

Supporting Information for
Efficient computation of global high-resolution Jacobian matrices for analytical
inversions of satellite observations of greenhouse gases: Application to the
Integrated Methane Inversion (IMI) version 2.3

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S1 Prior bottom-up emissions

Global anthropogenic emissions from the fuel exploitation, waste treatment, residential combustion, transportation and industry are obtained from the monthly Emissions Database for Global Atmospheric Research (EDGAR) v8 (Crippa et al., 2024) at $0.1^\circ \times 0.1^\circ$ resolution, superseded with the global livestock emissions from EDGAR v7 (Crippa et al., 2022) due to unexplained hotspots in that from EDGAR v8 (Hancock et al., 2026), the Global Fuel Exploitation Inventory (GFEI) v3 for oil, gas, and coal emissions (Scarpelli et al., 2025) at $0.1^\circ \times 0.1^\circ$ resolution, and the Global Rice Paddy Inventory (GRPI) for monthly rice emissions (Chen et al., 2025) at $0.1^\circ \times 0.1^\circ$ resolution, and with regional emission inventories of the U.S. Environmental Protection Agency (EPA) Inventory of U.S. Greenhouse Gas Emissions and Sinks (GHGI) version 2.0 Express Extension for the contiguous US (Maasakkers et al., 2023), and those for Mexico (Scarpelli et al., 2020) and Canada (Scarpelli et al., 2021) at $0.1^\circ \times 0.1^\circ$ resolution. We use the monthly prior wetland emissions at global $0.5^\circ \times 0.5^\circ$ resolution generated from the process-based Lund–Potsdam–Jena Wald Schnee und Landschaft (LPJ) dynamic global vegetation model (Zhang et al., 2016) driven by assimilated meteorological data from the Modern-Era Retrospective analysis for Research and Applications Version 2 (MERRA-2; <https://gmao.gsfc.nasa.gov/gmao-products/merra-2/>, last access: 20 April 2026) (LPJ-MERRA2) as it was shown to better capture the methane seasonality in the northern hemisphere (East et al., 2024). Other minor emissions include monthly biomass burning emissions from GFED v4.1s (Giglio et al., 2013) at $0.25^\circ \times 0.25^\circ$ resolution, geological seeps (Etiope et al., 2019; Hmiel et al., 2020) at $1^\circ \times 1^\circ$ resolution, hydroelectric reservoirs (Delwiche et al., 2022) at $0.1^\circ \times 0.1^\circ$ resolution, termites (Fung et al., 1991) at $4^\circ \times 5^\circ$ resolution, and soil uptake estimated from the process-based Methanotrophy Model (MeMo) v1.0 (Murguia-Flores et al., 2018) at $1^\circ \times 1^\circ$ resolution.

S2 The Tropospheric Monitoring Instrument (TROPOMI) methane observations

The Tropospheric Monitoring Instrument (TROPOMI) aboard the European Sentinel-5 Precursor (S5P) satellite with local solar overpass time of 13:30 retrieves the dry column mixing ratio of methane (X_{CH_4}) at $5.5 \times 7 \text{ km}^2$ nadir resolution from solar backscatter radiance measurements in the $2.3 \text{ }\mu\text{m}$ methane absorption band (Hu et al., 2018).

We use a blended satellite product leveraging the fine spatial resolution of TROPOMI corrected with more accurate but sparser retrievals from the Greenhouse gases Observing SATellite (GOSAT) instrument with reduced retrieval biases of X_{CH_4} than the standard TROPOMI product (Balasus et al., 2023).

Figure S1 shows the observation count and super-observations of X_{CH_4} from the blended TROPOMI product with the mean observation count of 87 and X_{CH_4} of 1866 ppbv over the Permian in May 2024.

