Continuous sub-monthly monitoring of global methane emissions from an ensemble Kalman filter at 2°×2.5° degrees using TROPOMI observations: application to interpretation of 2020–23 surge

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Abstract. We use 2018-2023 bias-corrected TROPOMI satellite observations of atmospheric methane to quantify global methane emissions at 2°×2.5° resolution and five-day temporal resolution with a localized ensemble transform Kalman filter (LETKF) inversion. From the inversion we derive optimal posterior estimates of emissions from anthropogenic and natural sources along with their seasonalities and year-to-year evolution over the TROPOMI period. The sensitivity of the inversion to wetland assumptions is evaluated by using two alternative wetland inventories (WetCHARTS and LPJ-wsl) as prior estimates. Our best posterior estimate of global emissions (557 Tg a-1 for 2023) closes the global methane budget imbalance with a seasonal cycle peaking in August and September. Consistent with previous studies, we attribute the 2020 methane surge to a 14 Tg a^{-1} increase in emissions from sub-Saharan Africa. We also find that the elevated emissions in the region persist into later years. We find a strong seasonal cycle in oil and gas emissions from the Permian basin, which may be due to equipment weatherization practices.

We built a **near-real-time system** for estimating **global methane emissions** with TROPOMI data, then applied it to 2018-2023 to study rapidly increasing atmospheric methane concentrations.

We attribute the 2020 **methane surge** to a 14 Tg a^{-1} increase in emissions from sub-Saharan Africa which has persisted.

We find **strong seasonality** in methane emissions, peaking in late summer, but also unexpected seasonality in the Permian basin.

CHEEREIO website

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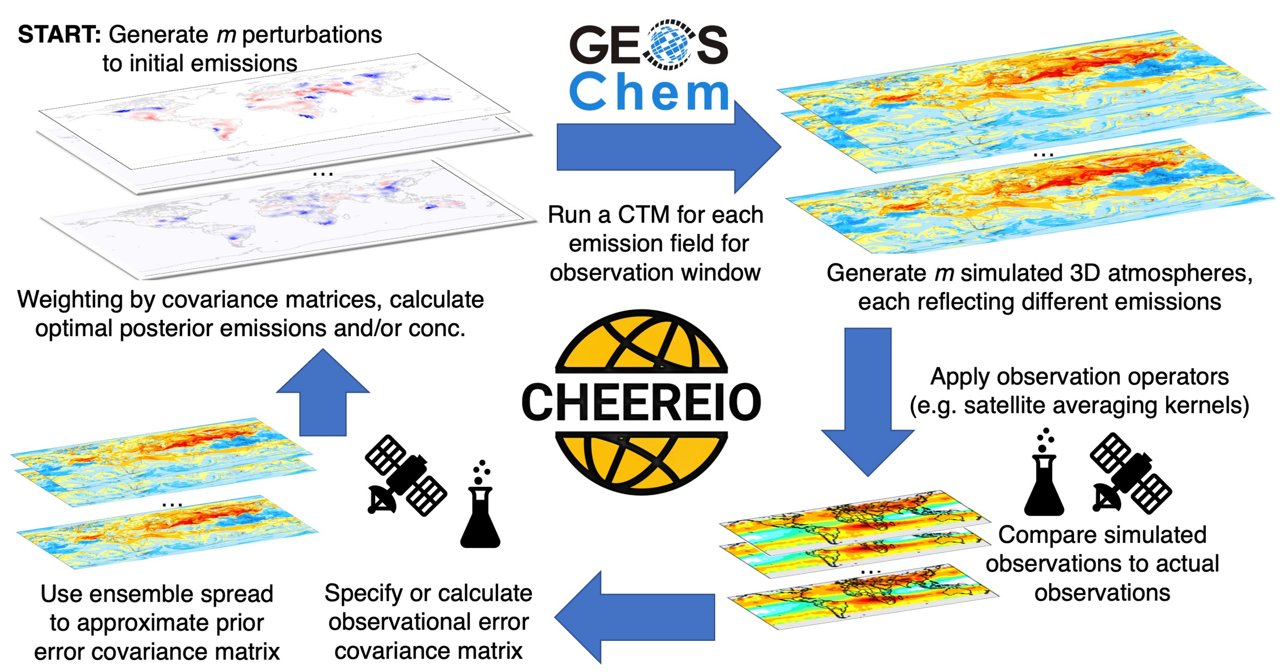
CHEEREIO GMD paper

