Satellite constraints on the latitudinal distribution and temperature sensitivity of wetland CH_4 emissions

-- A Bayesian approach to reconcile bottom-up and top-down estimates

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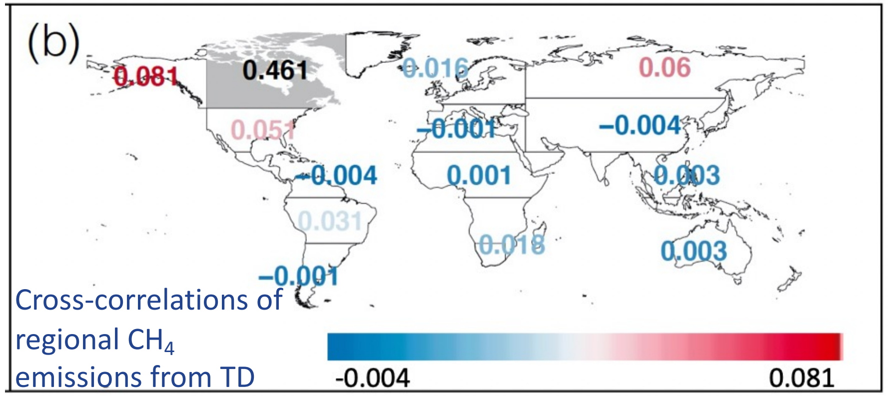

(Ma et al. under review)

- Reconciling top-down (TD) and bottom-up (BU) wetland CH_4 estimates is key to understand the spatial distribution and climate sensitivity of methane emission.
- Top-down fluxes have strong noises from prior estimates and cross-correlation.
- We use a novel Bayesian approach to remove these noises, and refine bottom-up wetland CH_4 estimates with satellite-informed CH_4 flux estimates

1. We find ~25% less global emissions from best-fit models while the relative contribution of tropical emissions to the total is ~10% higher
2. We show a lower-than-expected sensitivity of global wetland CH_4 emissions to temperature.
3. We find tropical wetland emissions are dominated by water availability; Non-tropical CH4 emissions are dominated by temperature and carbon availability

(1) Datasets for evaluating biogeochemical models

- **Prior estimates** (prior emissions, $\boldsymbol{x_a}$; prior error covariance, $\boldsymbol{S_a}$): WetCHARTs CH_4 fluxes
- **Posterior estimates and inversion diagnostics** (posterior emissions, $\hat{\boldsymbol{x}}$; posterior error covariance, $\hat{\boldsymbol{S}}$; averaging kernel, **A**): Inverse analysis of GOSAT observations
- **Land model simulations**: 42 biogeochemical models ($\boldsymbol{x_{model}}$): WetCHARTs, GCPv1, GCPv2

(2) Accounting for uncertainties and cross-correlation between regions → Project $\boldsymbol{x_{model}}$ with $\boldsymbol{x_a}$ and **A**, get $\hat{\boldsymbol{x}}_{\boldsymbol{model}}$

(3) Evaluating projected biogeochemical models with satellite constraints → Compare $\hat{\boldsymbol{x}}_{\boldsymbol{model}}$ and posterior, calculate weighted RMSE with posterior covariance matrix

(Ma et al. under review)

