Applying Data-constrained Models To Better Understand the Carbon Cycle

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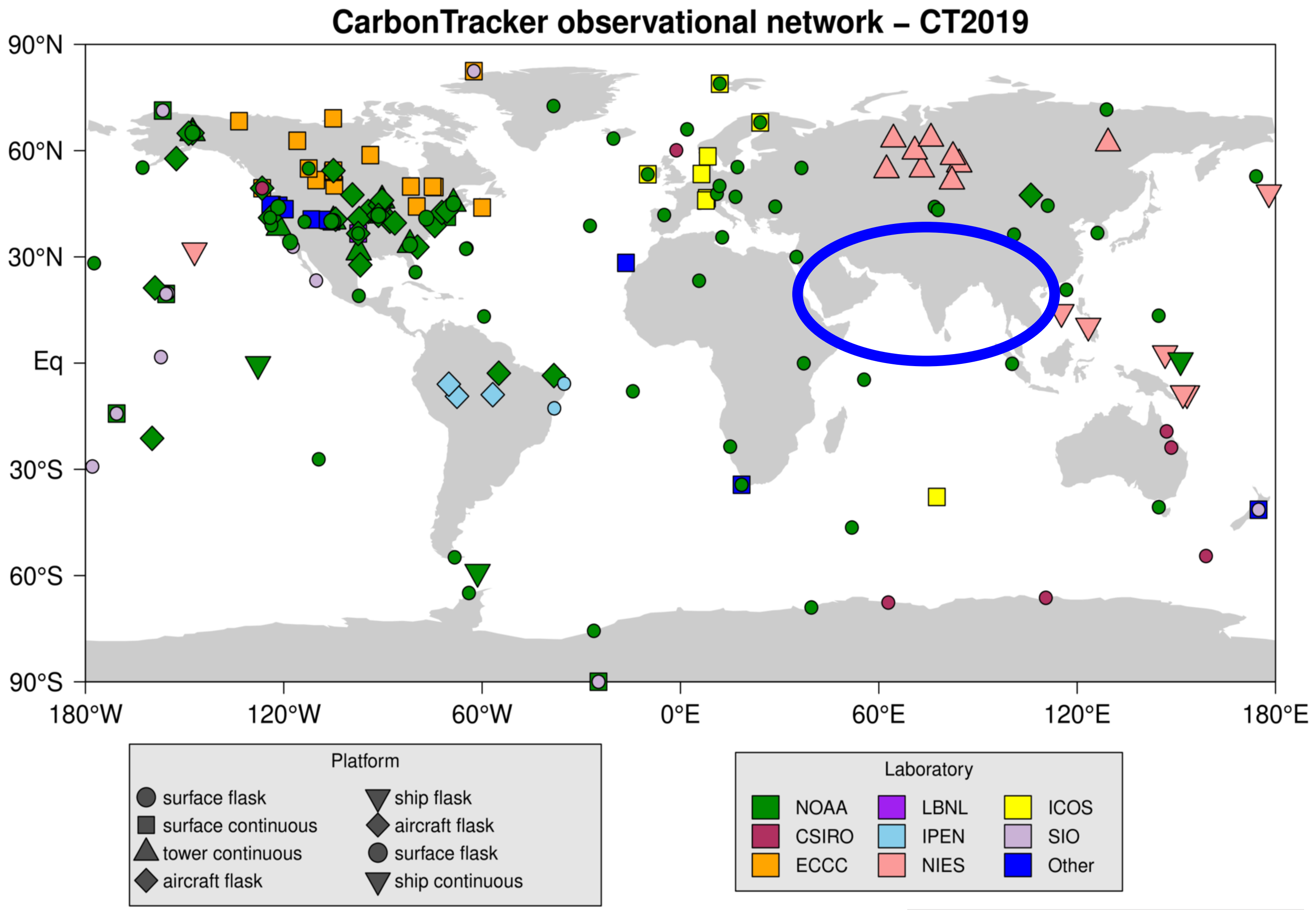
Overview

I. Direct application of remote-sensing: regional CO_2 fluxes in South Asia using OCO-2 (Philip et al., 2022)

II. Indirect application of remote-sensing: Estimating seasonality of global lake and reservoir CH_4 emissions (Johnson et al., 2022)

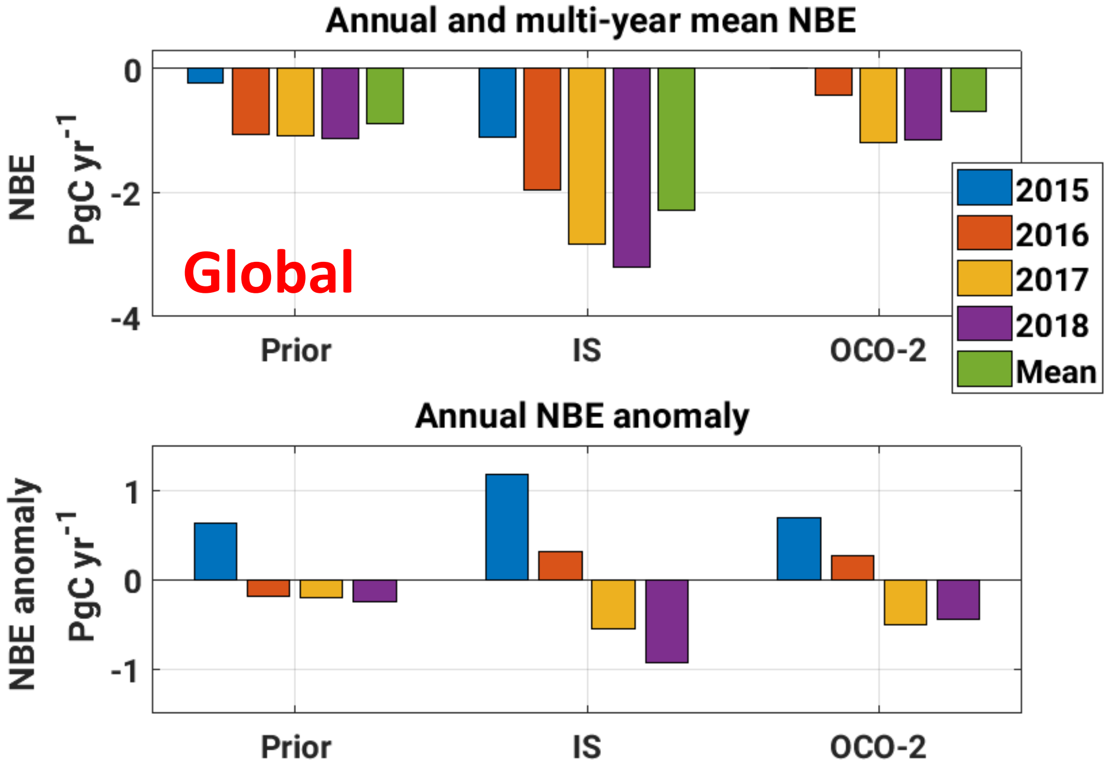
Scarcity of in situ CO_2 and CH_4 measurement data

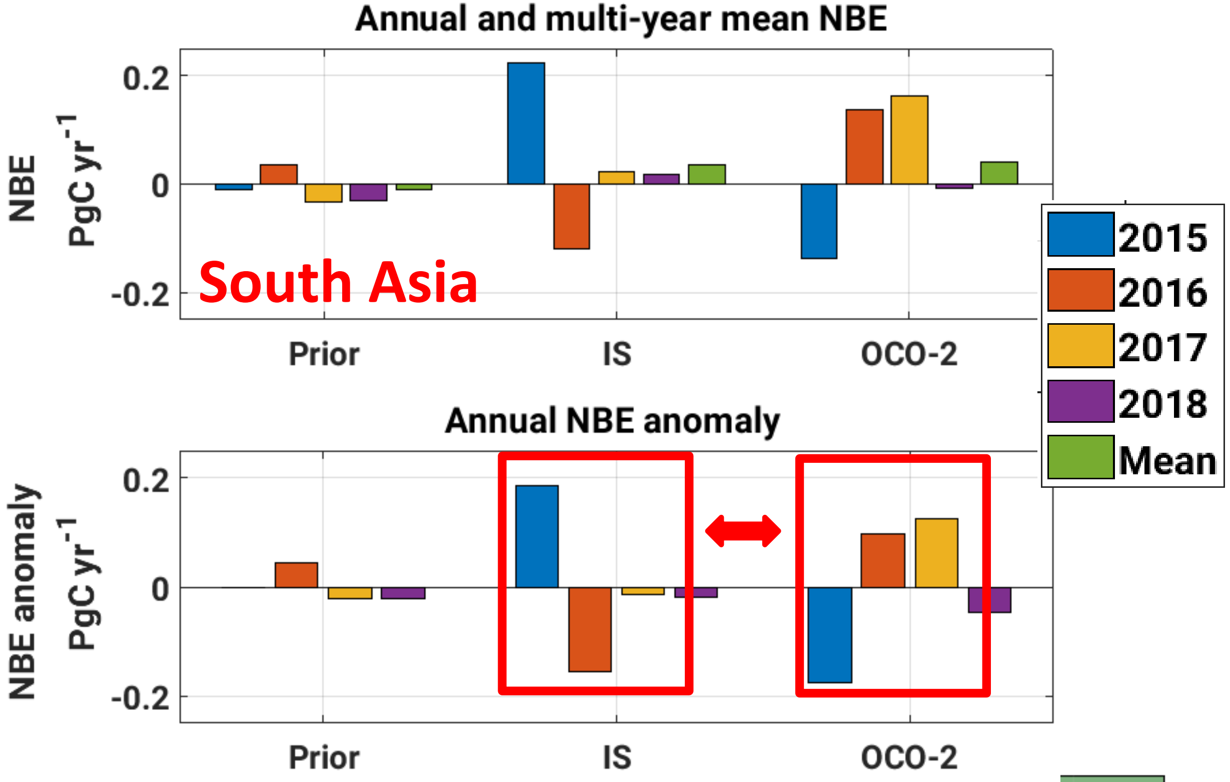
- **Major limitation for estimating GHG fluxes has historically been the scarcity of in situ data.**
- **Large uncertainty exists in the "bottom-up" and "top-down" estimates of GHG surface fluxes in many regions.**
- **Observational coverage of satellite products is an advantage for estimating GHG fluxes.**



