CO_2 inverse modeling with satellite XCO_2 retrievals, ground-based observations and a high-resolution tracer transport.

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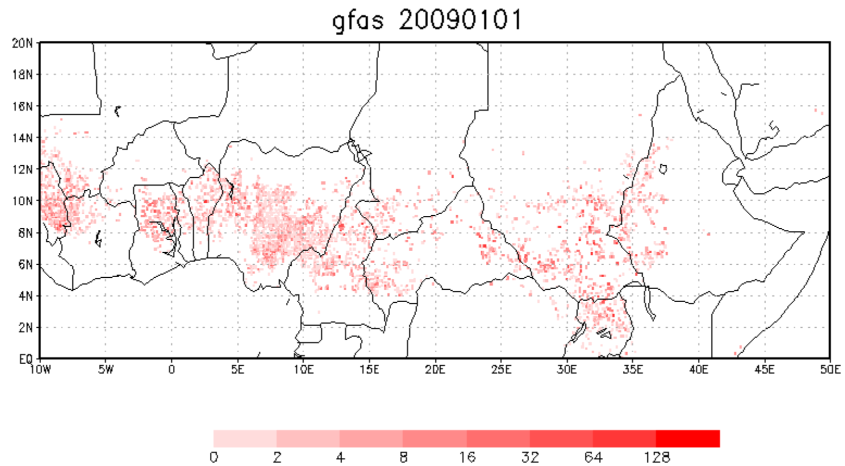
Towards using data from constellation of the greenhouse gas observing satellites, case study wth GOSAT and OCO-2

- Why multiple satellites?
- CO_2 data from multiple satellites GOSAT, GOSAT-2, OCO-2, …. are available for use in inverse modeling, with potential for better constrain on surface CO2 fluxes.

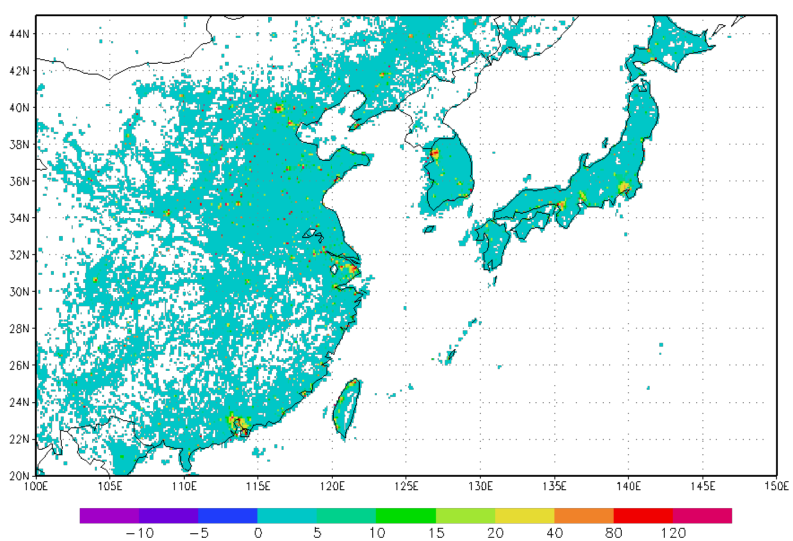
- Why use high resolution?
- Assimilating gound-based data from continental locations, especially in populated regions, is not a trivial task, due to contamination from fossil sources
- [We hope] High resolution transport modeling helps reducing crosstalk between various sources: anthropogenic/fossil, ecosystem sink/respiration, biomass burning
- It was shown recently (Janardanan 2016), that transport modeling at resolution of GOSAT footprint (0.1 deg) is efficient in quantifying concentration enhancements from localized sources of CO_2

Prior CO_2 fluxes at 0.1 degree resolution



Africa: biomass burning by GFAS, (gC/m2/day)

Forest fire/biomass burning:
GFAS daily at 0.1 degree derived from MODIS fire radiative power (FRP) product, Kaiser et al, 2012



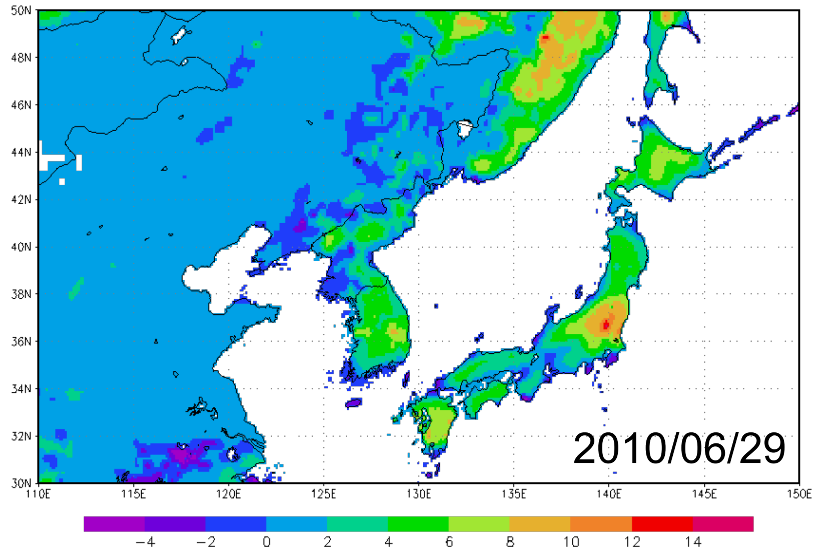
GrADS: COLA/IGES

E Asia fossil emissions ODIAC, Jan 2010

ODIAC fossil fuel emissions aggregated to 0.1 degree

ODIAC (Oda & Maksyutov, 2011) combines CARMA power plan emissions database, and DMSP nightlights 1 km resolution observation as proxy for population map, country totals same as CDIAC