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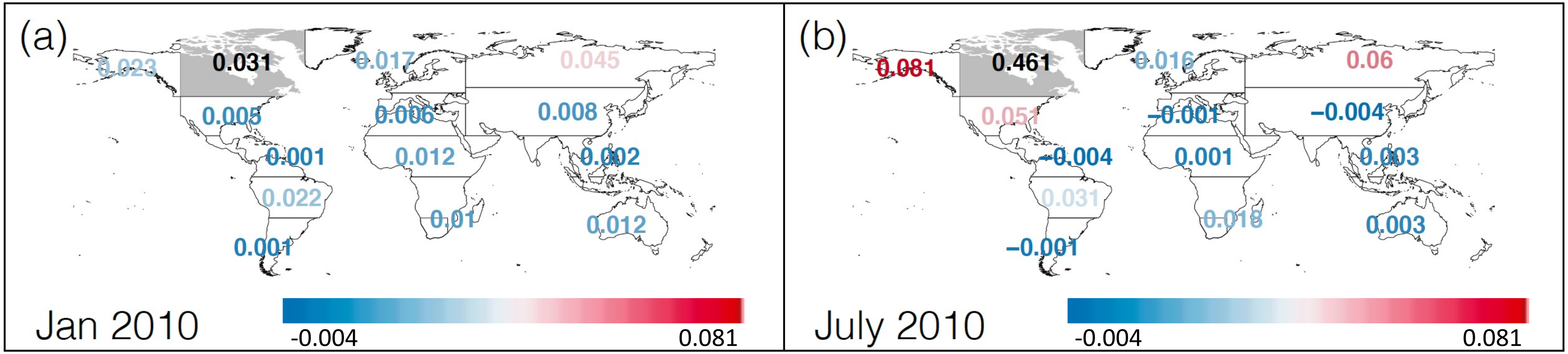
Uncertainties and cross-correlations of regional CH_4 emissions from TD estimates



Global map of diagonal and cross-terms in the averaging kernel matrix (A) in Jan and July of 2010 from atmospheric inversion, taking boreal North America region for example.

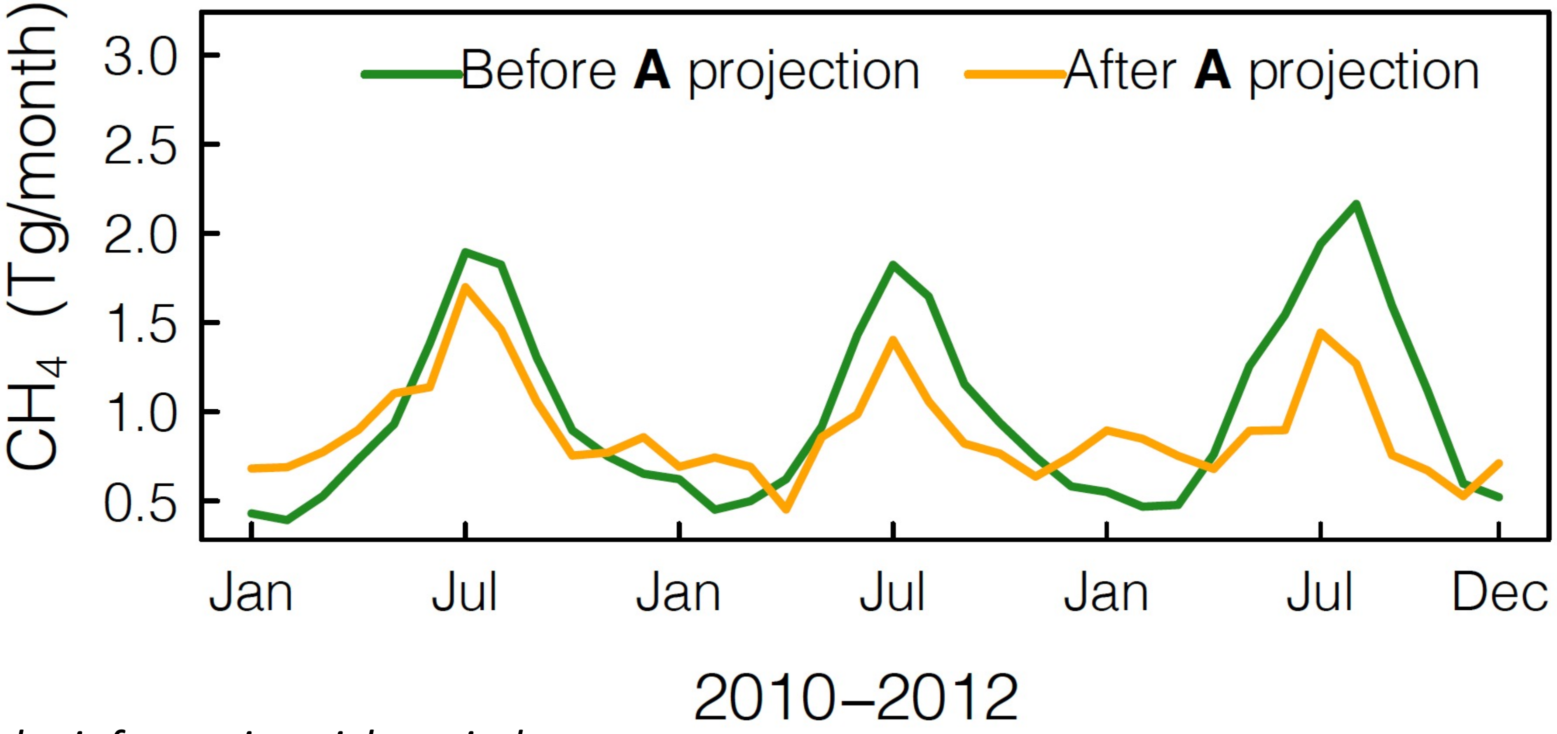
Numbers in the boreal North America region represent the sensitivity of the inversion results to the satellite observation. The numbers outside of the boreal North America area are the cross-terms in Jan/July and indicate the sensitivity of other regions out of boreal North America that affect the inversion results for boreal North America CH_4 emission. Larger numbers indicate a larger impact of the cross-correlations.

