Inverse modeling of methane and carbon dioxide fluxes using high resolution transport and the data by GOSAT and surface observations.

Shamil Maksyutov[1], Rajesh Janardanan[1], Fenjuan Wang[1], Aki Tsuruta[2], Tomohiro Oda[3], Greet Janssens-Maenhout[4], Tsuneo Matsunaga[1]
and OBSPACK/WDCGG/GCP-CH4 observation data contributors.

[1]NIES, Tsukuba, Japan, [2]FMI, Finland, [3]USRA/NASA GSFC, USA, [4]JRC EC, Italy

Motivation – estimating anthropogenic emissions with satellite observations (made close to the sources)

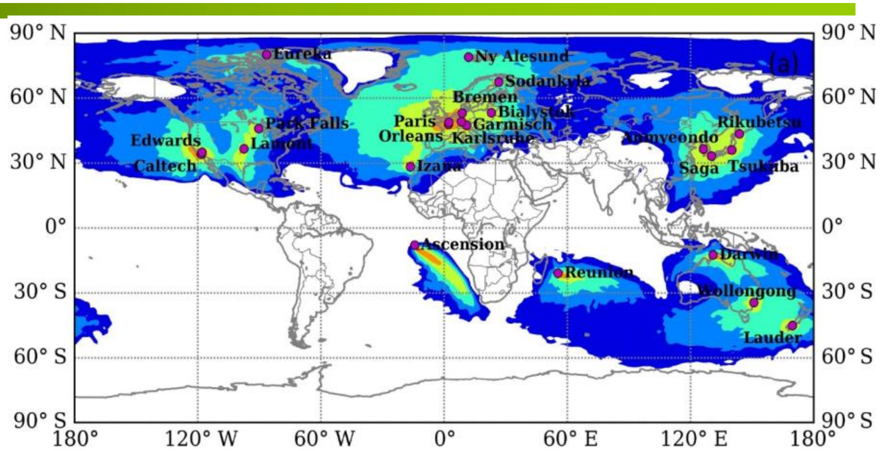
- Anthropogenic GHG emissions are recognized as cause of the climate change, so extra focus is now on slowing down and reversing global warming (Paris agreement), through GHG emission reduction by all UNFCCC parties
- UNFCCC system for emission reduction/trends reporting set time periods of 5 years, eg 2016-2020, the countries national emission inventory reports (using IPCC Guidelines on Inventories) will be summarized in a step called global stocktake (3 years later, 2023), and compared to observed GHG trends.
- Studies made for National Emission Inventory verification targeting CH_4 emissions in Switzerland (Henne 2016), UK (Manning 2011), India (Ganesan et al 2017) use high resolution (0.1 to 0.3 degrees) regional Lagrangian transport modeling, as most efficient for studying anthropogenic emissions of CH_4
- Global inverse modeling products, assessments such as CAMS, GCP-CH4 would benefit from upgrading to use of high resolution transport resolving the anthropogenic plumes at resolution of the satellite pixel (7 – 10 km)

Transport model: Coupled Eulerian-Lagrangian transport model (NIES TM + Flexpart) at 0.1 degree spatial resolution

-Configuration of NIES-TM
- resolution 2.5 degree
- reduced grid near poles
- mass conserving meteorology, mass fluxes on hybrid isentropic vertical coordinates

-Configuration of Flexpart
-JCDAS meteorology (1.25 deg, 40 model levels, 6 hourly)
-surface flux footprints estimated on 0.1x0.1 deg, daily step
-time window 3 days (for coupling to NIES-TM at 0 GMT)
-for coupling to NIES-TM, 3D concentration footprints estimated on hybrid-isentropic vertical grid at 2.5 deg horizontal resolution

-Adjoint of coupled model
- hand-coded adjoint with same CPU cost in forward and adjoint modes, revised after Belikov et al GMD 2016



Example of adjoint model simulation of the observation footprint. Sensitivity of CO_2 concentrations ppm/(μmol/(m^2/s)) to surface fluxes, at TCCON site locations: Belikov et al ACP 2017