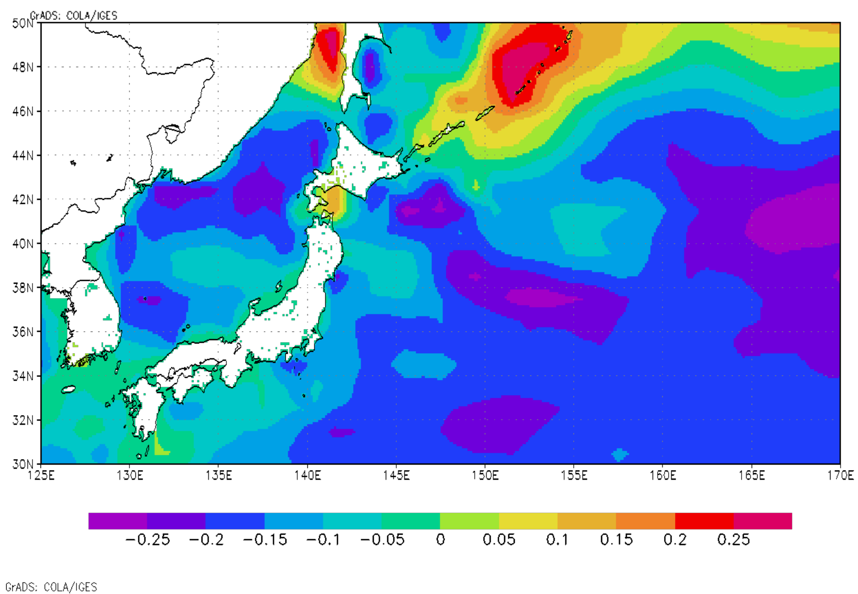
CO_2 prior fluxes at 0.1 deg resolution



Terrestrial biosphere

VISIT NEE 0.5 deg daily fluxes for 16 veg types mosaic (JCDAS),
Saito et al GMD 2014,

Optimized with atm. CO_2 and other data.
Use SYNMAP 1 km vegetation mosaic to remap 0.5 deg fluxes to 0.1 degree



Ocean CO2 surface exchange
Data assimilation of LDEO pCO2 dataset with ocean transport and biogeochemistry model OTTM and its adjoint monthly 1x1 deg fluxes
(Valsala, Tellus, 2010)
interpolated to 0.1 deg, using MODIS 1 km land/ocean mask

Coupled Eulerian-Lagrangian transport model (NIES TM + Flexpart)

-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/hourly time 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

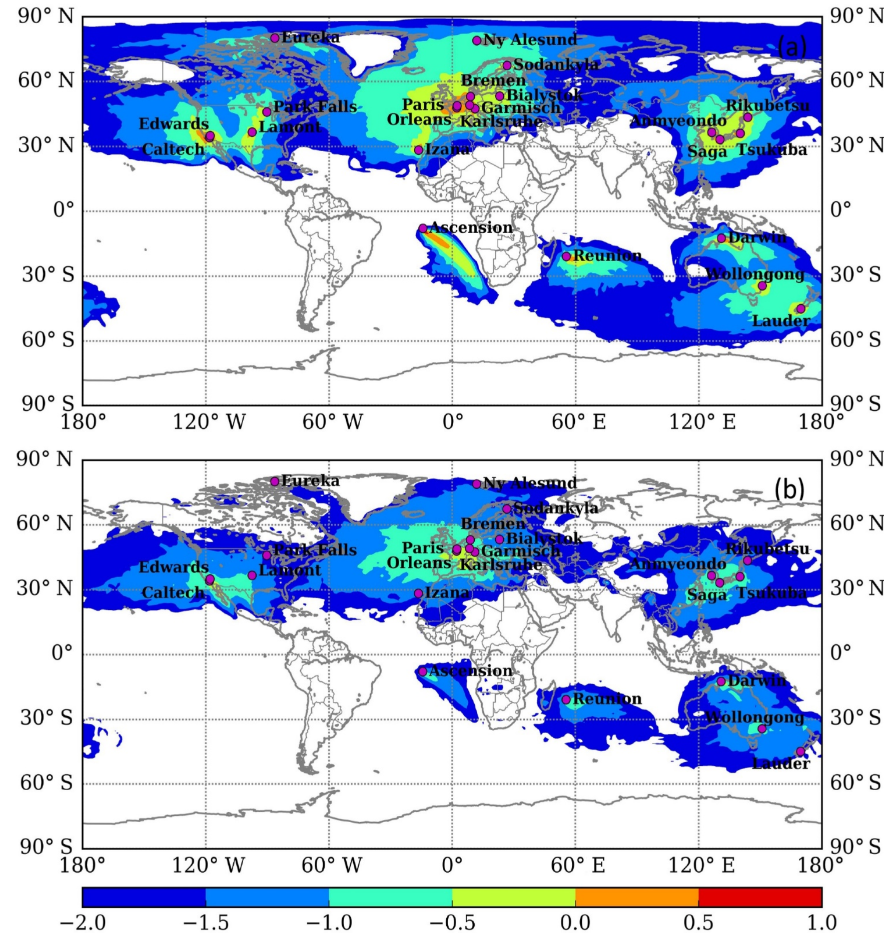


Figure 1. Global distribution of the sensitivity of CO_2 concentrations ppm/(μmol/(m^2/s)) with respect to surface fluxes, at TCCON site locations:
(a) observation height of 1000m, (b) 3000m
Belikov et al ACP 2017