(Ma et al. under review)

Removing cross-correlations and spatial uncertainties for comparison

Projecting bottom-up model simulations with the observation operator

$$\hat{\boldsymbol{x}}_{\boldsymbol{model}} = \boldsymbol{x}_{\boldsymbol{a}} + \mathbf{A}(\boldsymbol{x}_{\boldsymbol{model}} - \boldsymbol{x}_{\boldsymbol{a}})$$



$\boldsymbol{x}_{\boldsymbol{model}}$: BU model estimated CH_4
$\hat{\boldsymbol{x}}_{\boldsymbol{model}}$: projected model emissions
$\boldsymbol{x}_{\boldsymbol{a}}$: prior estimates
A: averaging kernel matrix

BU-TD model mismatch is enlarged during the information-rich period and reduced for the poor signal period.

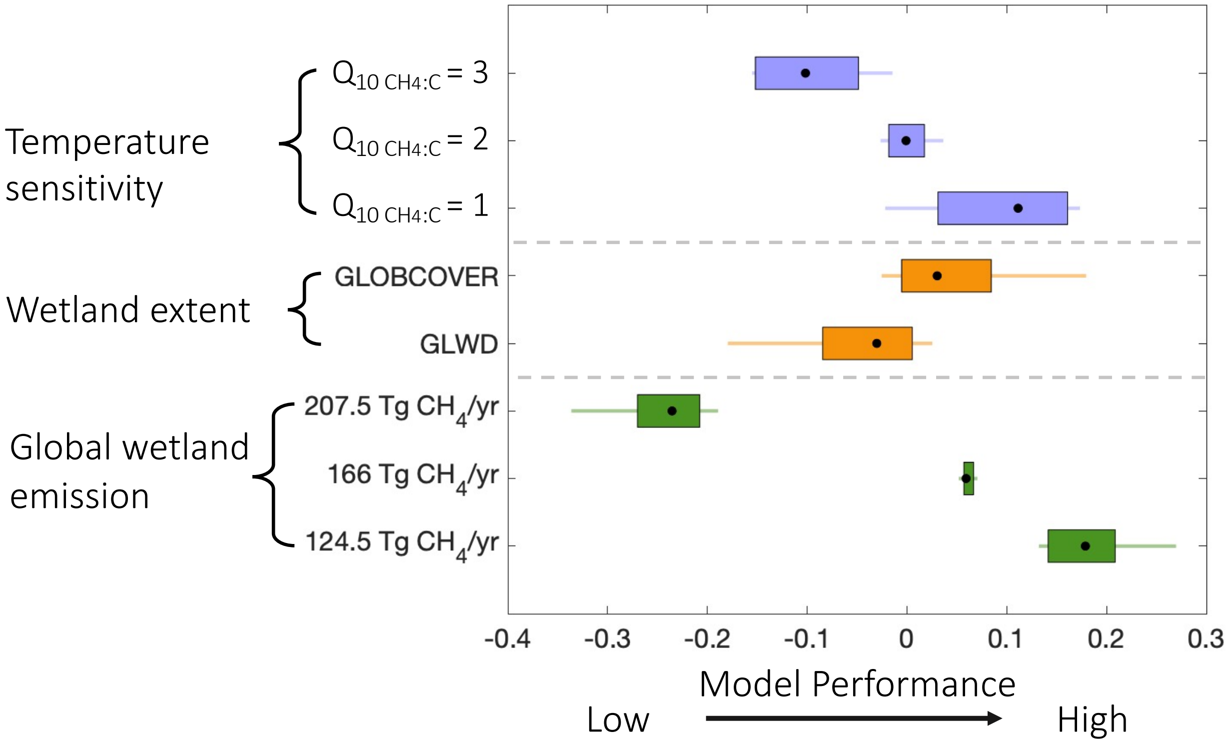
(Ma et al. under review)