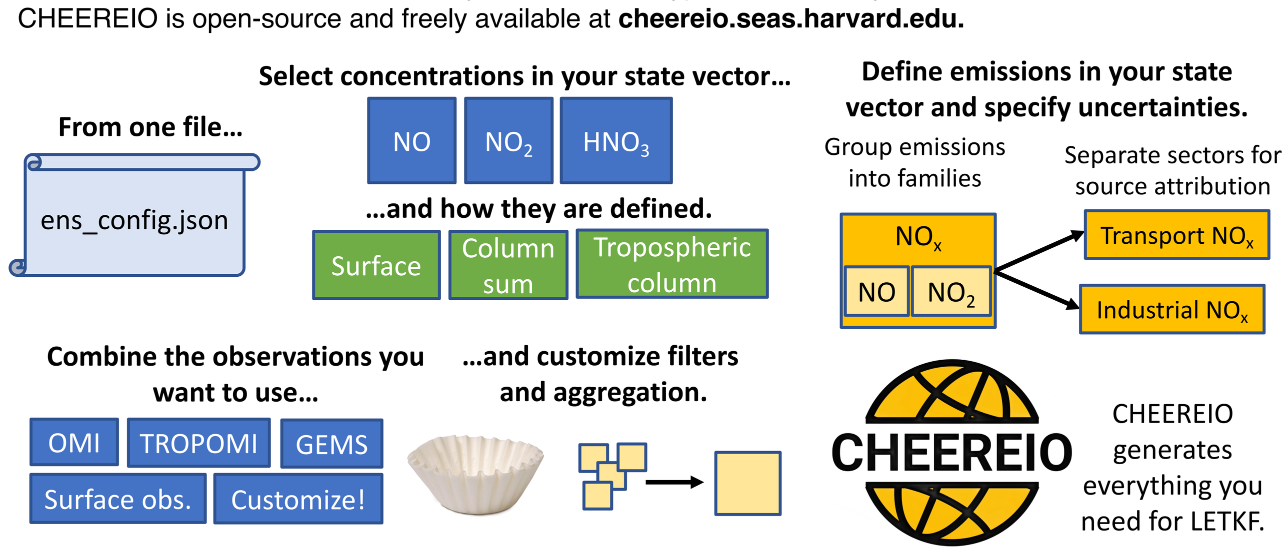
The LETKF algorithm

The **Localized Ensemble Transform Kalman Filter** (LETKF) is a Bayesian algorithm that can optimize emissions or concentrations of chemical species; LETKF uses an ensemble of chemical transport model (CTM) simulations, each driven by randomly perturbed emissions such that the CTMs represents the spread of atmospheric states that could result given emissions uncertainty. LETKF compares this suite of artificial atmospheres to real observations and uses the difference to calculate an update to the prior.



CHEEREIO data assimilation platform

CHEEREIO is a Python- and Shell-based wrapper for the GEOS-Chem CTM, automating the deployment of LETKF ensembles for a wide variety of observation types. In this study, we use CHEEREIO 1.3.0. CHEEREIO is open-source and freely available at **cheereio.seas.harvard.edu.**



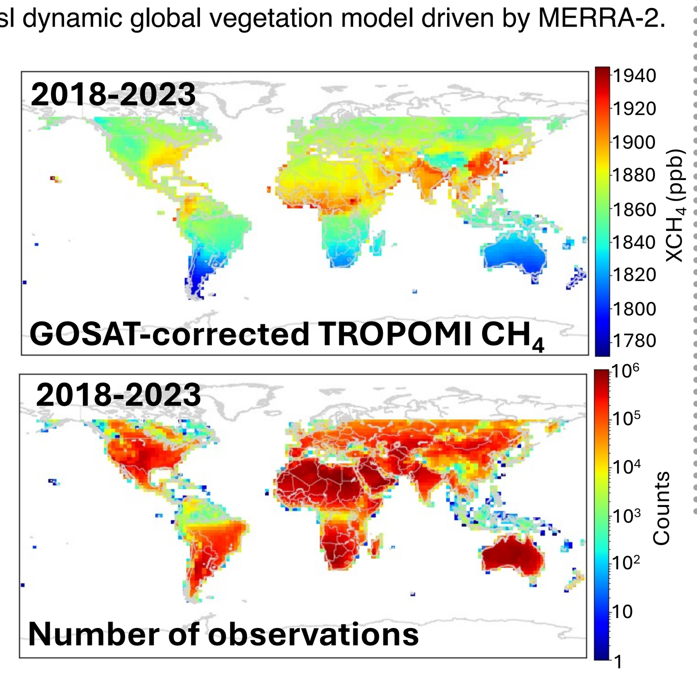
Emissions and TROPOMI observations

Prior emissions from oil, gas, and coal are from GFEIv2 and other anthropogenic emissions are from EDGARv6; both are overwritten over the US, Mexico, and Canada by national inventories. Anthropogenic emissions are assumed to be aseasonal, except for manure management and rice for which we apply seasonal scaling factors. Fires are from GFED4, termites from Fung et al. (1991), and geological seeps from Etiope et al. (2019). OH is prescribed by fields archived from a GEOS-Chem full-chemistry simulation scaled to match methyl chloroform observations. **For wetland emissions, we run different inversions for two separate inventories**. We use the high-performance subset of WetCHARTs v1.3.1 and compare it to the LPJ-wsl dynamic global vegetation model driven by MERRA-2.