Flux inversion problem

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

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

Here, *y* – CO_2 observations, *H* – transport model (linear operator), x_p – prior flux, x – grid-resolving flux correction field

As the problem is ill-constrained in case of large dimension of *x*, regularization is applied by adding regularization term $x^T B^{-1} x$ to the cost function *J*:

$$J = \frac{1}{2}(r - H \cdot x)^T R^{-1}(r - H \cdot x) + \frac{1}{2} x^T B^{-1} x \quad \text{where} \quad r = y - H \cdot x_p$$

r - residual misfit, *B* - flux error covariance matrix, *R* -data uncertainty.
Optimization problem can be reduced by applying substitutions:

$$B = D \cdot L \cdot L^T \cdot D^T \qquad x = L \cdot D \cdot z \equiv L' \cdot z \qquad R = \sigma \cdot \sigma^T \qquad b = \sigma^{-1} r \qquad A = \sigma^{-1} H \cdot L'$$

Note: in matrix *L* - non diagonal elements declining as ~*exp(-x^2/r^2)* with distance between grid points, *D* – diagonal matrix of flux uncertainties

Inverse model setup and technical spec

-Observational data: Obspack GVPlus 2015, WDCGG+Siberia

-Prior uncertainty at 0.1 deg : CO_2
land: monthly MODIS GPP (multiplied by 0.2)
ocean: monthly inter-annual variability of the OTTM 4d-var model fluxes

-Time window: for 2015: bi-weekly fluxes Oct 1, 2014 – Mar 31,2012. Week defined as ¼ of a month

-Optimization problem: reconstruct fluxes at resolutions of 0.1 deg

Some technical data: size of Lagrangian H matrix

- Obspack 6 GB/year, GOSAT 26 GB/year, OCO-2 240 GB/year (daily 0.1 deg)
- memory use by optimization program >=450 GB (server with 512 GB RAM)

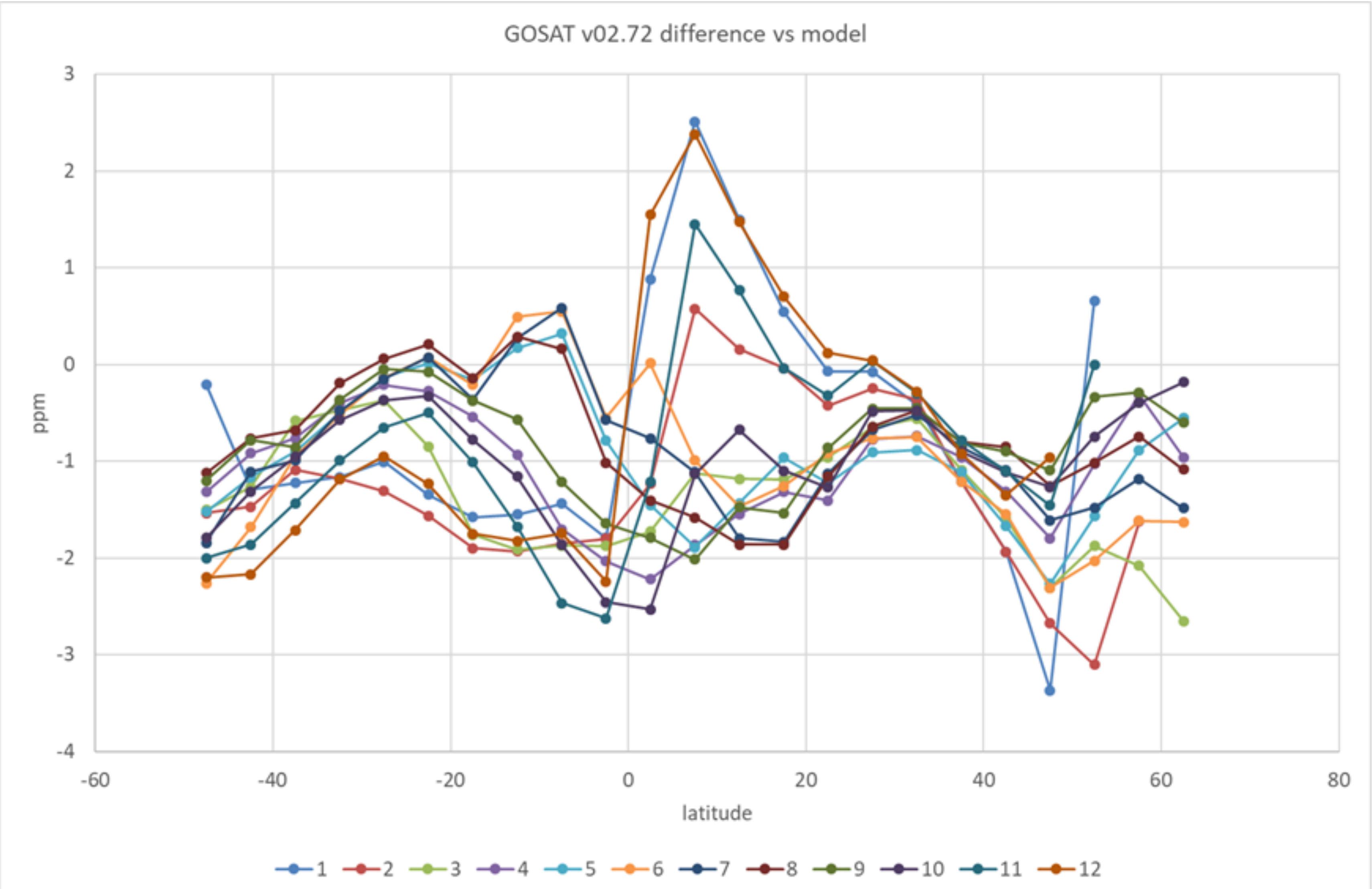
Preparation of Obspack, GOSAT and OCO-2 Level 2 data