- **Large impact of cross-correlation and spatial uncertainties in evaluating BU performance:**
- **Identify drivers and parameters that better agree with atmospheric CH_4 measurements:**

Models	wRMSE_not_projected	Models	wRMSE_AK_projected
WETCHART1914	1.75707	GCPv2 LPX	1.37549
WETCHART1924	1.91357	GCPv2 JSBACH	1.40944
WETCHART1923	1.93158	WETCHART1914	1.46307
WETCHART1913	1.93832	GCPv2 TRIPLEX-GHG	1.46799
WETCHART2914	2.00613	WETCHART2914	1.53402
WETCHART1933	2.00755	GCPv2 LPJ-WSL	1.54159
WETCHART1934	2.03092	GCPv1 LPX-Bern	1.54718
WETCHART2924	2.13672	GCPv2 VISIT	1.55576
GCPv2 JSBACH	2.18363	WETCHART1913	1.56959
WETCHART2923	2.23359	GCPv2 JULES	1.5858
WETCHART2934	2.28367	GCPv2 CLASS-CTEM	1.58948
WETCHART2933	2.3109	GCPv2 DLEM	1.5901
WETCHART2913	2.3378	GCPv1 JULES	1.62616

$$\text{weighted RMSE} = \left(\frac{(\hat{x}-\hat{x}_{model})\hat{S}^{-1}(\hat{x}-\hat{x}_{model})^{T}}{N}\right)$$