We use **TROPOMI observations bias-corrected with GOSAT** (Balasus et al., 2023) and aggregate the data into "super-observations" by averaging onto the 2.0°×2.5° GEOS-Chem grid. To model error, we follow a two-component error variance equation which separates contributions due to forward model transport error variance ($\sigma^2_{\text{transport}}$) from satellite error variance for a single retrieval (σ_i^2):

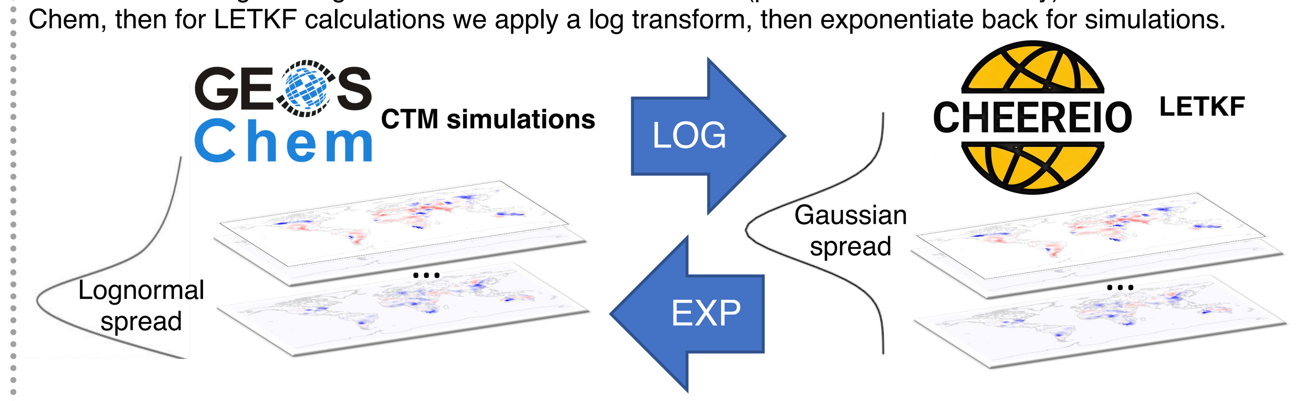
$$\sigma_{\text{super}} = \sqrt{\left[\left(\frac{1}{n}\sum_{i=1}^{n}\sigma_i\right)\cdot\left(\frac{1-c}{n}+c\right)\right]^2 + \sigma^2_{\text{transport}}}$$

Here n is the number of observations aggregated and c is the error correlation between the retrievals averaged (e.g. due to shared surface features). We use the residual error method to obtain $\sigma_i = 17$ ppb, $\sigma_{\text{transport}} =$ 6.1 ppb, and $c = 0.28$.