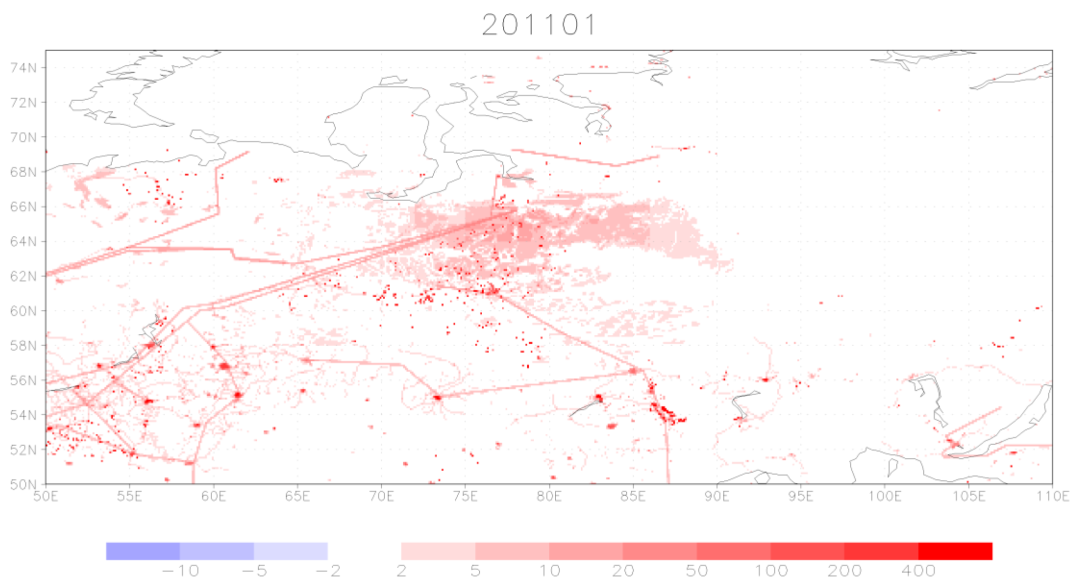
More details in papers:

Janardanan, R., et al: Country-Scale Analysis of Methane Emissions with a High-Resolution Inverse Model Using GOSAT and Surface Observations, Remote Sensing, 12, 375, 2020.

Wang, F., et al.: Methane Emission Estimates by the Global High-Resolution Inverse Model Using National Inventories, Remote Sensing, 11, 2489, 2019.

Maksyutov, S., et al: Technical note: A high-resolution inverse modelling technique for estimating surface CO2 fluxes based on the NIES-TM – FLEXPART coupled transport model and its adjoint, Atmos. Chem. Phys. Discuss, 2020.

Prior fluxes for CH_4 flux optimization with flux resolution of 0.1 deg



Prior fluxes, sinks:

- EDGAR 4.3.2 anthropogenic: fossil/industrial, coal, oil and gas, municipal and agriculture

2. VISIT - wetland and soil sink
3. GFAS fire (daily)
4. Termites, ocean, geological as in Transcom-CH4
5. 3D monthly OH, O^1D, Cl as in Transcom-CH4

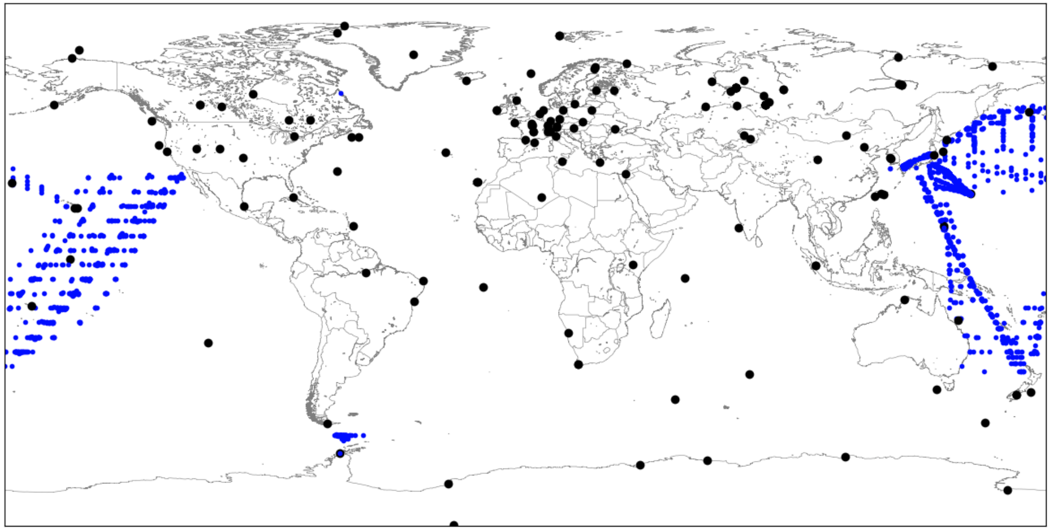
VISIT wetland fluxes remapped from original 0.5 deg to 0.1 degree using maps of wetland area (GLWD 1km)

Flux corrections estimated for 2 flux categories

1. Anthropogenic, uncertainty 0.3 of EDGAR 4.3.2, monthly
2. Wetlands, uncertainty 0.5 of VISIT (Cao), monthly climatology-Time window: 18 month, from Oct, prev. year – Mar , following year.

