

High-resolution inverse model estimates of country level methane emissions inferred using GOSAT and surface observations

Rajesh Janardanan, Shamil Maksyutov, Fenjuan Wang, Tsuneo Matsunaga

Satellite Observation Center, Earth System Division,
National Institute for Environmental Studies, Tsukuba, Japan

Background

We used methane observations from global surface observation networks and GOSAT satellite in a high-resolution methane inverse model to infer surface anthropogenic fluxes over major emitting countries. The model uses prior information on fluxes and corrections to the input fluxes are made iteratively to bring the misfit between the observed concentrations and the simulated concentrations to minimum so that we get optimized flux. We have conducted two sets of inversion using surface observations and GOSAT observations. The results on country-scale emissions are discussed in this poster

NTFVAR Inverse Modeling System

- ❖ Global Eulerian–Lagrangian coupled model NIES-TM-FLEXPART-VAR (NTFVAR)
- ❖ Consists of the National Institute for Environmental Studies (NIES) model as a Eulerian three-dimensional transport model, and FLEXPART (FLEXible PARTicle dispersion model) as the Lagrangian particle dispersion model (LPDM).
- ❖ The model development were reported Belikov et al. (2016) and Maksyutov et al. (2021) and application to methane inversion reported in Janardanan et al., (2020) and Wang et al., (2019).
- ❖ The forward model simulates the observed concentrations using the input (initial) fluxes. Depending on the difference between the observations and the simulations (misfit), the input flux is corrected iteratively until the misfit between the observations and the simulation using adjusted fluxes becomes minimum. This optimized flux (output of inverse model), constrained by available observations are estimated on biweekly time step.
- ❖ The model uncertainty were not estimated, but the estimated flux totals were evaluated comparing recent reports on country-scale budgets and uncertainties (Worden et al., 2022).

Data

CH₄ concentration observations used

1. Greenhouse Gas Observing Satellite (GOSAT) Observations (NIES Level 2 product, v.02.95)
2. Obspack CH₄ (v4.0) and observations from ICOS network

Input fluxes

1. Monthly anthropogenic emission was from the Emissions Database for Global Atmospheric Research (EDGAR v6) at a spatial resolution of 0.1°×0.1°
2. Emissions from wetland taken from Sauniois et al (2020) and soil sink follows Murgia-Flores et al (2018).
3. Emission from biomass burning was taken from Global Fire Emission Database (GFED4s) data at 0.1° resolution
4. The emission from termites was from Sauniois et al (2020). The emissions due to oceanic exchange were taken from Weber et al, (2019) and geological emissions from Etiope et al., (2019)

Meteorological data

The meteorological data used for the transport model, were obtained from the Japanese Meteorological Agency (JMA) Climate Data Assimilation System (JCDAS, Onogi et al., 2007) at 1.25°×1.25° spatial resolution, 40 vertical hybrid sigma-pressure levels, and a temporal resolution of 6 h.

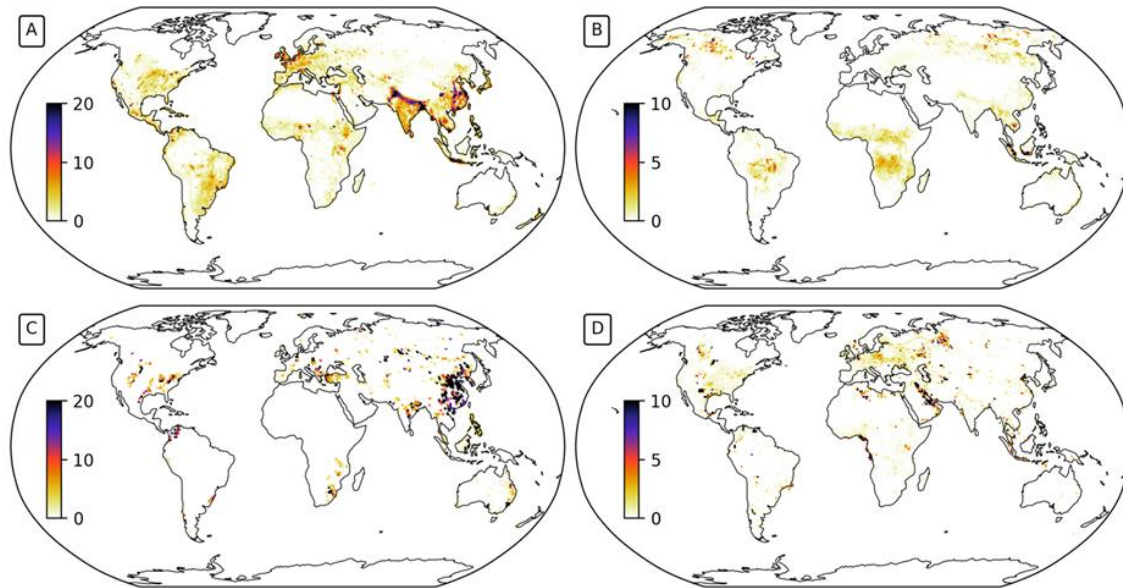


Figure 1. The global anthropogenic fluxes estimated by the high-resolution inverse model from a) agriculture and waste sector combined b) from biomass burning and biofuels c) coal mine and d) oil and gas exploitation averaged over 2009-2020 period. The units are in $\text{gCH}_4/\text{m}^2/\text{yr}$ and the scales for different sectors should be noted.