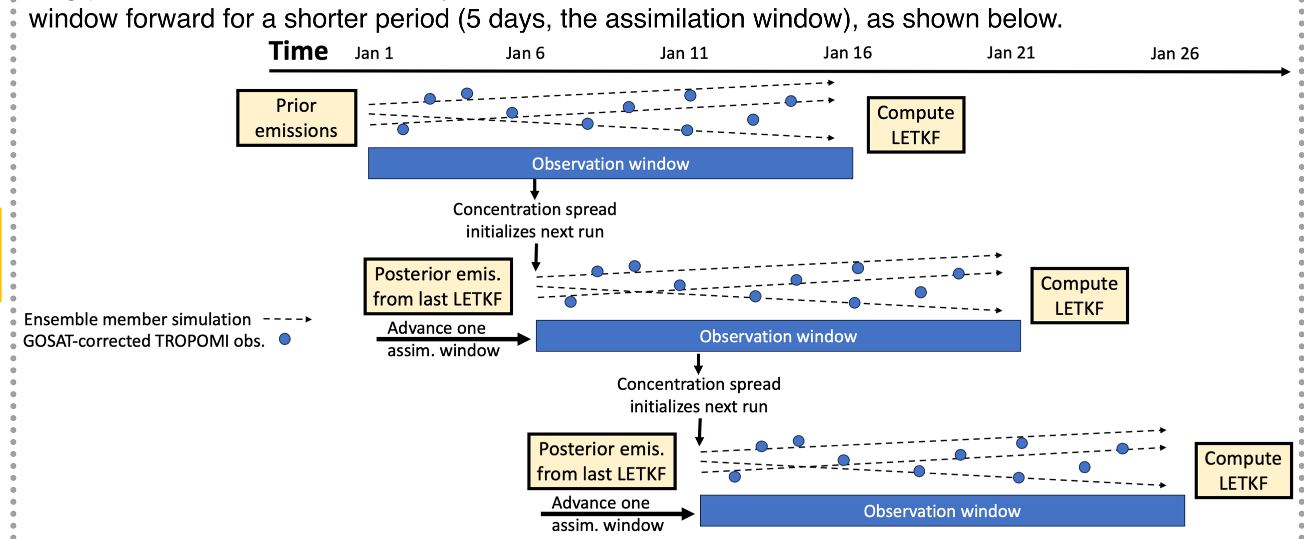
LETKF modifications for methane

Lognormal errors better capture the methane emissions distribution and prevent unphysical negative emissions, but imposing a lognormal distribution across ensemble members violates the LETKF equations. We solve this problem by sampling methane emissions scaling factors for each ensemble member according to a lognormal distribution centered on 1 (prior emissions inventory) and run GEOS-Chem. Then for LETKF calculations we apply a log transform, then exponentiate back for simulations.

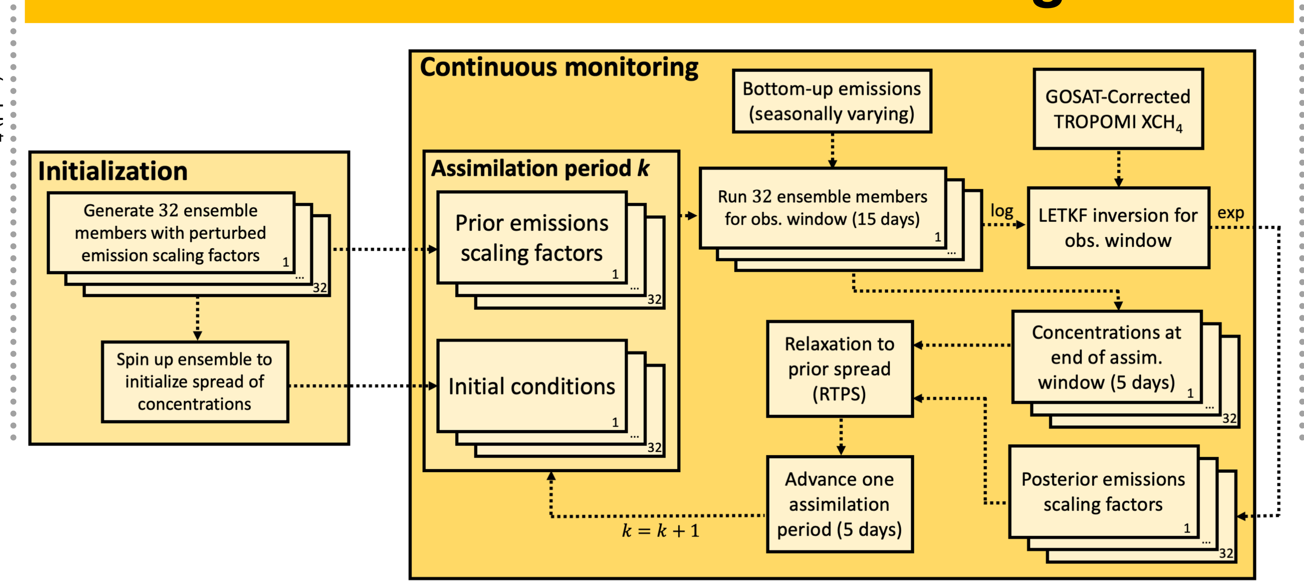


Relaxation to prior spread inflation helps counter shrinking dispersion between ensemble members which can lead to vanishingly small prior error estimation and thus for observations to be discarded. Following Bisht et al. (2023), we use the Relaxation to Prior Spread (RTPS) inflation method, which inflates the posterior ensemble standard deviation to a fixed percentage of the prior (0.7 here).

Run-in-place (RIP) assimilations recycle observations so that methane emissions estimates benefit from a longer observational record. With RIP, we calculate the LETKF assimilation update using a long period of observations (15 days, called the observation window), but then advance the assimilation window forward for a shorter period (5 days, called the assimilation window), as shown below.