Optimization problem: reconstruct bi-weekly fluxes, at resolutions of 0.1 deg,“week” defined as ¼ of a month

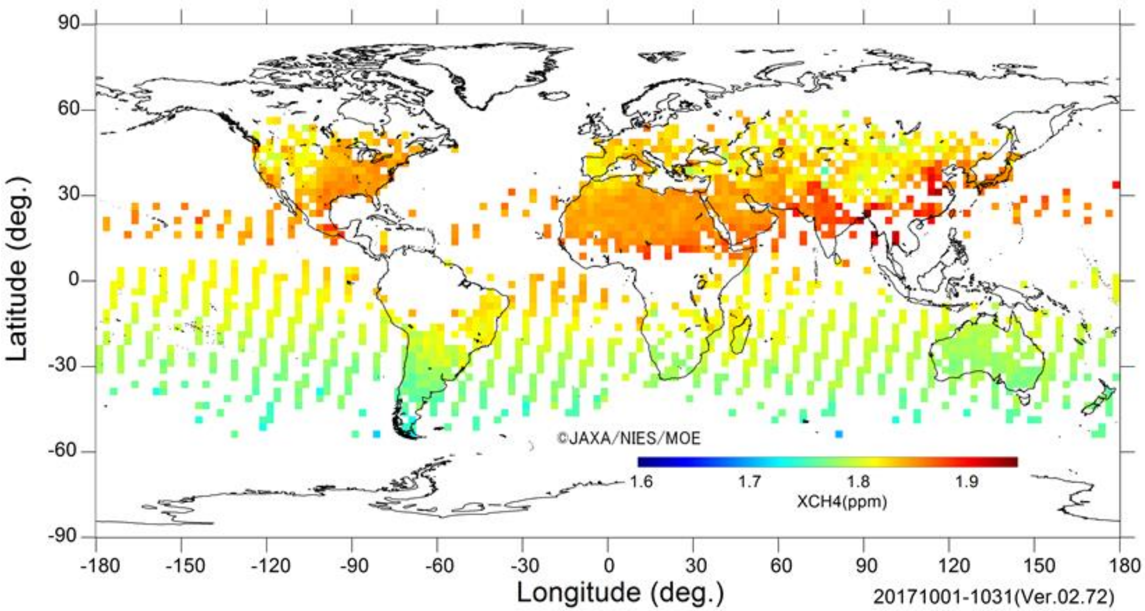
Inverse model input – ground-based and GOSAT data



Location of ground-based measurement sites of atmospheric CH4.

-Data providers: WDCGG, NOAA, ECCC, LSCE, ICOS, JR-STATION, NIES/CGER, FMI

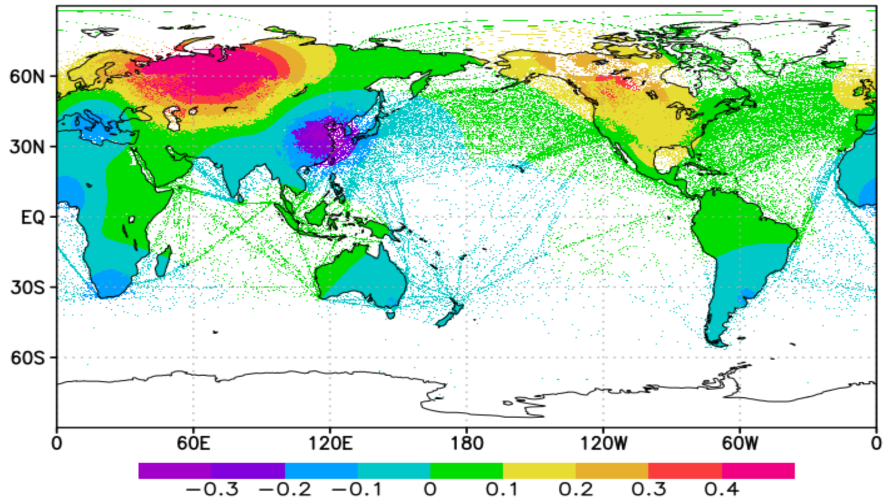
Black: stationary sites
Blue: ship cruises