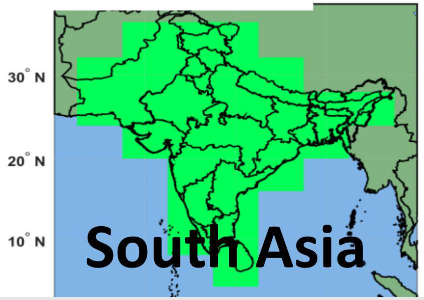
Images credit: NOAA

New insights gained with OCO-2 data: Robust constraint on regional terrestrial biospheric CO_2 fluxes





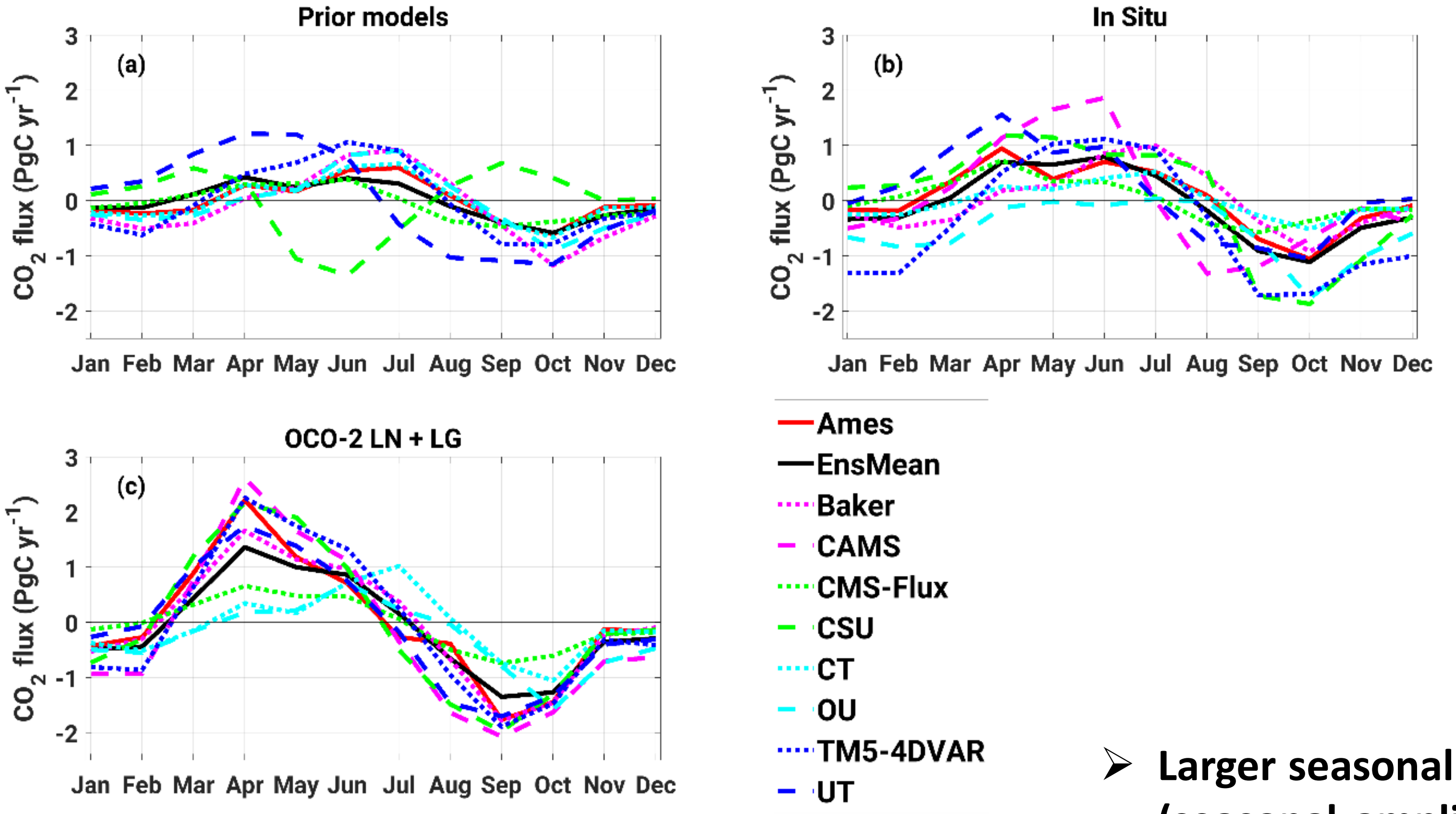
- Investigating the ability of XCO2 data to constrain subcontinental CO_2 fluxes.
- OCO-2 captures different NBE signals compared to in situ data during the 2015-2016 El Niño event which reduced CO_2 uptake in the tropics. Near-neutral NBE flux of 0.04 ± 0.14 PgC yr^{-1}.
- Satellite data is vital as South Asia has no operational in situ measurements.

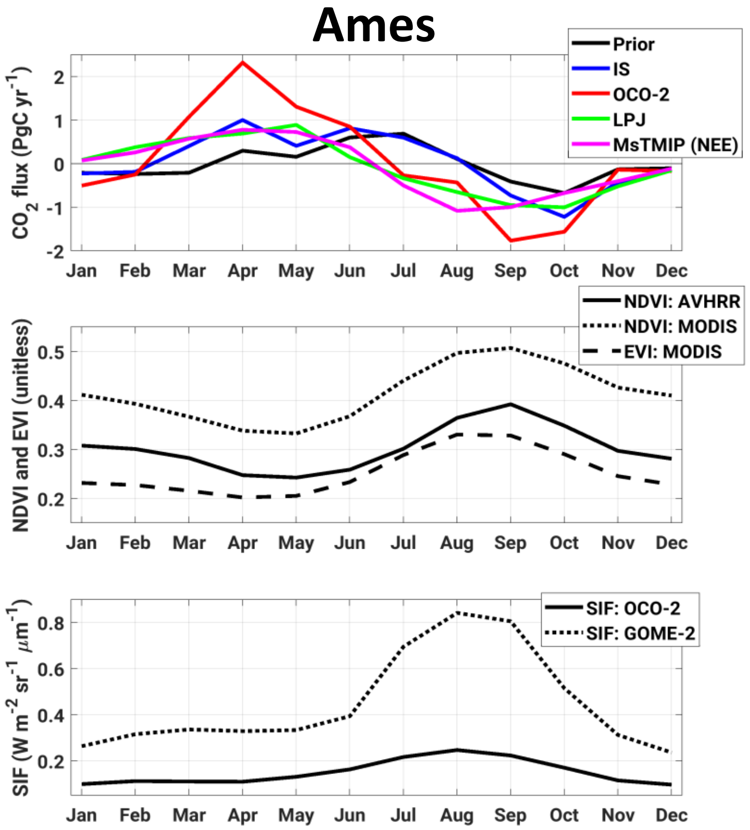


Philip et al., 2022, JGR

New insights gained with OCO-2 data: Robust constraint on regional terrestrial biospheric CO_2 fluxes