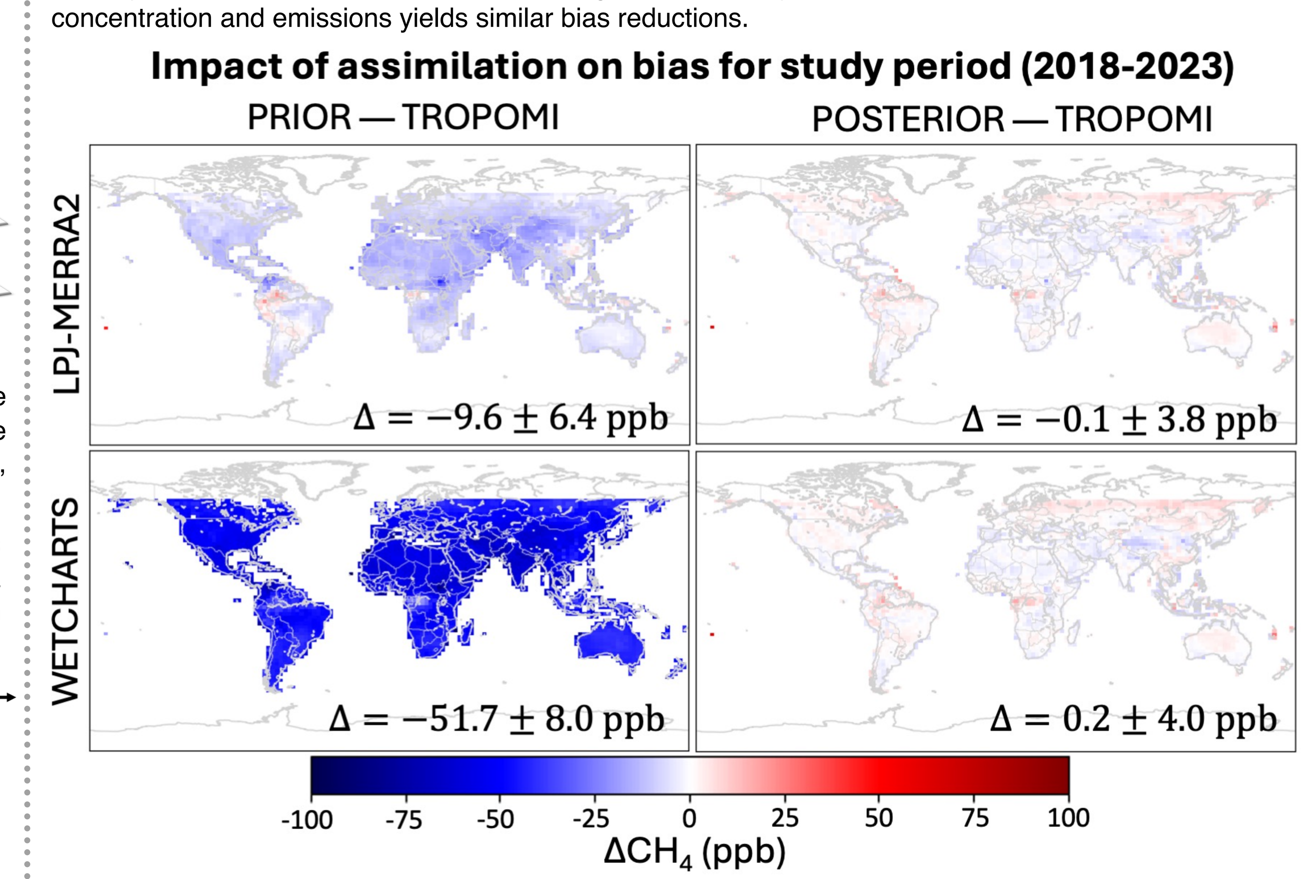


Workflow for continuous monitoring

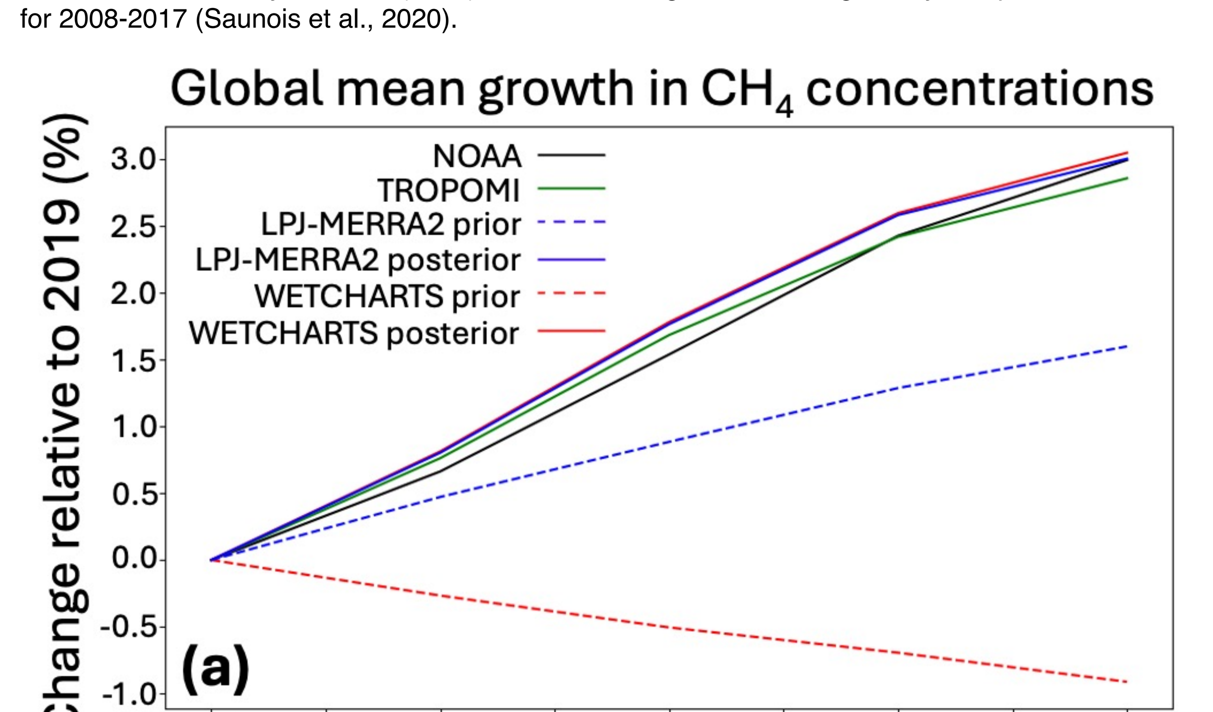


Assimilation evaluation

Below we show simulated methane columns from GEOS-Chem with GOSAT-corrected TROPOMI observations for June 2018 through December 2023. Top row shows the simulation with the LPJ-MERRA2 wetland prior and the bottom with the Wetcharts prior; posterior simulations are shown in the right column as compared with the priors in the left, with global biases relative to TROPOMI inset. Here we only show results for simulations optimizing emissions only; simultaneous optimization of concentration and emissions yields similar bias reductions.

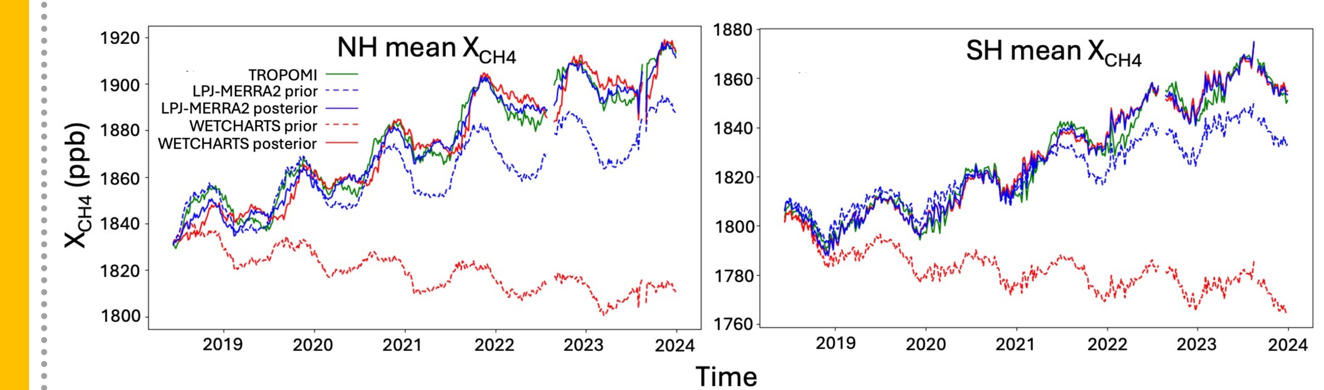


Below we show relative growth in global annual mean methane concentrations over the study period including in NOAA mean concentrations from marine sites. Prior simulations cannot reproduce the observed concentration trends because of an imbalance between sources and sinks specified in the model, but posterior simulations have similar annual emissions (559 Tg a^{-1} and 555 Tg a^{-1} for WetCHARTs and LPJ-MERRA2 respectively in 2023) leading to close agreement with TROPOMI and NOAA datasets. Our best estimate of 543 Tg a^{-1} for 2019 is slightly lower than the 556-570 Tg a^{-1} calculated for 2019 by Qu et al. (2021) and 550–594 Tg a^{-1} from a large array of top-down inversions for 2008-2017 (Saunois et al., 2020).