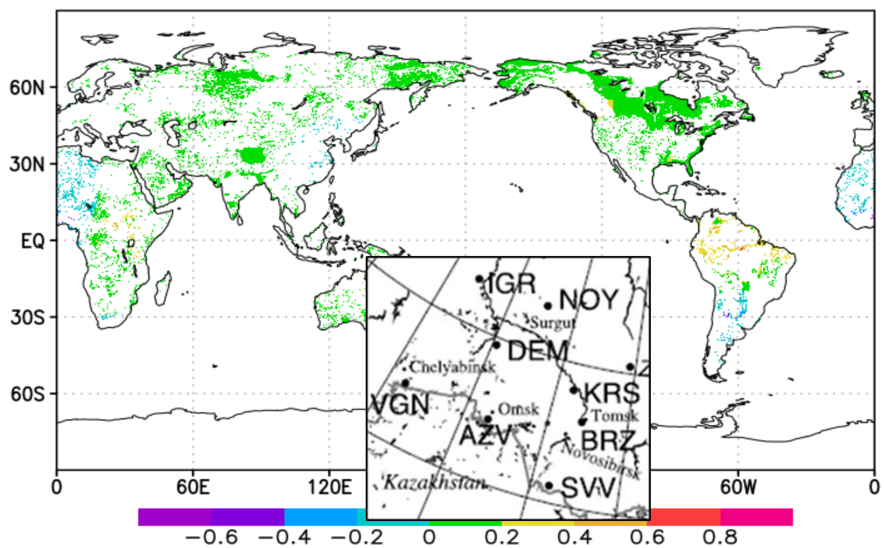


GOSAT CH4 retrievals v02.72

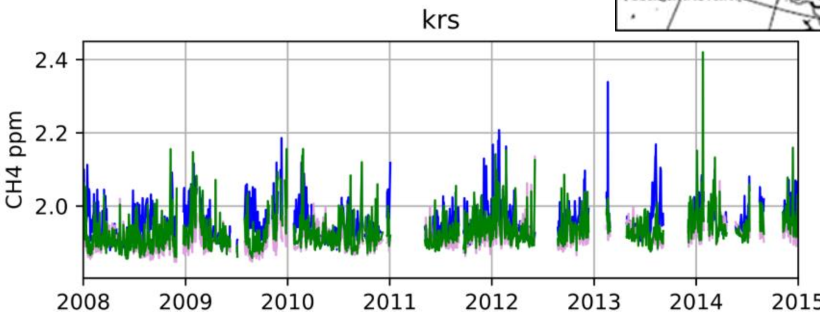
Optimized: emission scaling factors, and concentrations

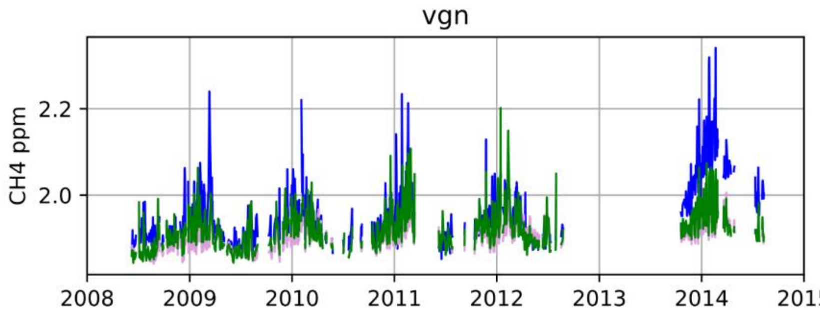
Annual mean relative corrections (scaling factors) to anthropogenic (top) and wetland (bottom) emissions (Wang et al. 2019)

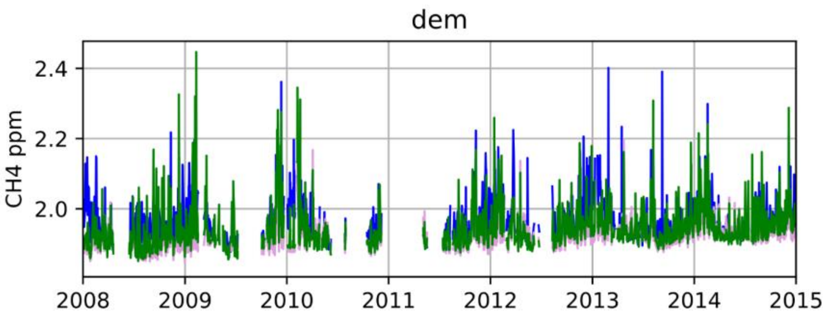




Siberian JR-STATION network: Optimized (green), forward(plum), observed(blue)