OCO-2 v9 MIP



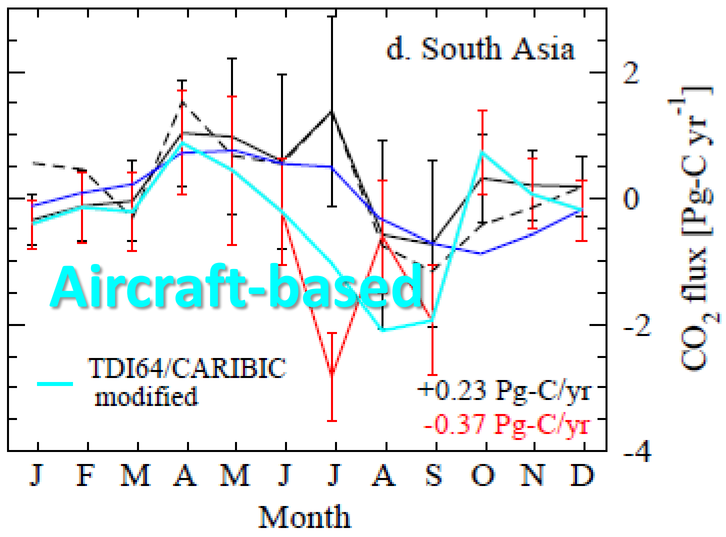


Philip et al., 2022, JGR

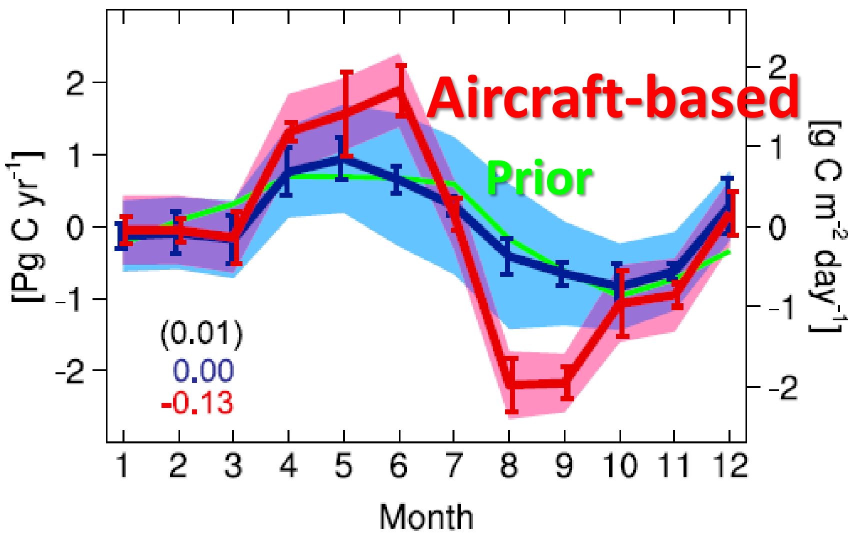
- **Larger seasonality of NEE fluxes estimated by assimilating OCO-2 (seasonal amplitude of 4.1 PgC yr^{-1}) and global IS (2.2 PgC yr^{-1}) compared to the prior model (1.4 PgC yr^{-1}).**
- **OCO-2 data imposed a robust phase shift in the seasonal cycle.**

New insights gained with OCO-2 data: Robust constraint on regional terrestrial biospheric CO_2 fluxes

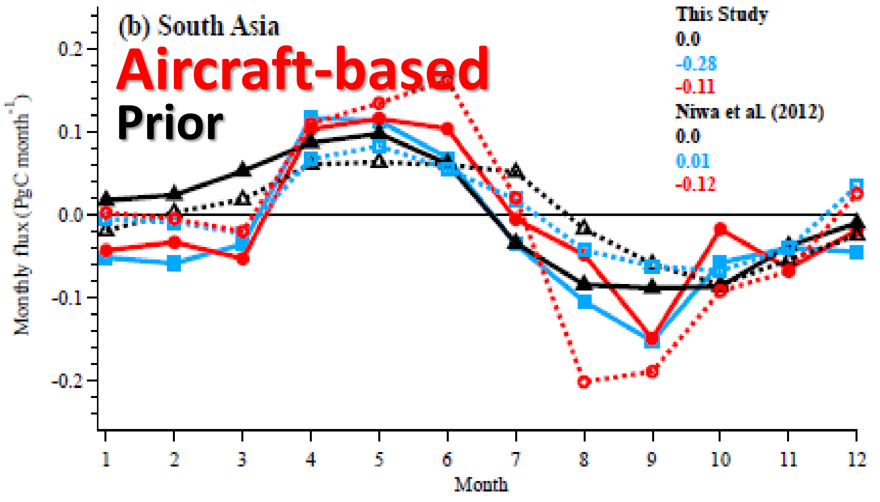
Patra et al., 2011



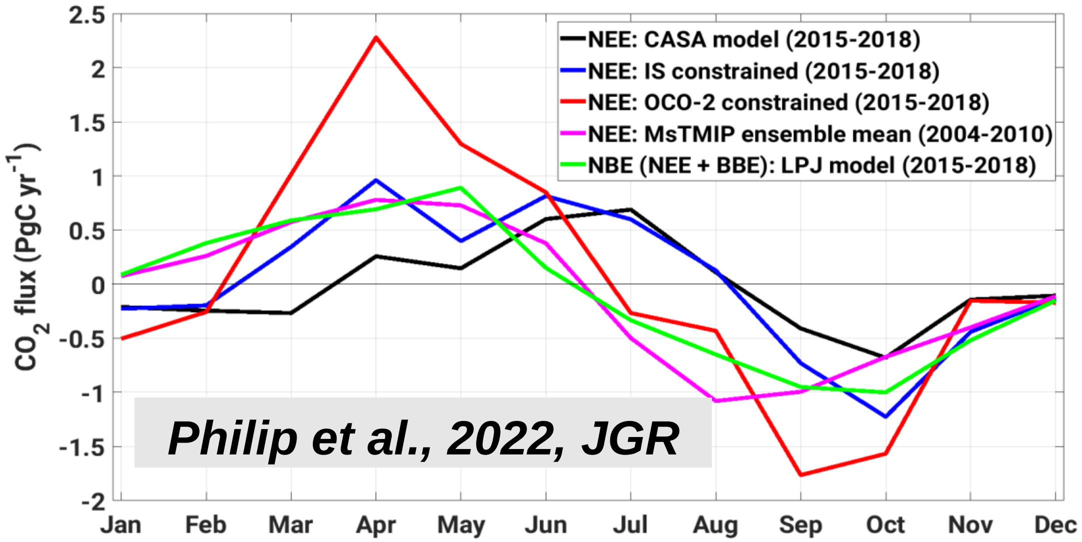
Niwa et al., 2012



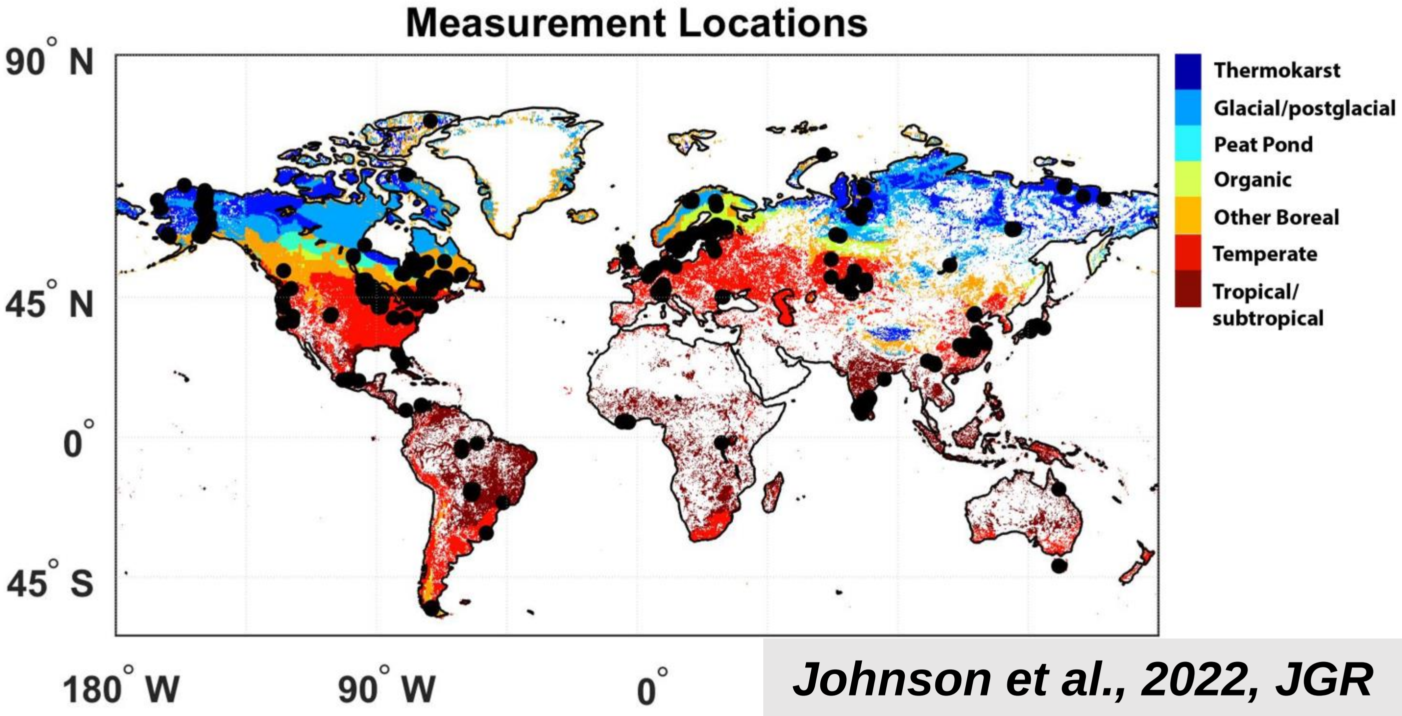
Jiang et al., 2014



- OCO-2 optimized NEE seasonality is consistent with three previous studies assimilating passenger aircraft-based (CARIBIC and CONTRAIL) regional in situ data.
- Satellites provide a similar constraint over South Asia compared to dense aircraft in situ observation networks.