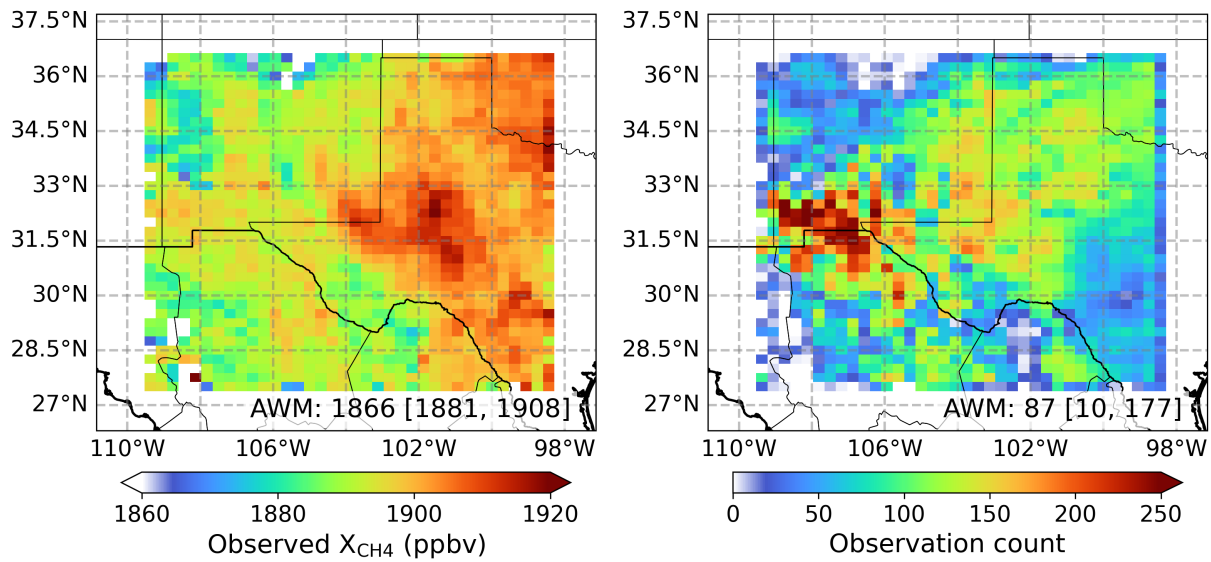


Figure S1. The spatial distribution of the observed dry column mixing ratio of methane (X_{CH_4}) from the blended TROPOMI product (left) and the observation count per simulation grid box (right) over the Permian in May 2024. The inset value at the bottom right is area-weighted mean (AWM) and the 5th and 95th percentiles in the square bracket.