To match horizontal resolution 0.1 deg of the flux data, OCO-2 v9 lite data are aggregated into two 1 second averages, with 4 footprints merged together in 2 groups (1 to 4) and (5 to 8). Only land nadir data are used.

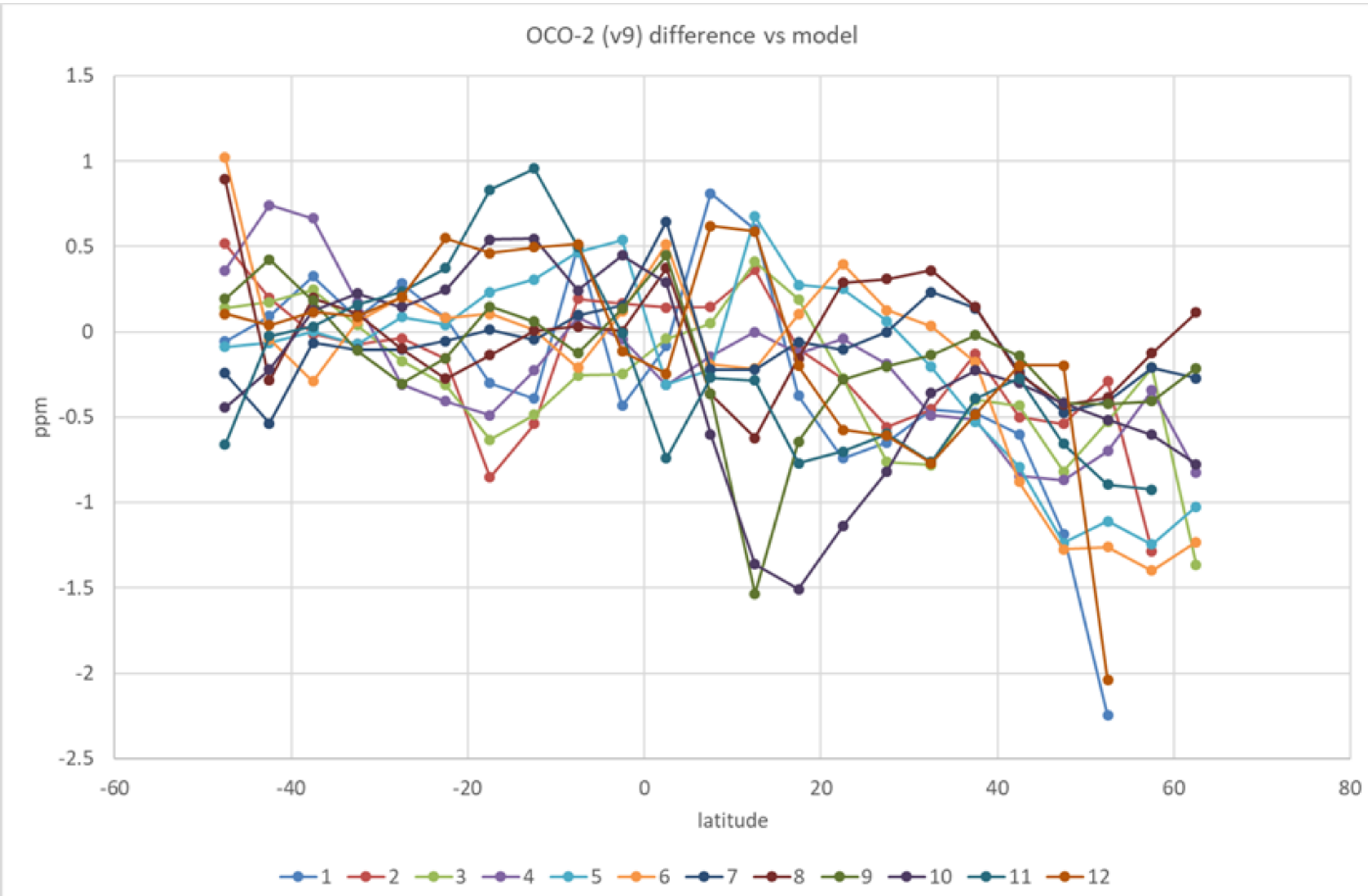
Single scan GOSAT NIES L2 v02.72 data are used without averaging