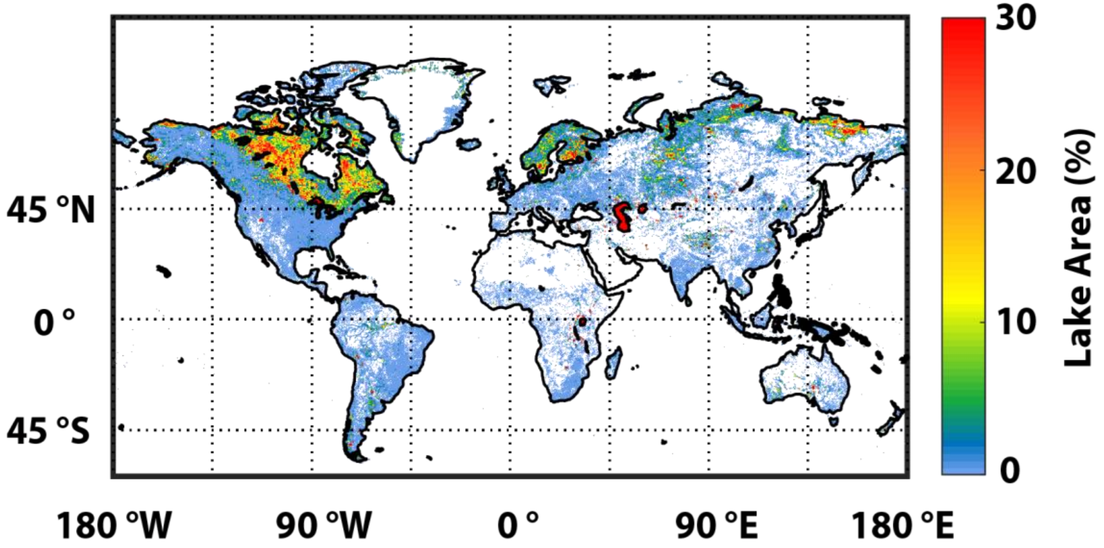
Estimating global lake and reservoir CH_4 emissions seasonality



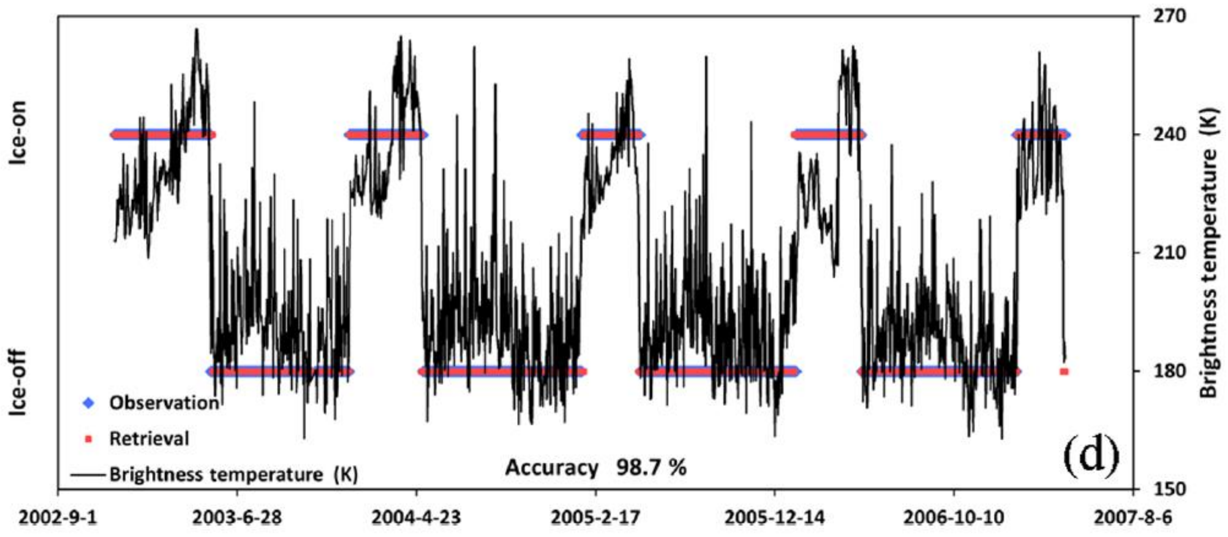
Johnson et al., 2022, JGR

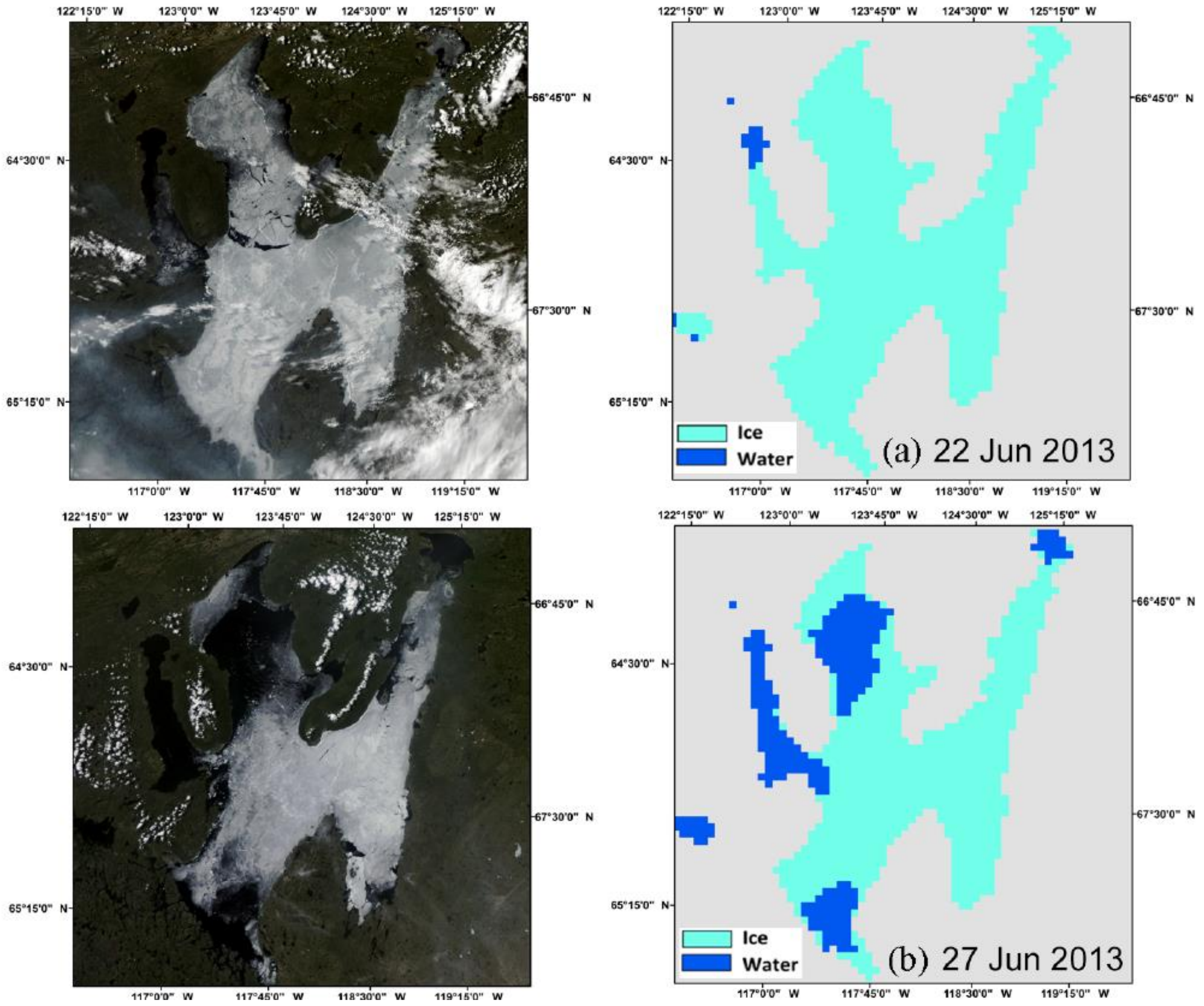
- CH_4 flux measurements are spatiotemporally sparse.
- Flux data for 575 individual lake systems and 881 aggregated flux values (674 diffusion; 207 ebullition).
- Many regions have little to no lake and reservoir flux information. Thus, eco-climatic lake/reservoir types are not well represented.

- A major variable for deriving global lake emissions is defining flux seasonality driven by lake-ice phenology.
- Number of monitoring sites for lake freeze/thaw is extremely sparse.
- Remote-sensing greatly increases the observational coverage for constraining lake freeze/thaw on a global scale.