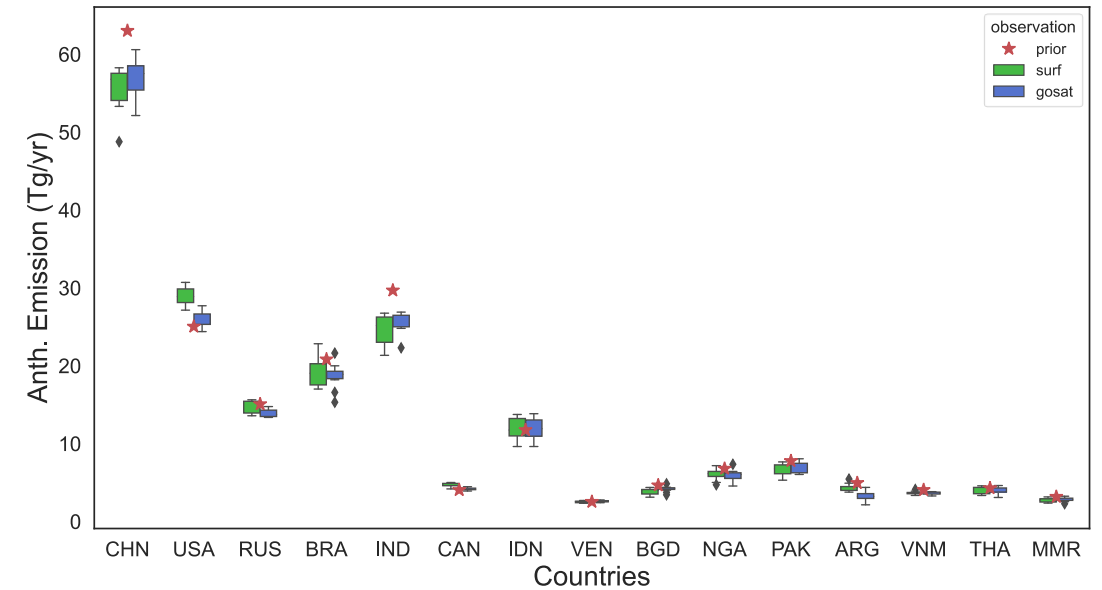


Figure 2. The country total methane emissions estimated by the inverse model using surface observations (green) and GOSAT observations (blue) along with the input fluxes (red star). The range in the emission is for the study period 2009-2020

Optimization of anthropogenic sectors and natural emissions

- ❖ Our model makes flux adjustments for the natural (wetland) and agriculture, biomass burning, waste, oil and gas and coal sectors of the anthropogenic emissions.
- ❖ This will allow detailed sector-wise analysis of methane emissions on a country-scale.
- ❖ The model performance was evaluated using two sets of inversions using satellite (GOSAT) and surface methane observations.

Country total anthropogenic emissions

- ❖ Anthropogenic emission totals calculated from EDGAR v6 data were highest for China (63.0 Tg yr^{-1}), Russia (15.1 Tg yr^{-1}), United States (25.0 Tg yr^{-1}), India (29.7 Tg yr^{-1}), Brazil (20.8 Tg yr^{-1}) and Indonesia (11.8 Tg yr^{-1}) to list countries emitting more than 10 Tg yr^{-1} .
- ❖ The anthropogenic flux estimated by the inverse model using surface observations were, for China 55.6 Tg yr^{-1} (difference from inventory: -7.4 Tg ; 11.7%), Russia 14.5 Tg yr^{-1} (-0.54 Tg ; 3.6%), United States 29.0 Tg yr^{-1} (3.9 Tg ; 15.7%), India 24.5 Tg yr^{-1} (-5.1 Tg ; 17.4%) and Indonesia 11.9 Tg yr^{-1} (0.11 Tg ; 1%).
- ❖ Estimate using GOSAT v02.95 data yielded comparable figures with China 57.0 Tg yr^{-1} (-6.0 Tg ; 9.5%), Russia 13.9 Tg yr^{-1} (-1.1 Tg ; 7.6%), United States 25.9 Tg yr^{-1} (0.9 Tg ; 3.6%), India 25.6 Tg yr^{-1} (-4.1 Tg ; 13.8%) and Indonesia 11.9 Tg yr^{-1} (0.16 Tg ; 1.4%).
- ❖ Most of the large emitting countries were found to have the inverse model corrections within the flux uncertainty range reported by recent studies (e. g. Worden et al., 2022).
- ❖ Emission estimate for China and United States were slightly beyond the uncertainty by a model correction of 7.4 Tg and 3.9 Tg compared to 7.1 and 3.3 Tg uncertainties, respectively.

Summary

- We carried out inverse estimation of methane fluxes for twelve years from 2009-2020 using GOSAT satellite and surface observations using a high-resolution inverse model NIES-TM-FLEXPART-VAR (NTFVAR).
- Optimization was applied to natural (wetland only) and five anthropogenic emission sectors on a bi-weekly time step, and the results were analyzed on a country scale globally.
- We used the latest EDGAR v6 anthropogenic methane emission inventory as input to the model.
- Anthropogenic emission was found to differ from the initial input fluxes for China by around 10-12% (6-7.4 Tg), the United States by 4-16% (0.9-3.9 Tg) and India by 14-17% (4.1-5.1 Tg) which is larger than the uncertainty range estimated for respective countries by Worden et al., 2022., but not by large margin.
- Bangladesh had the largest downward revision of 17.0% in anthropogenic emissions in the Asian countries along with Myanmar (14.4%, 0.5 Tg).
- For other countries, the flux adjustments by the inverse model on average for the study period of 2009-2020 were not large enough to exceed the emission uncertainty for those countries.

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