Obspack data processing: pair of flask is averages onto one observation, continuous data over land averaged from 2pm to 4 pm into one observation per day, one data point early morning average for mountain sites

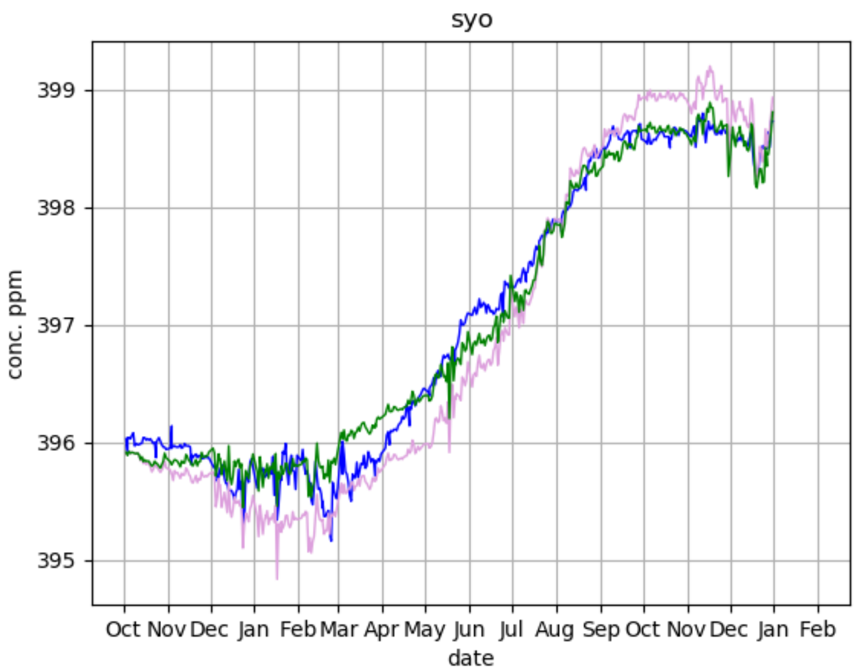
Bias correction of GOSAT Level 2 data (NIES v2.72) in 2015 via comparison to XCO2 simulation optimized with surface inversion



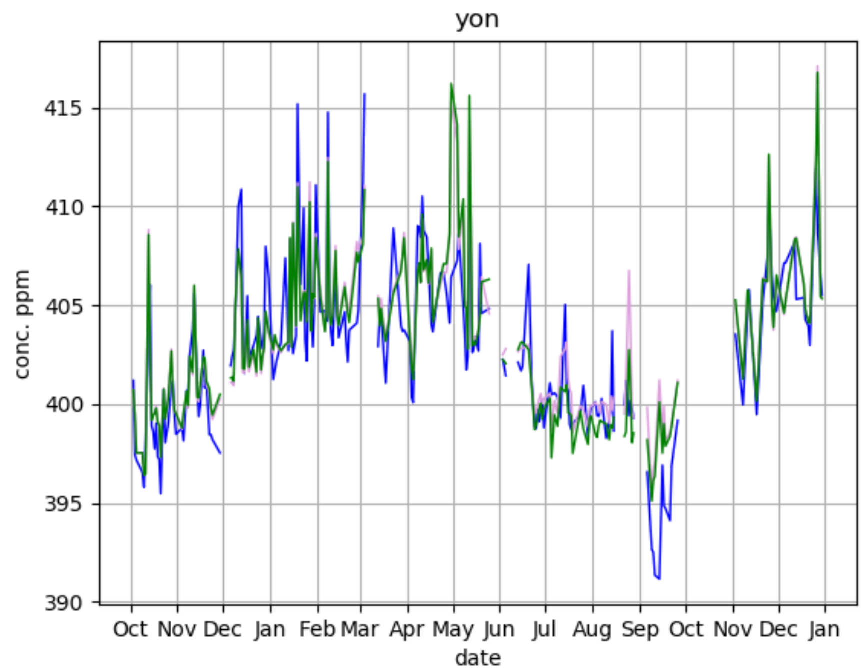
Bias correction of OCO-2 Level 2 data (v.9 lite), for 2015 via comparison to XCO2 simulation optimized with surface inversion