Remote-sensing ice-cover for constraining aquatic CH_4 emission



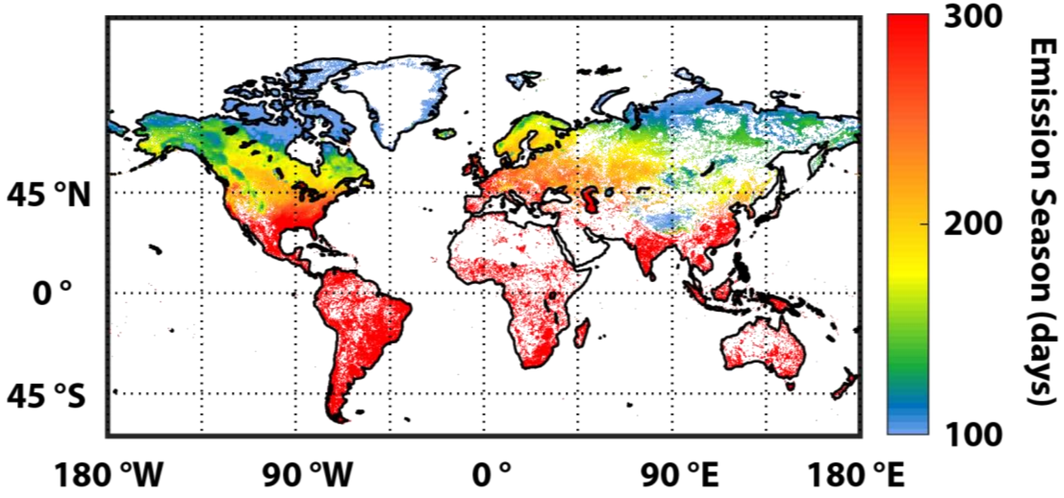


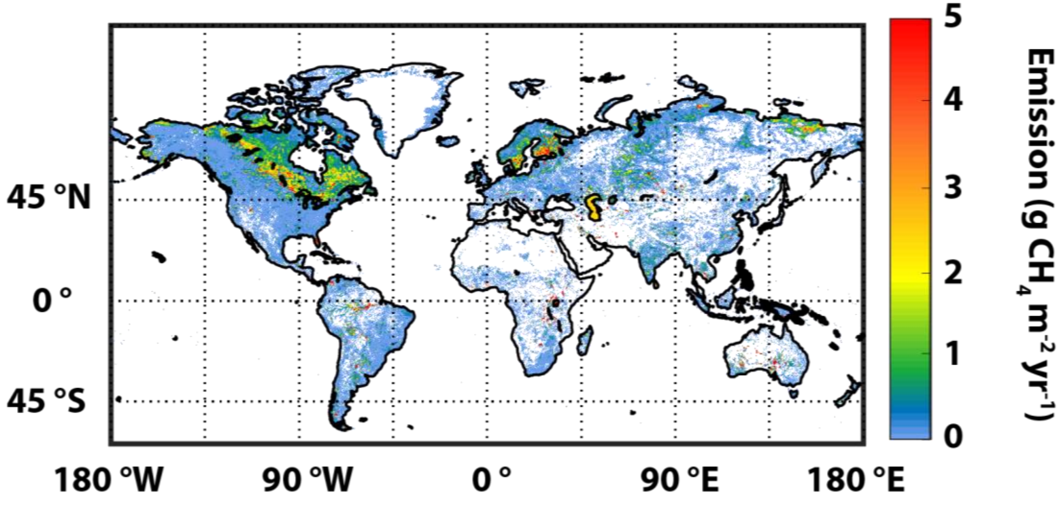
- For the first-time satellite data (Advanced Microwave Scanning Radiometer for EOS (AMSR-E), AMSR-2, Special Sensor Microwave Imager (SSM/I), SSM/I Sounder (SSMIS) satellite 36.5 GHz brightness temperature data) used for reservoir freeze/thaw dynamics globally.

Du et al., 2017, Cryosphere

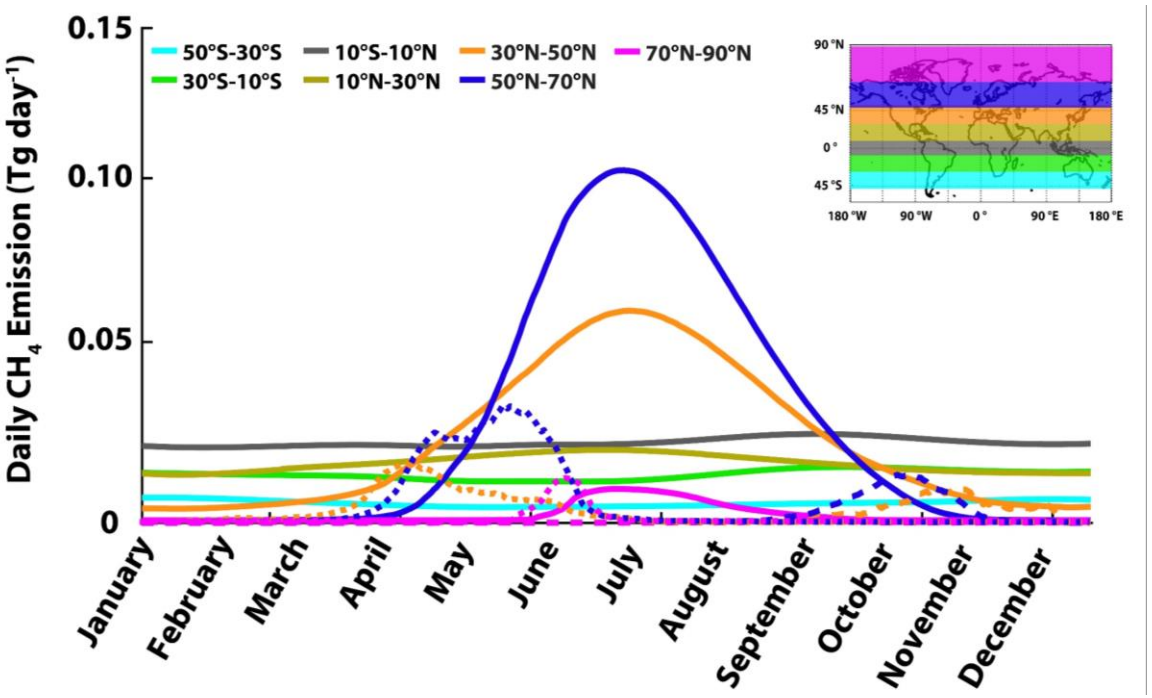
- Prior to Johnson et al. (2021, 2022) using satellite remote-sensing to define lake and reservoir freeze/thaw dynamics, inland aquatic CH_4 emission seasonality was estimated using: 1) simple latitude-dependent assumptions, 2) assumptions based on modeled air temperature, and 3) other non-observation driven methods.

Global lake CH_4 emission seasonality





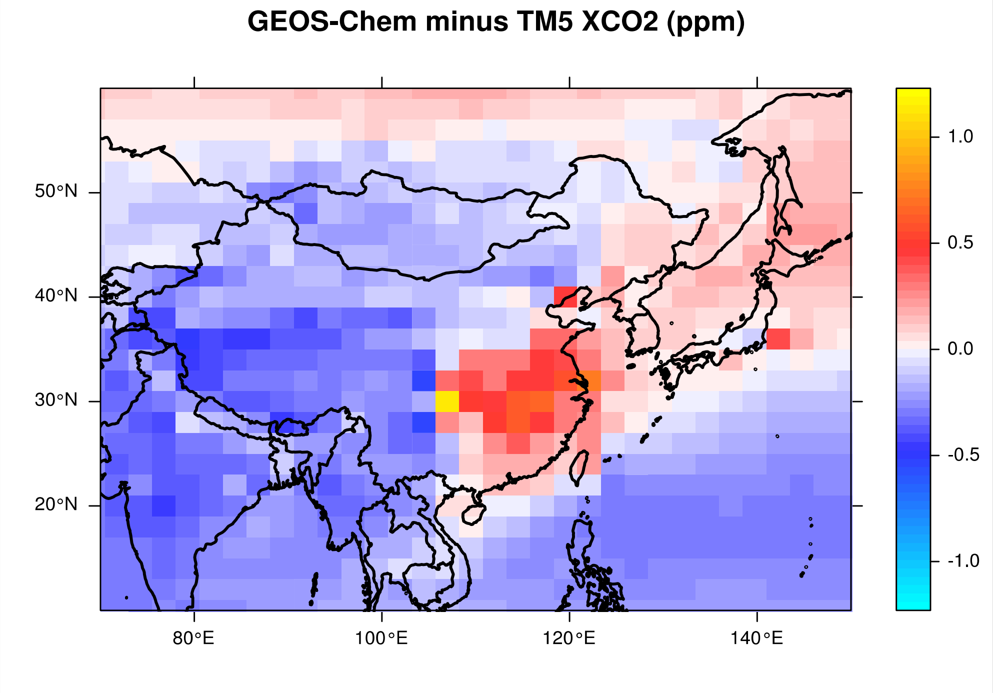
- 41.6±18.3 Tg yr^{-1} from diffusion (14.1 Tg), ebullition (23.4 Tg), ice-out (3.1 Tg), and fall column turnover (1.1 Tg) fluxes.