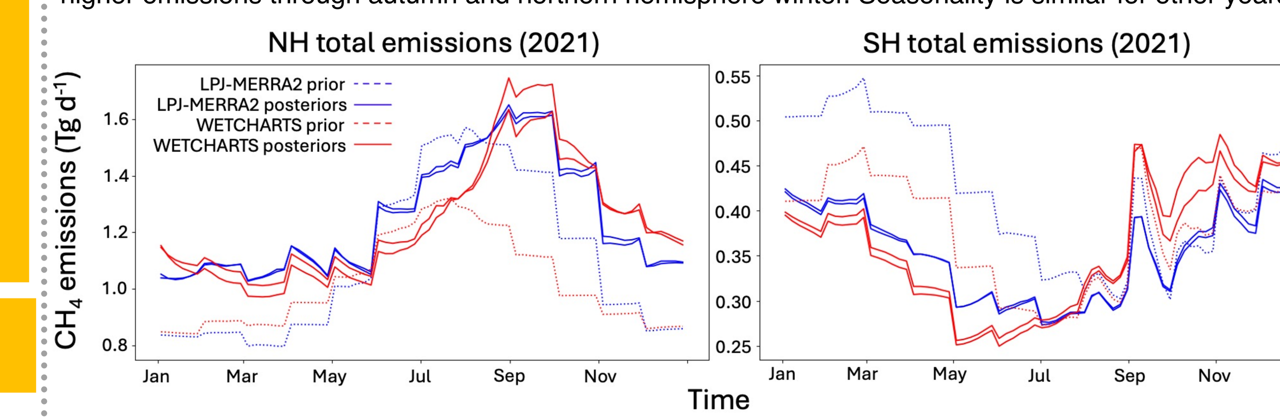


Methane trends and seasonality

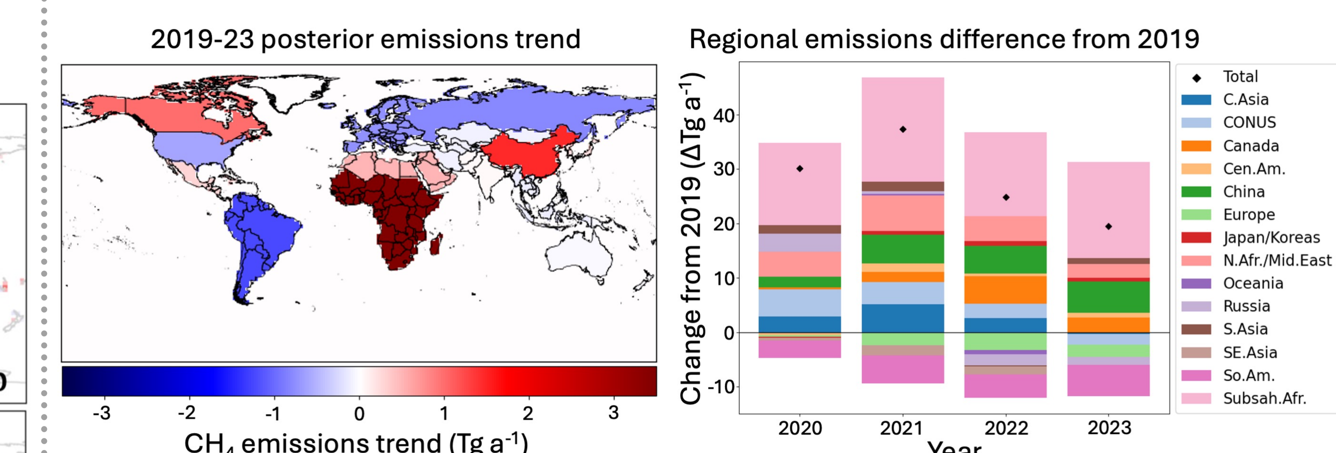
Below we compare global mean methane dry-column methane mixing ratios (XCH$_4$) from TROPOMI and from GEOS-Chem prior (dashed) and CHEEREIO posterior (solid) runs. A complication of our analysis is that no TROPOMI operational data is available for a monthlong period near August in both 2022 and 2023, the period of highest emissions. In our posterior emissions, we find sharper northern hemisphere peaks in 2022 and 2023 after the missing observational period ends, because LETKF persists July emissions through the period of missing data and increases emissions suddenly when observations resume.