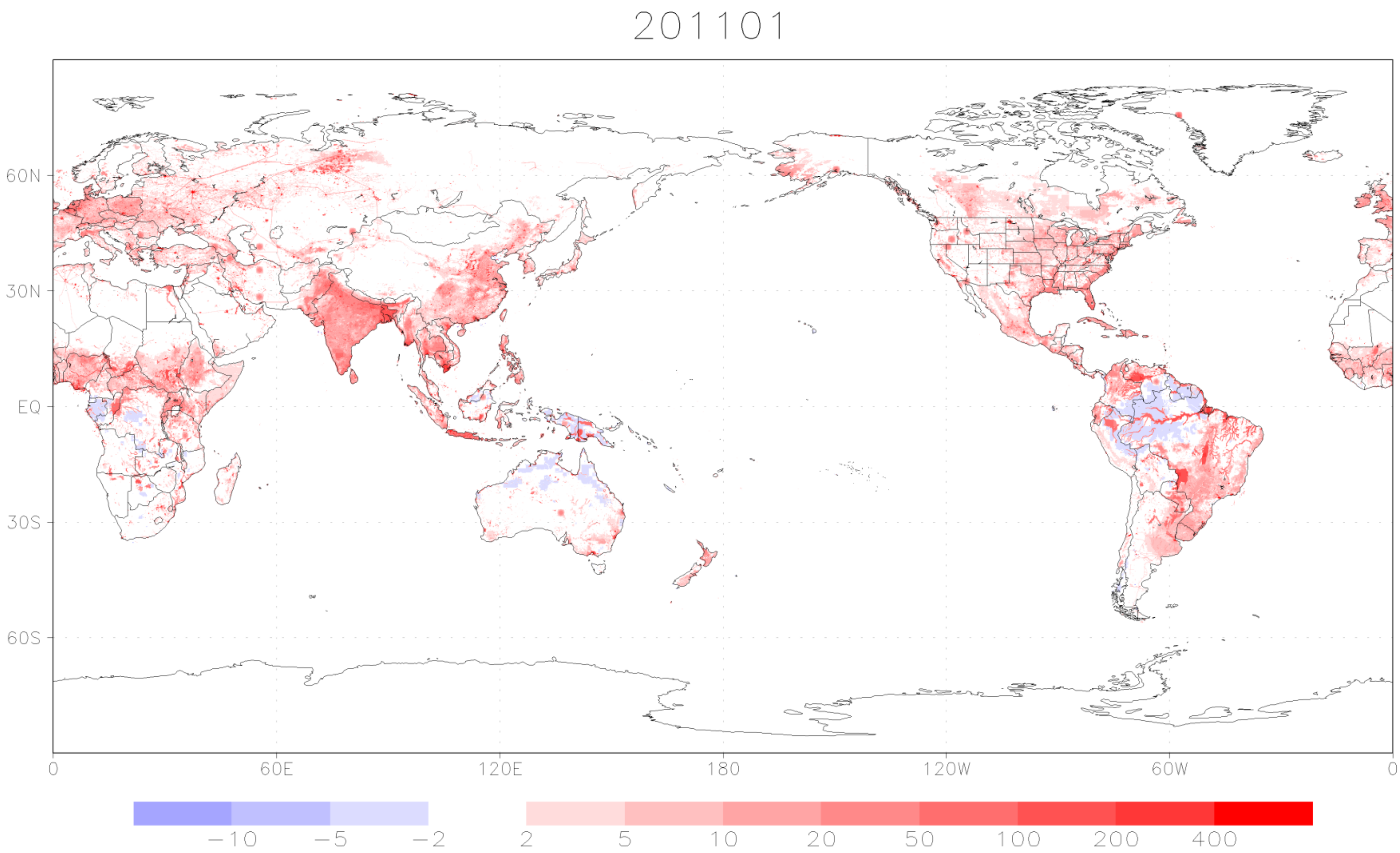






Estimated (optimized) total CH_4 emissions

- Flux map in 0.1x0.1 grid ($mgCH_4$/m2/day)



National-scale CH_4 emissions (from Janardanan et al, 2020)

Country	Prior total	Posterior total	Natural	Anthropogenic	Anthropogenic-NIR	Uncertainty
CHN	60.1	52	6.3	45.7	−8.6	8.6
USA	51.6	55.7	25.9	29.8	2	7.8
RUS	47.8	45.2	13.2	31.9	−2.3	7.8
BRA	45.6	56.2	39.8	16.5	0.1	10
IND	29.9	36.5	12.3	24.2	4.1	5.3
CAN	23.4	16.4	12.2	4.2	0.5	4.5
IDN	19.5	20.6	8.7	11.8	0.7	2.5
VEN	9.2	11.6	8.3	3.2	0.2	2
BGD	8.6	11.1	5.9	5.2	0.6	1.7
NGA	8.3	8.5	2.4	6.1	0.2	1.5
PAK	7.7	8	0.6	7.4	0.2	1
ARG	7.7	7	3.8	3.3	−0.6	1.2

Difference between estimated anthropogenic emissions and National Inventory report is within uncertainty

Inverse model setup for CO_2 inversion with Obspack-GVP data details in: Maksyutov et al ACPD 2020

-Observational data: Obspack GVPlus 2015 (2010-2012)