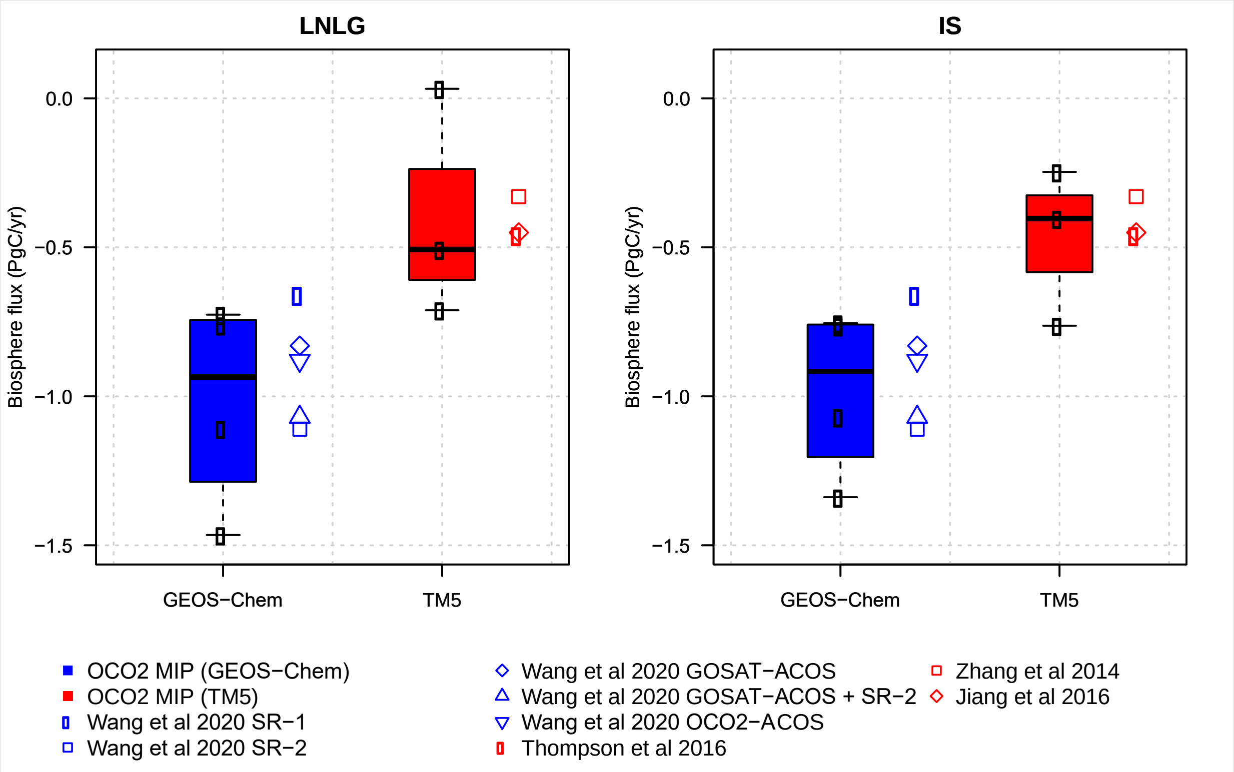
- Large spatiotemporal variability in lake CH_4 emission imposed by remote-sensing freeze/thaw dynamics.
- Satellite-derived emission season lengths are 10-50% shorter in the higher latitudes compared to those using simplified, non-observational-driven assumptions.

Johnson et al., 2022, JGR

3. Need for improved satellite observations BUT… we can improve our models too!



Schuh et al., 2022, Nature



- **Wang et al. (2020) used GEOS-Chem simulations to show that China has larger annual biospheric CO_2 uptake compared to prior knowledge; thus offsetting 45% of Chinese fossil fuel emissions, as opposed to 18% or less reported by previous studies.**
- **Using the OCO-2 v9 MIP product, we show that different transport models (i.e., GEOS-Chem v. TM5) result in very different NEE estimates in China. Model ensembles can help define transport uncertainty impacts on results.**

ALL the speakers are requested to send their presentation(s) in pdf or ppt, as a back-up solution to avoid technical problems arising during the sessions. All the presentations should be sent to ENVMAIL@esa.int.

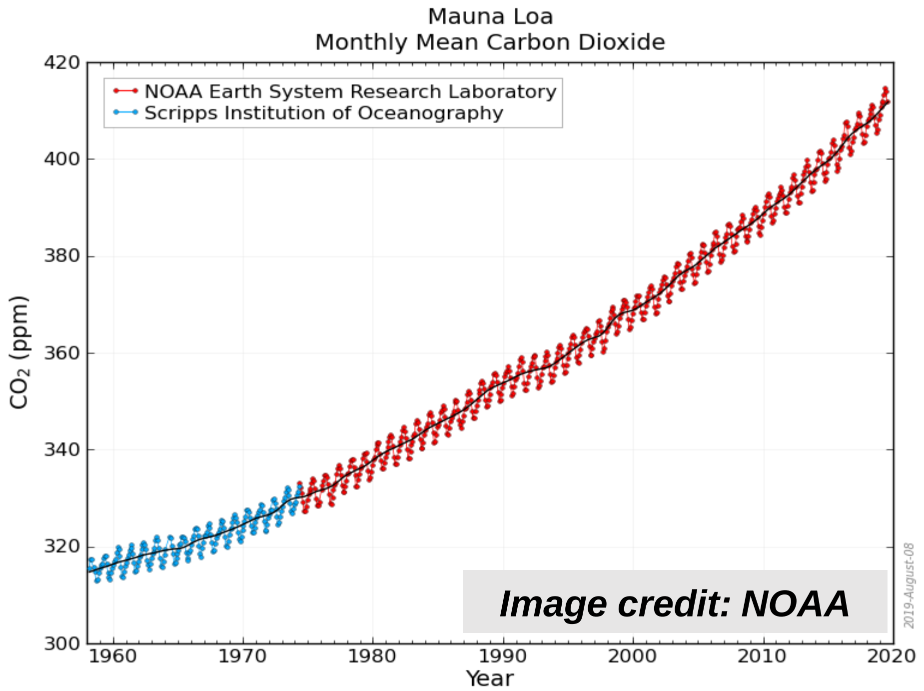
Talk is 12 minutes long. Questions will be asked in the last 30-minute session so can use the whole time.

Thanks!

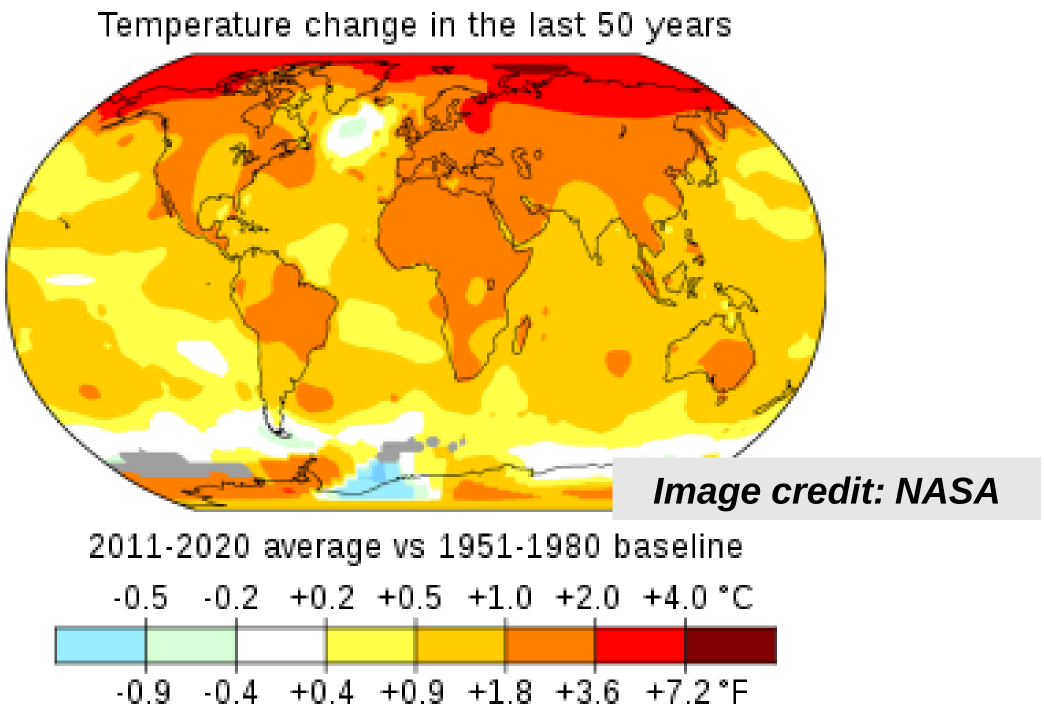
Questions?