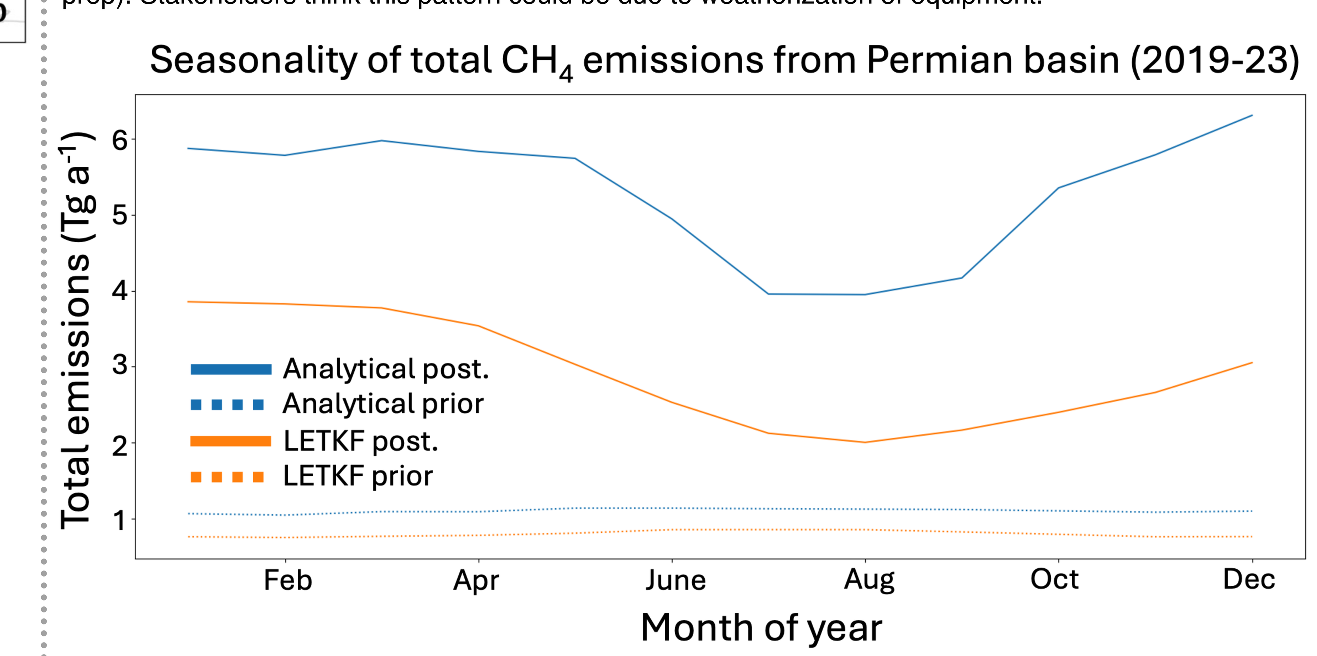
WetCHARTs and LPJ-MERRA2 posterior emissions differ in projected seasonality (two posteriors shown; one simultaneously optimizes concentrations and emissions, the other just emissions). In northern hemisphere winter, both posterior solutions project higher methane emissions than suggested in the prior and adjust peak emissions from a consistent high across northern hemisphere summer to a sharper peak in late summer and early autumn. The WetCHARTS posterior suggests sharper late summer peaks and higher emissions through autumn and northern hemisphere winter. Seasonality is similar for other years.



Below we show regional trends in annual posterior emissions. We attribute the 2020 methane surge to a 14 Tg a^{-1} increase in emissions from sub-Saharan Africa, as in previous studies (Qu et al., 2022; Feng et al., 2023), and we find that the elevated emissions persist into later years. Because of the 2020-22 methane surge, overall 2019-23 trends are weak in the study period. Regions like Central Asia, North Africa and the Middle East, and the continental US all show a substantial surge and decline in emissions.



Below we compares our 2019-2023 results for the Permian Basin in Texas and New Mexico to a 0.25°×0.3125° weekly analytical inversion (Varon et al., in prep) where we regrid our results and sample at the same downscaled Permian grid cells as in the higher resolution analysis. Despite substantial methodological differences, we can reproduce the same pronounced seasonal cycle in Permian emissions, though our results show minimal week-to-week variability in contrast to Varon et al. (in prep). Stakeholders think this pattern could be due to weatherization of equipment.



Acknowledgements, contact, and links

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Scan for CHEEREIO website

Contact Drew Pendergrass at **pendergrass@g.harvard.edu**

CHEEREIO website: **cheereio.seas.harvard.edu**

Download and use the CHEEREIO code: **bit.ly/cheereio**

CHEEREIO documentation: **bit.ly/CheereioDocs**

CHEEREIO model description paper (GMD 2023): **doi.org/10.5194/gmd-16-4793-2023**

Scan for 2023 CHEEREIO GMD paper