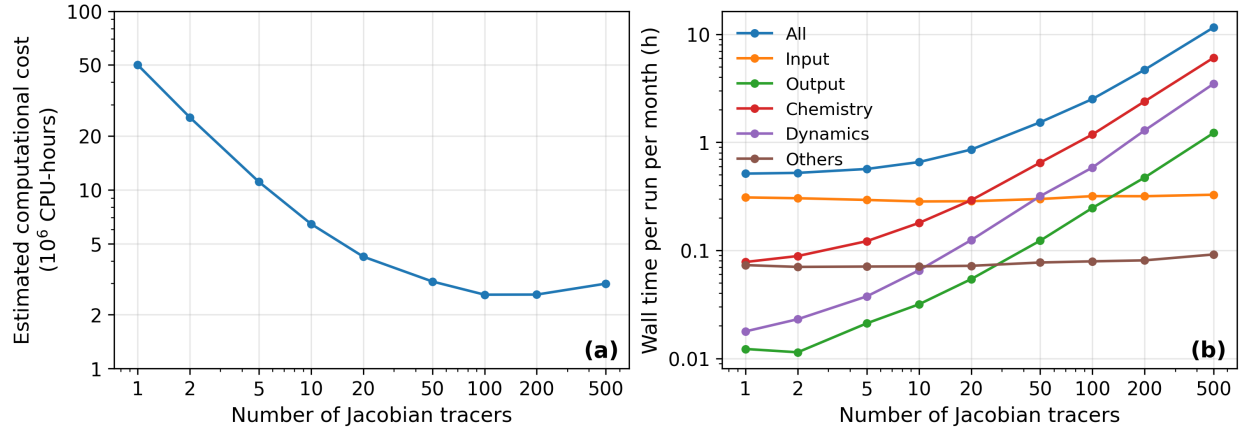


Figure S2. Optimization of the number of state vector elements per perturbation run (Jacobian tracers). a) Estimated total computational cost as a function of the number of Jacobian tracers with the number of state vector elements for all target faces as shown in Figure 1. b) Decomposition of the wall time per perturbation run per month with varying number of Jacobian tracers at C36S10 resolution. The performance tests were conducted with 48 cores per node with shared partition on the local server Cannon at Harvard. Note that the 1-month perturbation run was using the MERRA-2 meteorological inputs at $0.5^\circ \times 0.625^\circ$ resolution instead of GEOS-FP meteorological inputs at $0.25^\circ \times 0.3125^\circ$ resolution, which would result in shorter wall time on input.

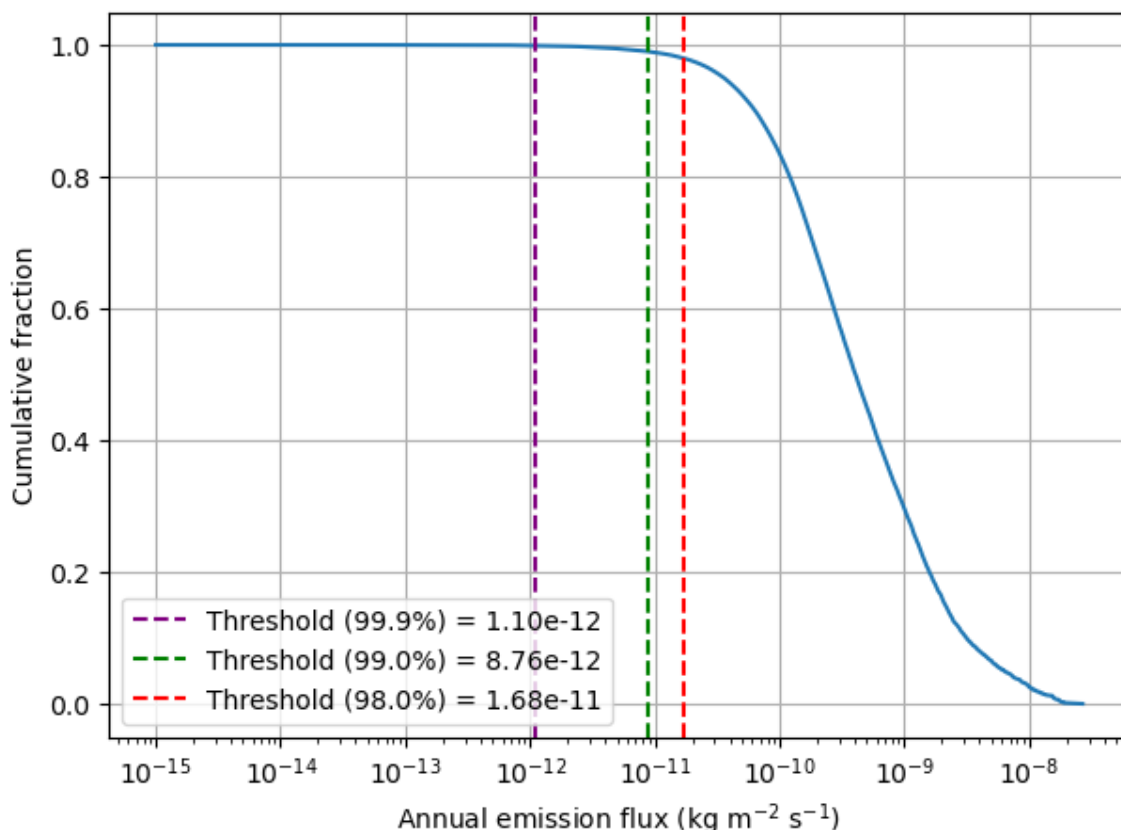


Figure S3. Cumulative fraction of total prior emissions (Estrada et al., 2025) versus the emission flux at $0.25^\circ \times 0.3125^\circ$ resolution.

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