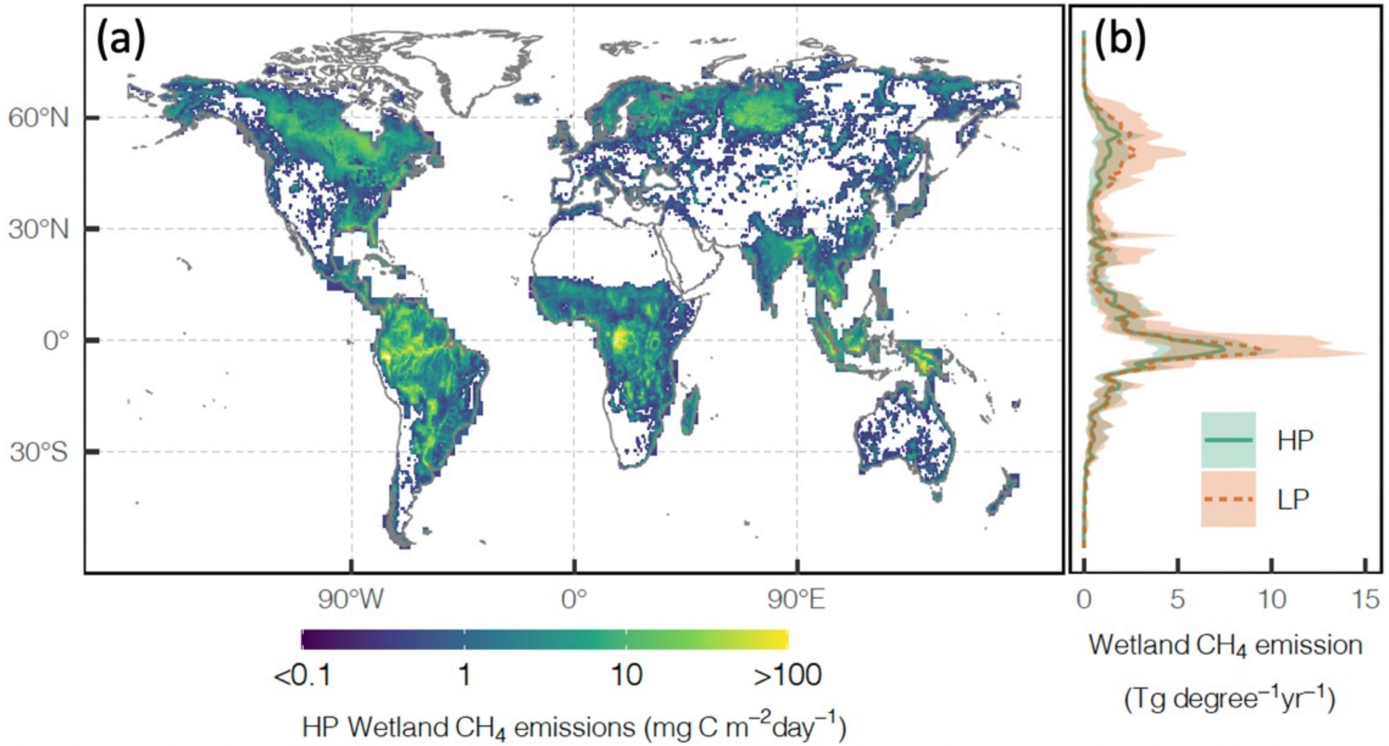
$\hat{x}_{model}$: projected model emissions
$\hat{x}$: posterior estimates
$\hat{S}$: posterior covariance
N: number of elements in $\hat{x}$



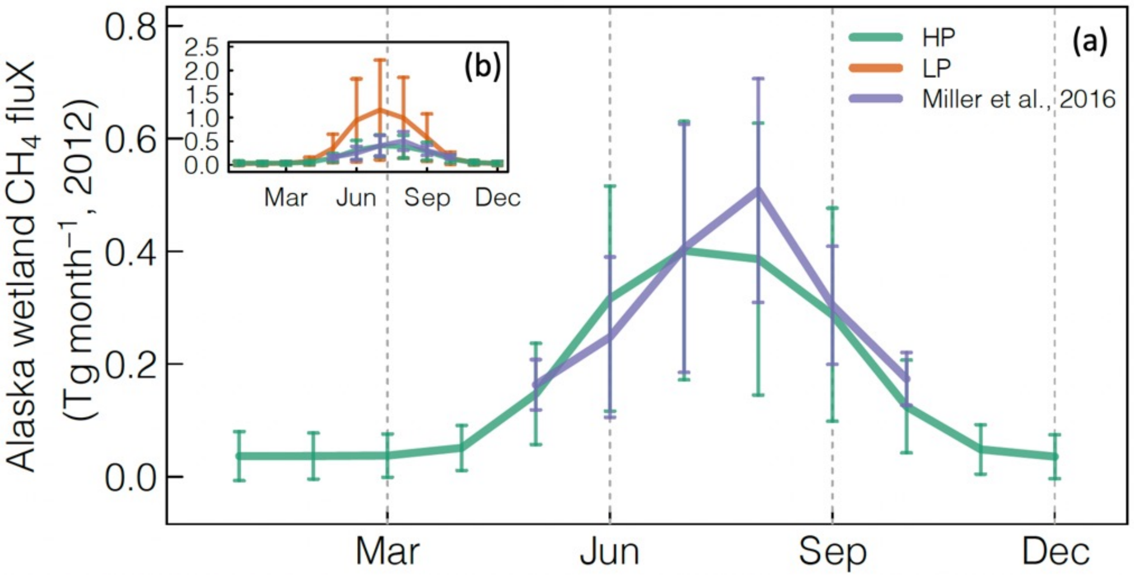
1. Lower-than-expected temperature sensitivity
2. Lower mean global wetland emissions
3. Satellite-based wetland extent (GLOBCOVER)