EXTRA SLIDES

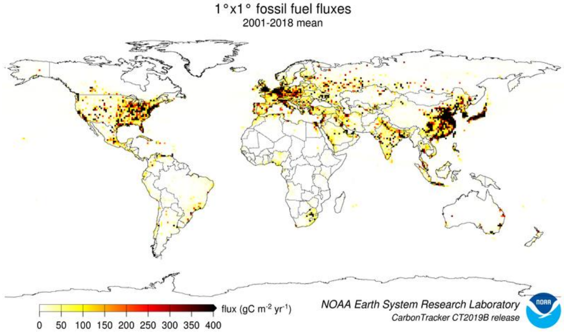
Understanding the global carbon cycle: A requirement for future climate predictions

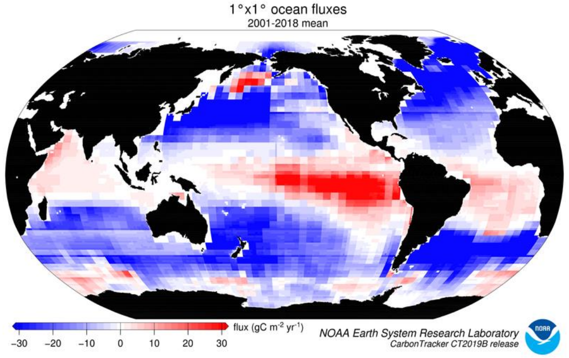


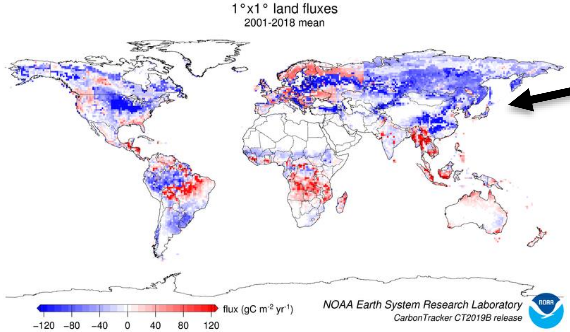
Atmospheric carbon dioxide monthly mean mixing ratios from the Mauna Loa Obervatory, Hawaii. Data prior to May 1974 are from the Scripps Institution of Oceanography (SIO, blue), data since May 1974 are from the National Oceanic and Atmospheric Administration (NOAA, red). A long-term trend curve is fitted to the monthly mean values. Contact: Dr. Pieter Tans, NOAA ESRL Carbon Cycle, Boulder, Colorado, (303) 497-6678, pieter.tans@noaa.gov, and Dr. Ralph Keeling, SIO GRD, La Jolla, California, (858) 534-7582, rkeeling@ucsd.edu.