Optimized CO_2 concentrations



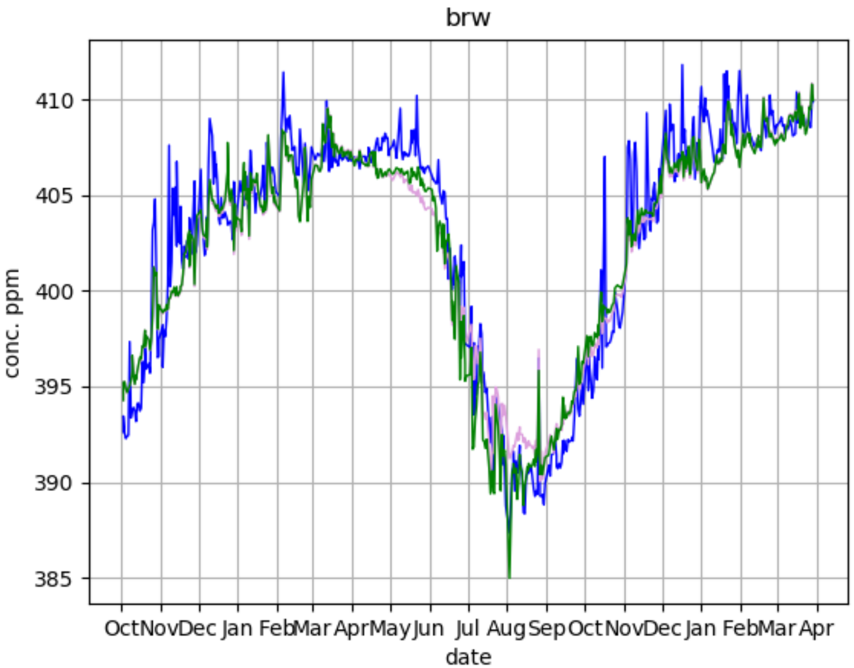
Syowa, Antarctica



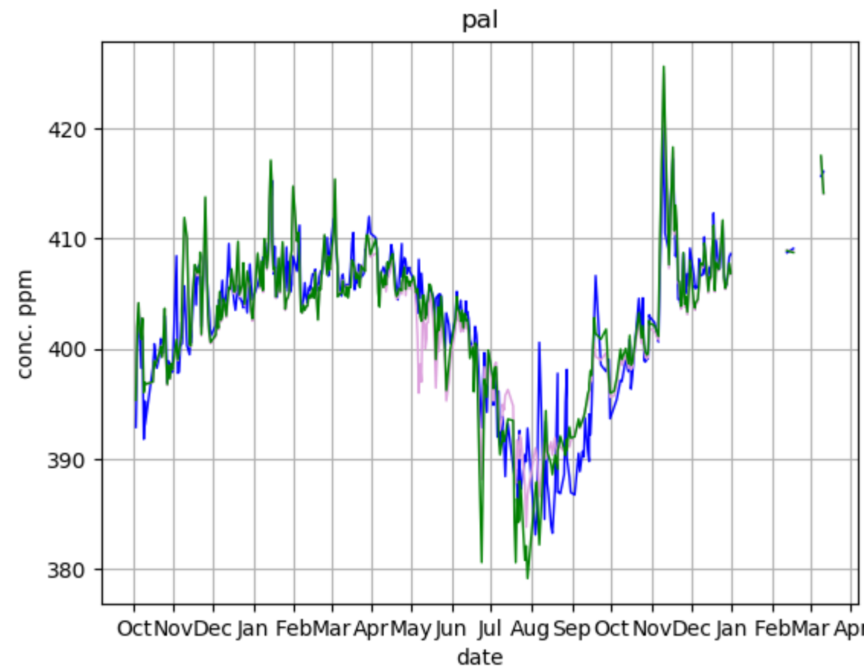
Yonagunijima
(Okinawa pref)

observations (blue), forward/prior (plum), inversion (green)