(Ma et al. under review)

High-Performance models: ~25% less global emissions; Tropical emissions contribute ~10% higher.



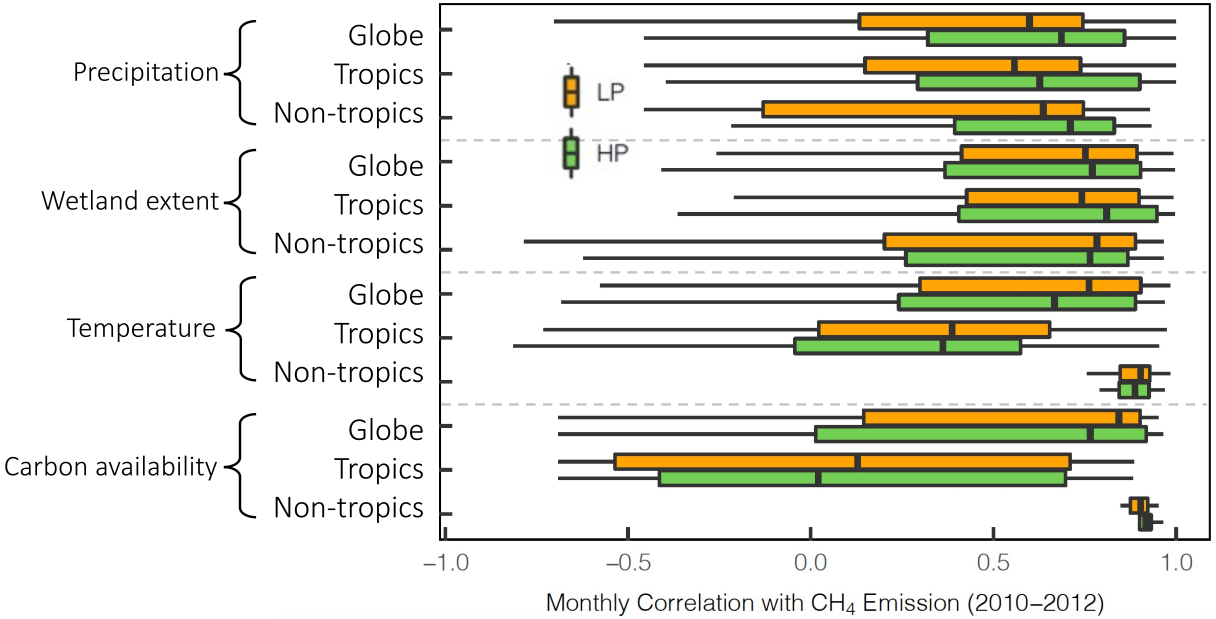
High-Performance models are more consistent with independent aircraft-based wetland CH_4 emission in the Alaska region



CARVE; Miller et al. 2016

(Ma et al. under review)

Tropical wetland emissions dominated by water availability
Non-tropical CH_4 emissions dominated by temperature and carbon availability



(Ma et al. under review)

Summary:

- *We provide a quantitative and comprehensive means to test global-scale biogeochemical models using satellite CH_4 measurements and provide a constraint on the uncertain role of wetlands in the global atmospheric CH_4 budget.*
- *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 such the tropic wetlands.*

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