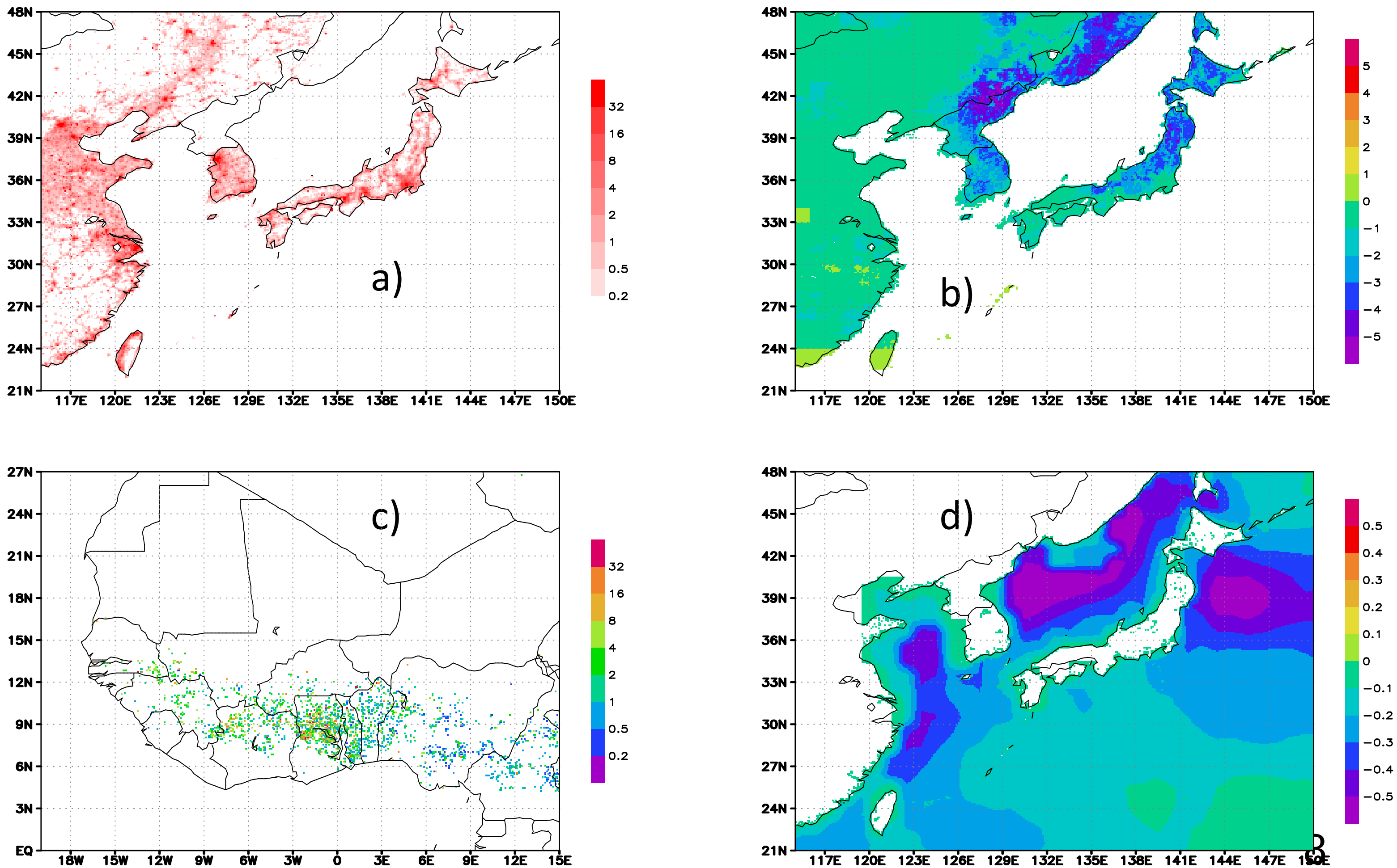
-Prior uncertainty:

land: monthly MODIS GPP (multiplied by 0.2)