Optimized CO_2 concentrations



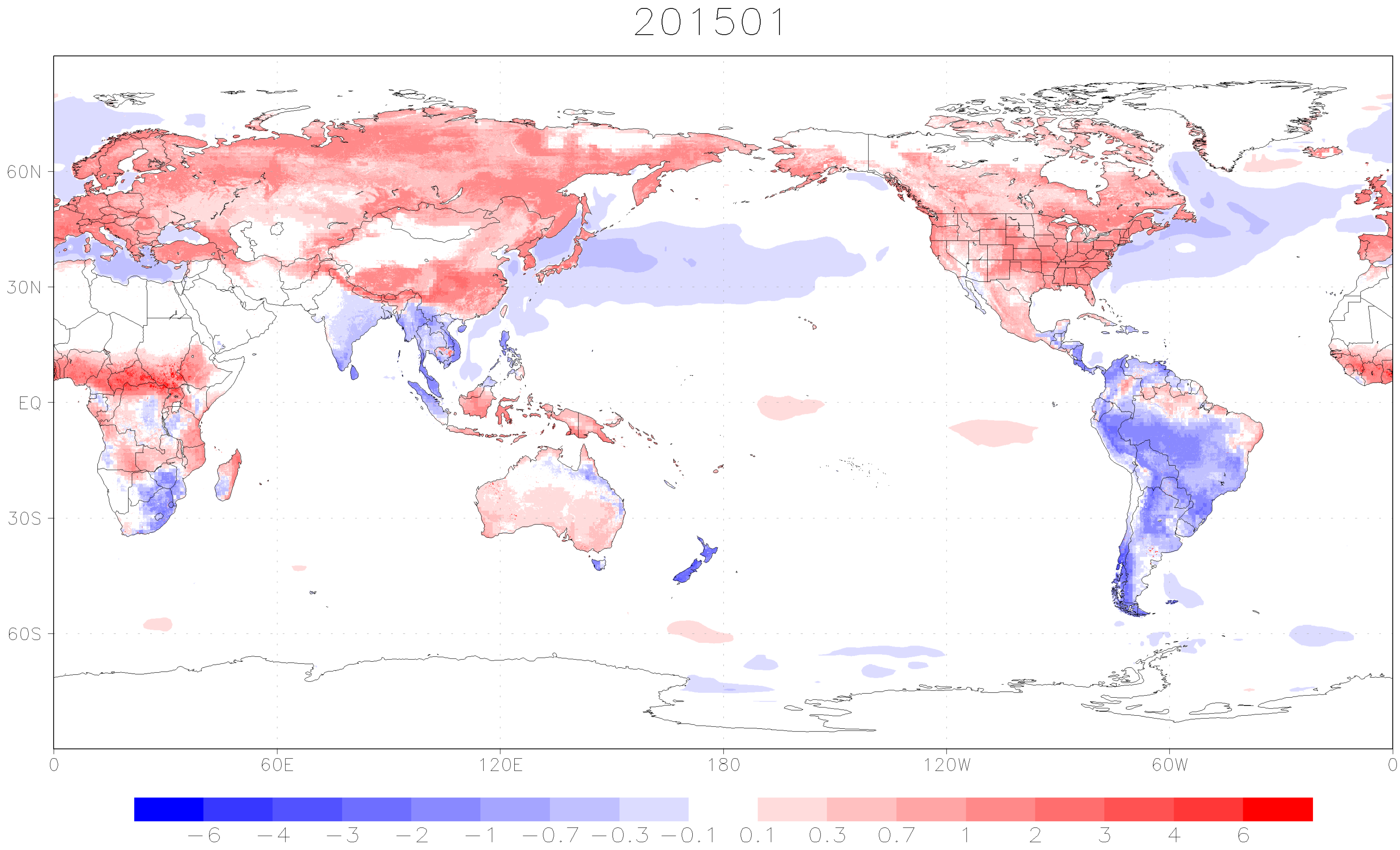
Barrow, Alaska



Pallas, N. Finland

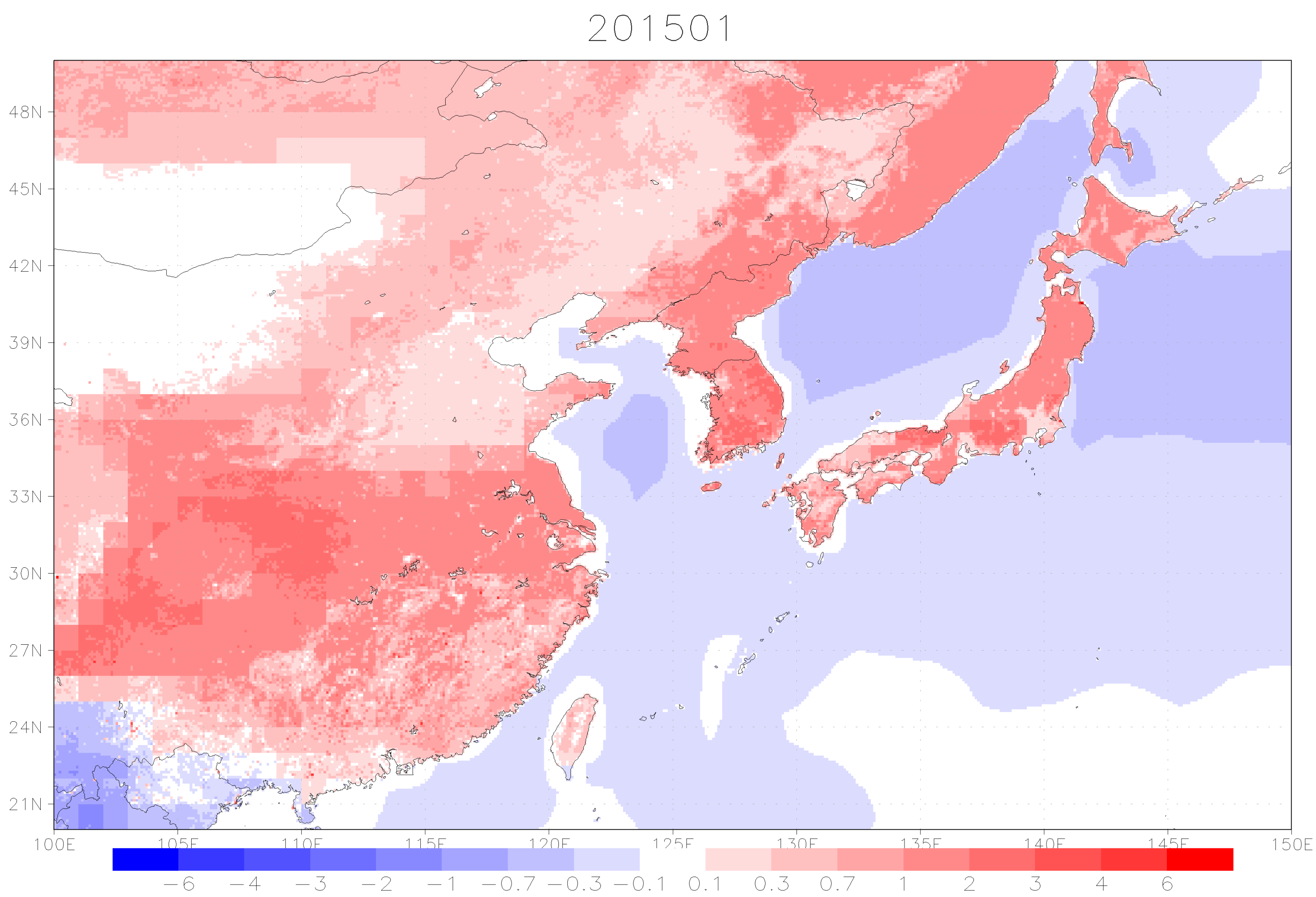
observations (blue), forward/prior (plum), inversion (green)

