/acp-21-4637-2021


https://doi.org/10.1002/2016GB005419


https://doi.org/10.1029/2003GL018625


https://doi.org/10.1038/nature20584

September 1). Global wetland contribution to 2000-2012 atmospheric methane growth rate

Barriers to predicting changes in global terrestrial methane fluxes: analyses using CLM4Me,
a methane biogeochemistry model integrated in CESM. Biogeosciences, 8(7), 1925–1953.
https://doi.org/10.5194/bg-8-1925-2011

Rodgers, C. D. (2000). Inverse Methods for Atmospheric Sounding. Series on Atmospheric,
Oceanic and Planetary Physics (Vol. Volume 2). WORLD SCIENTIFIC.
https://doi.org/doi:10.1142/3171


https://doi.org/10.5194/essd-8-697-2016


Figure 1. The workflow for constraining biogeochemical models with top-down (atmospheric inversion) CH$_4$ flux estimates. Datasets for our Bayesian methodology include 1) the prior estimates (WetCHARTs CH$_4$ emissions); 2) the posterior estimates and inversion diagnostics that allow for an explicit correction for the impact of the prior data; and 3) 42 biogeochemical land model simulations.
Figure 2. Mean wetland CH$_4$ emissions during 2010-2012 from the Highest-Performance (HP) model ensemble (a); Zonal profiles of wetland CH$_4$ emissions over 2010-2012 (b): Median of Lowest-Performance model ensemble (LP, brown dashed line) and 5$^{th}$-95$^{th}$ percentile range (brown area); Median of HP (green solid line) and 5$^{th}$-95$^{th}$ percentile range (green area).
Figure 3. Evaluation of the satellite-informed highest-performance (HP) and lowest-performance (LP) ensembles against independent aircraft-based (CARVE; Miller et al. 2016) estimates of wetland emissions over the Alaska region. Error bars represent one standard deviation.
Figure 4. Marginal RMSE performance (see section 2.4) of the factorial WetCHARTs model ensemble, with respect to individual temperature sensitivity of CH₄ emissions (Q₁₀ CH₄:C), global wetland emission scaling factors, and wetland extent datasets. The black dots represent medians, boxes represent the 25th-75th percentile ranges, and lines represent 5th-95th percentile ranges.