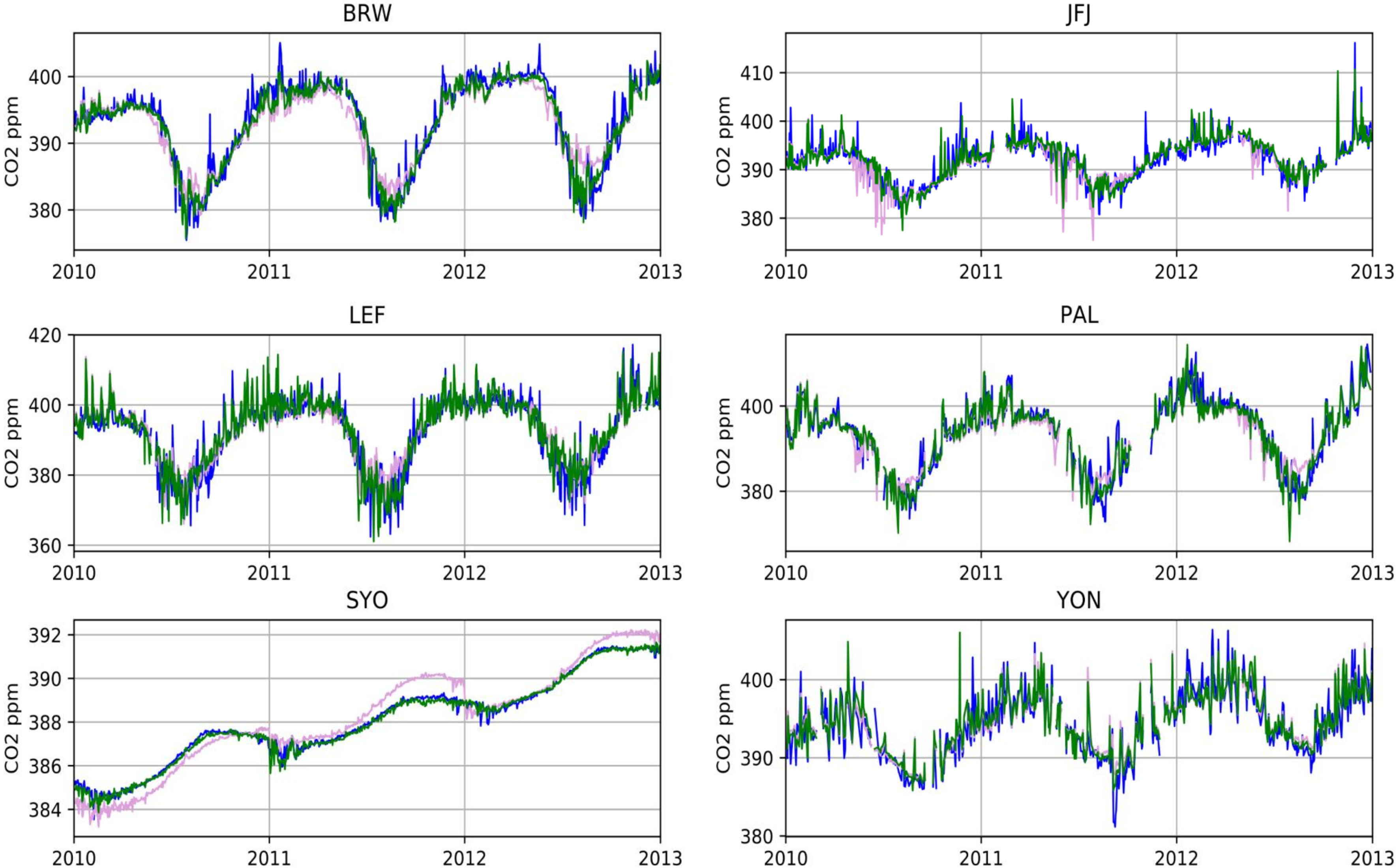
ocean: monthly inter-annual variability of the OTTM 4D-var model fluxes