Natural fluxes in 2015, global



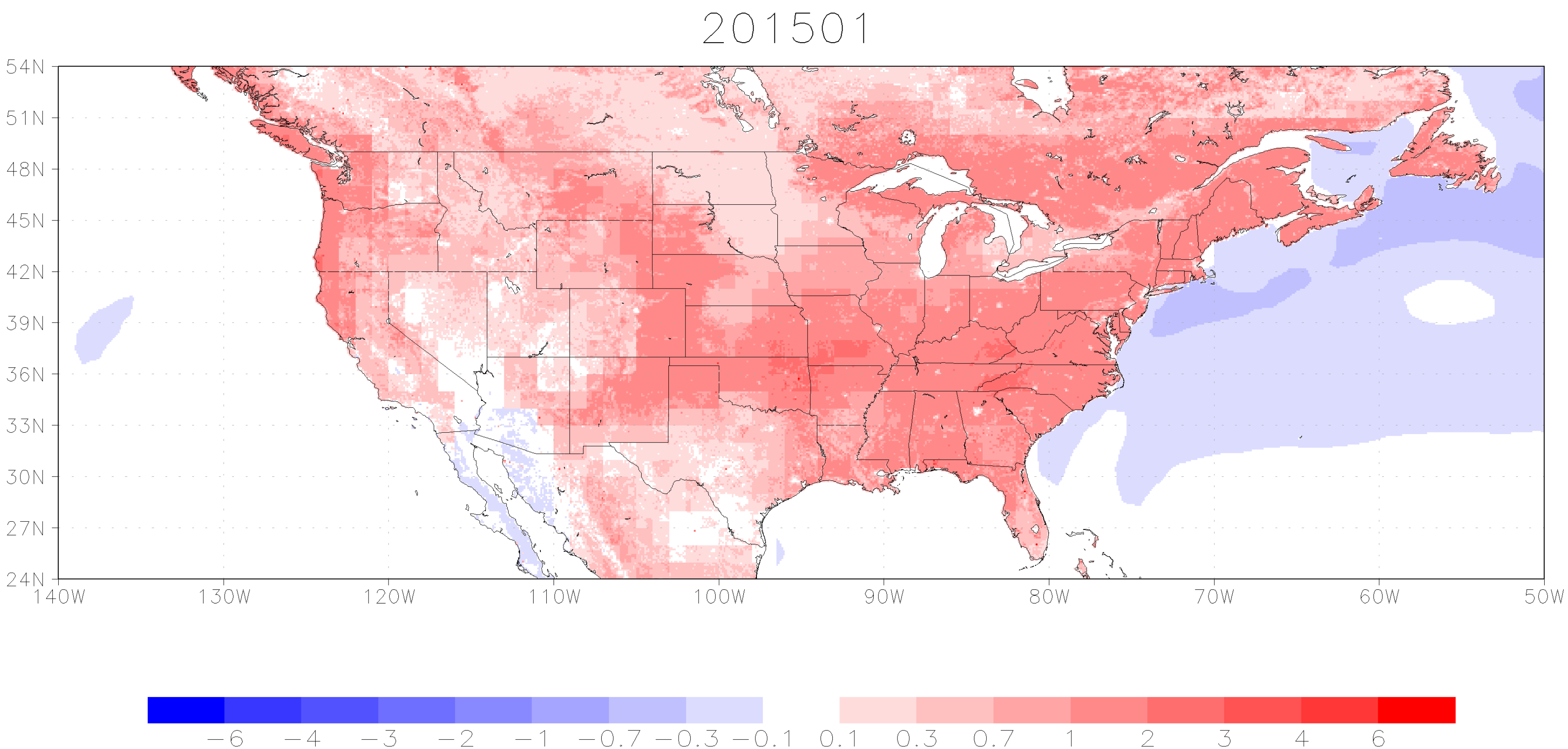
Surface fluxes gC/m2/day (without ODIAC)

Natural fluxes in 2015, East Asia



Surface fluxes (without ODIAC)

Natural fluxes in 2015



Surface fluxes (without ODIAC)

Summary

- Ability to quantify natural and anthropogenic fluxes of CO_2 from atmospheric observations is important for climate change mitigation.
- Until now low resolution Eulerian models were applied to understanding natural fluxes, for which anthropogenic emission plumes were providing an interference. The anthropogenic emission estimates had to be done using high resolution regional models. Simulation of continental continuous observations was difficult.
- We developed a computationally efficient approach for inverse surface flux modeling at fine-grid scale of 0.1 degree globally,
- We applied it to estimating sources and sinks of CO2 using combination of ground based, GOSAT and OCO-2 data.
- Inverse model optimized concentrations are used to implement bias correction for GOSAT (v02.72) and OCO-2 (v9) Level 2 data.

Poster presentations on high resolution methane transport and inversion:

- 36 Relationship between Methane Enhancements Observed by GOSAT and Country Scale Anthropogenic Emissions in Asia (R. Janardanan, NIES, Japan)
- 39. Comparing National Methane Emissions Inventories with Estimates by the Global High-resolution Inverse Model (F. Wang, NIES, Japan)
- 40. Modeling of Anthropogenic Methane Emissions Based on Ground-based Monitoring and GOSAT Satellite Retrievals (A. Tsuruta, FMI, Finland)

Optimized solution compared to OCO-2 Level 2 data (v.9 lite), OCO-2 plus surface inversion