Prior fluxes

a) Fossil ODIAC
b) Bio VISIT mosaic
c) Fire GFAS
d) Ocean OTTM

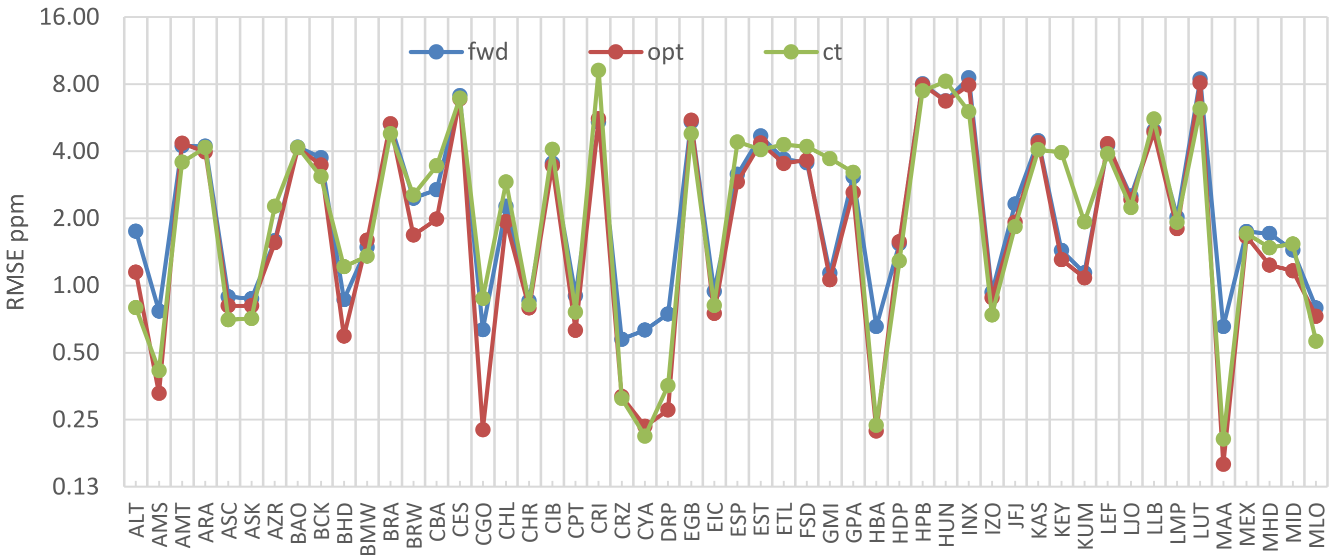


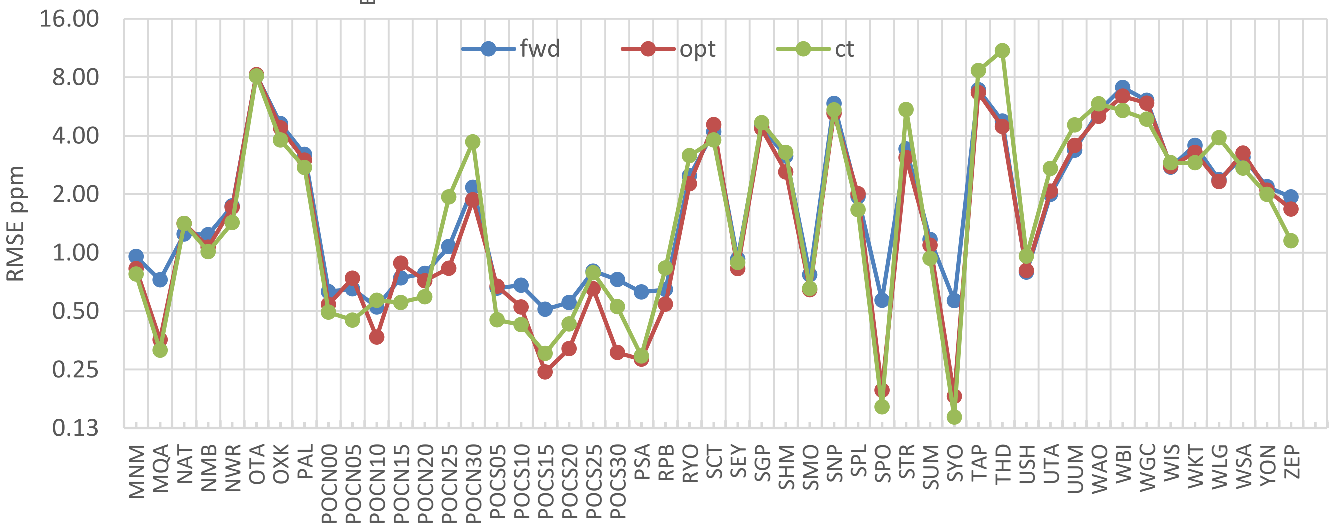
Optimized CO_2 concentrations



Simulated and observed concentrations (blue - observed, plum -forward (unoptimized), green – optimized) at Barrow (BRW), Jungfraujoch (JFJ), Wisconsin (LEF), Pallas (PAL), Syowa (SYO), and Yonagunijima (YON).

Residual misfit and comparison with NOAA Carbontracker 2017





Relative to CT2017 RMSE is smaller by just 14% on average

RMS difference between model and observations in 2010-2012 for (surface) sites included in inversion (blue – prior, red – optimized, green – CT2017)

Summary

Ability to quantify natural and anthropogenic fluxes of CH_4 and CO_2 by atmospheric observations is valuable for climate change mitigation.

The national anthropogenic emission estimates are mostly done made using high resolution regional Lagrangian models. – But we developed a computationally efficient approach for inverse surface flux modeling at fine-grid scale of 0.1 degree globally, demonstrated good model fit to ground based observations.

The model was applied to estimating the national scale anthropogenic/natural CH4 emissions with GOSAT data during 2010-2017, using national inventory estimate as prior. The estimated emissions are matching the national inventory reported amounts within the inverse model uncertainty range. Large uncertainty was estimated for Brazil and some other regions, due to influence from natural wetland emission uncertainty. Need to have more observations (Tropomi?) for stronger separation between anthropogenic and natural fluxes.

Inverse model application to CO2 flux estimates using surface observations only demonstrated good fit to observations, similar to other established inverse modeling systems like Carbontracker.

Inverse problem - find a surface flux field x that matches the observed CO2 concentrations *y*:

$$y = H \cdot (x_p + x)$$

Here, y – CH_4 observations, $H=H_E+H_L$ – transport model (linear operator), x_p – prior flux, x – grid-resolving flux correction field

The cost function $$J = \frac{1}{2}(r - H \cdot x)^T R^{-1}(r - H \cdot x) + \frac{1}{2} x^T B^{-1} x$$

smoothness constraint

where $$r = y - H \cdot x_p$$

r - residual misfit, *B* - flux error covariance matrix, *R* -data uncertainty

By applying substitutions:

$$B = D \cdot L \cdot L^T \cdot D^T \quad x = L \cdot D \cdot z \quad R = \sigma \cdot \sigma^T \quad b = \sigma^{-1} r \quad A = \sigma^{-1} H \cdot L$$

Derivative of *J* is used in Quasi-Newtonian method (M1QN3) to find solution $$\partial J / \partial z = -A^T (b - A \cdot z) + z$$