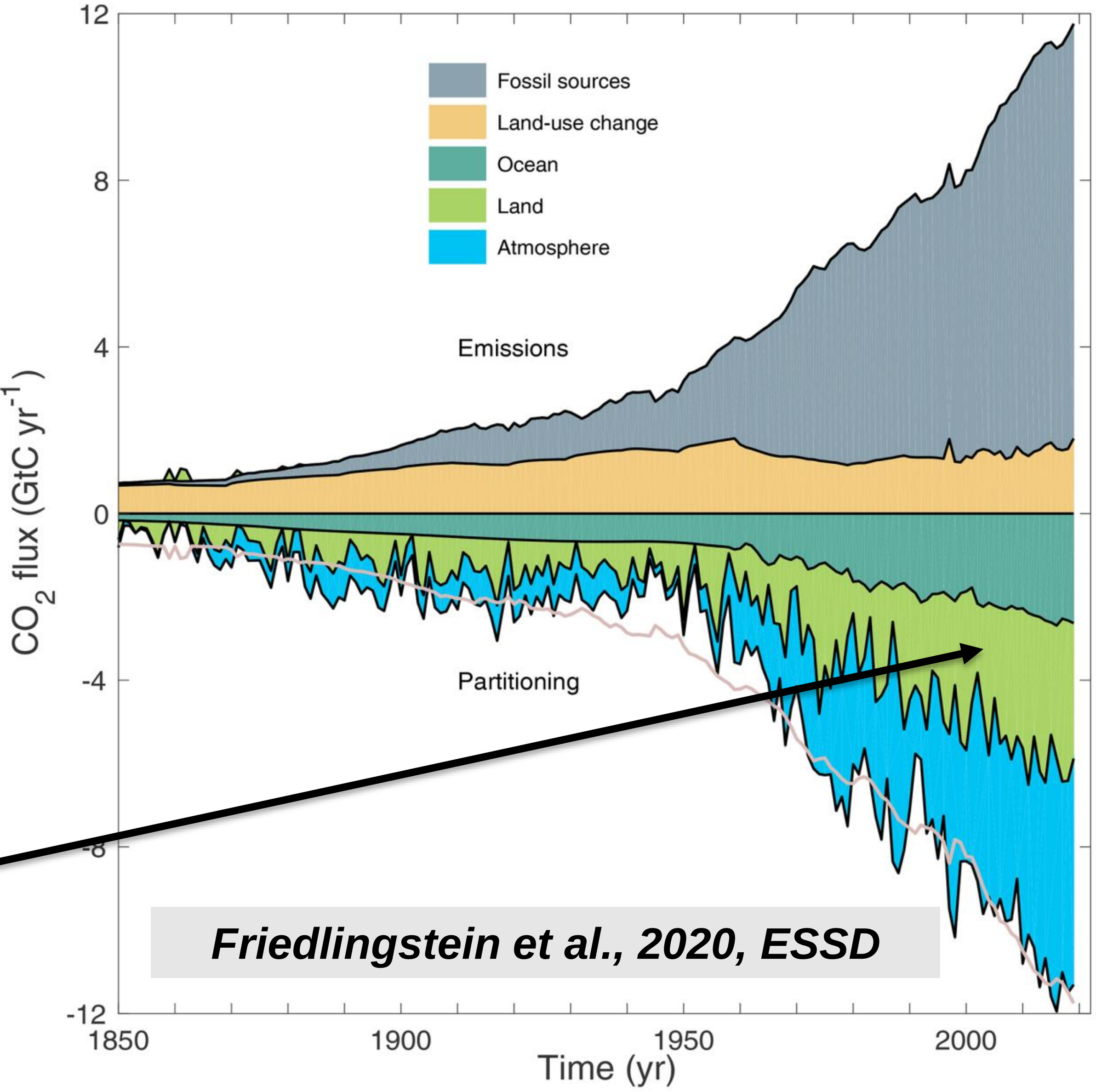


The terrestrial biosphere plays a significant role in the global CO_2 budget

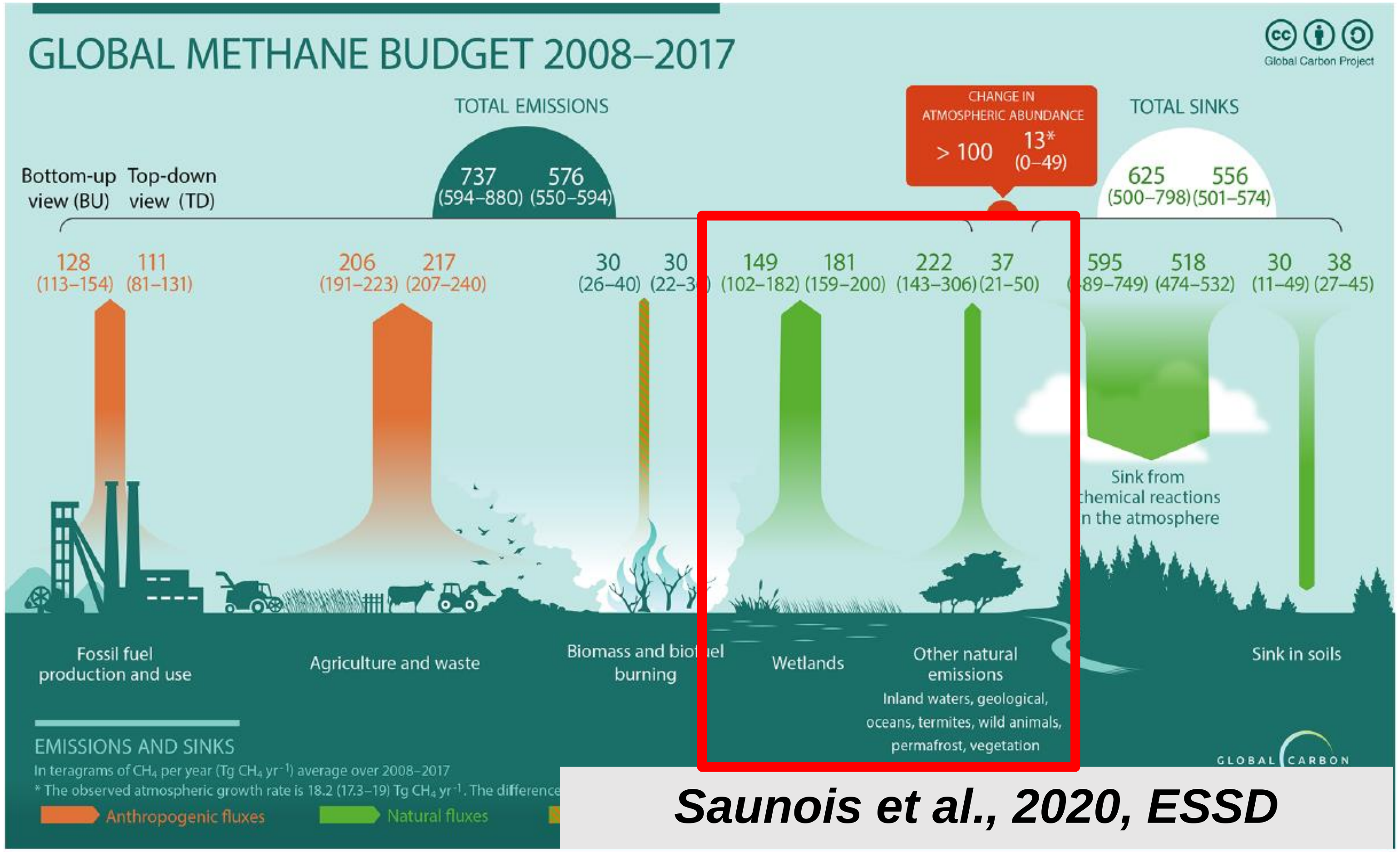








Inland water bodies play a significant role in the global CH_4 budget



Saunois et al., 2020, ESSD

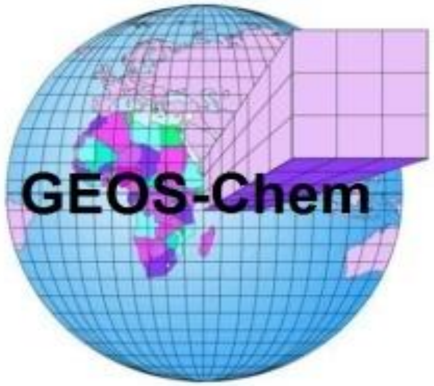
- **Majority of CH_4 emitted by fossil fuel production/consumption and agriculture/waste.**
- **Wetlands and inland water bodies contribute significantly to the global CH_4 cycle.**
- **Lakes and reservoirs are among the *most uncertain components* of the CH_4 budget.**

Satellite column CO_2 (XCO_2) to estimate CO_2 surface fluxes

The Orbiting Carbon Observatory-2 (OCO-2) is the first NASA satellite designed to infer surface CO_2 fluxes by retrieving XCO_2 from space.

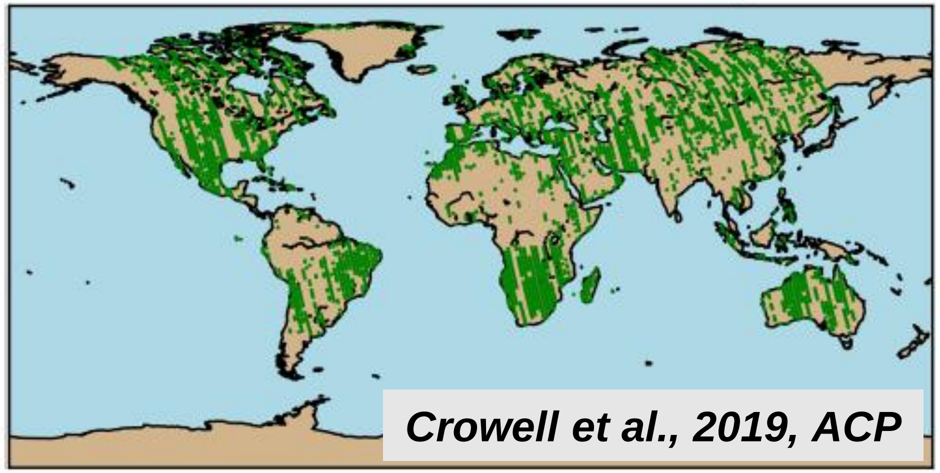
Images credit: NASA

Global CTMs are used to assimilate OCO-2 XCO_2 data to estimate surface CO_2 fluxes.



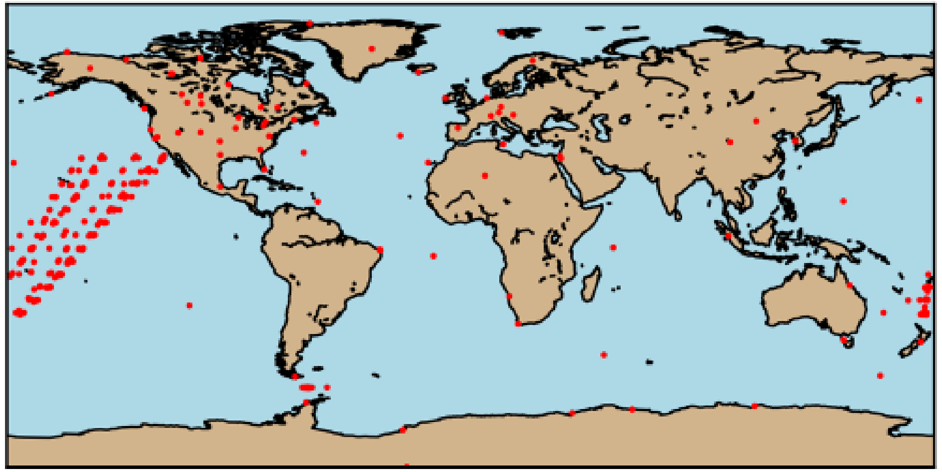
- ✓ Satellites increase the spatiotemporal coverage of observations.

(a) OCO-2 nadir 10 s observations (June 2016)



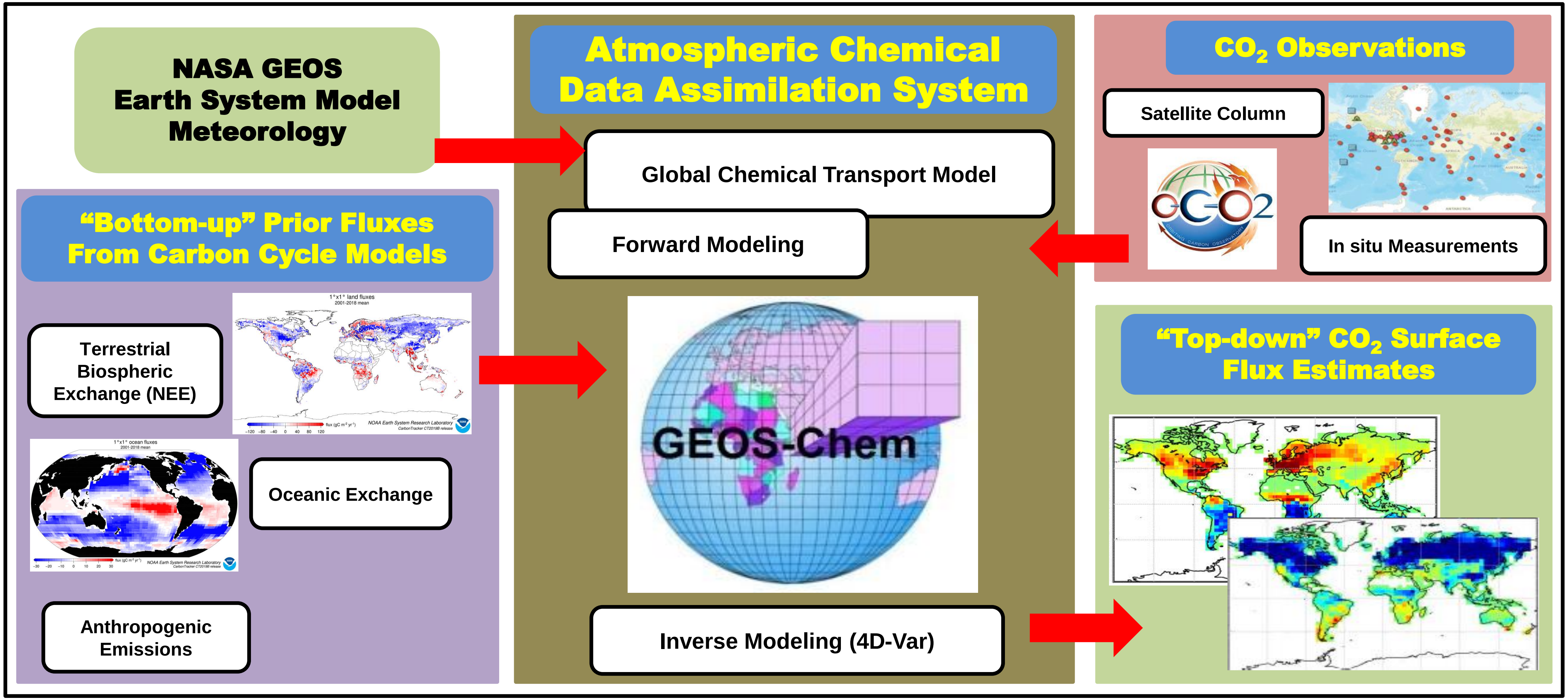
Crowell et al., 2019, ACP

(c) Assimilated in situ data locations



Estimation of "top-down" global CO_2 surface fluxes

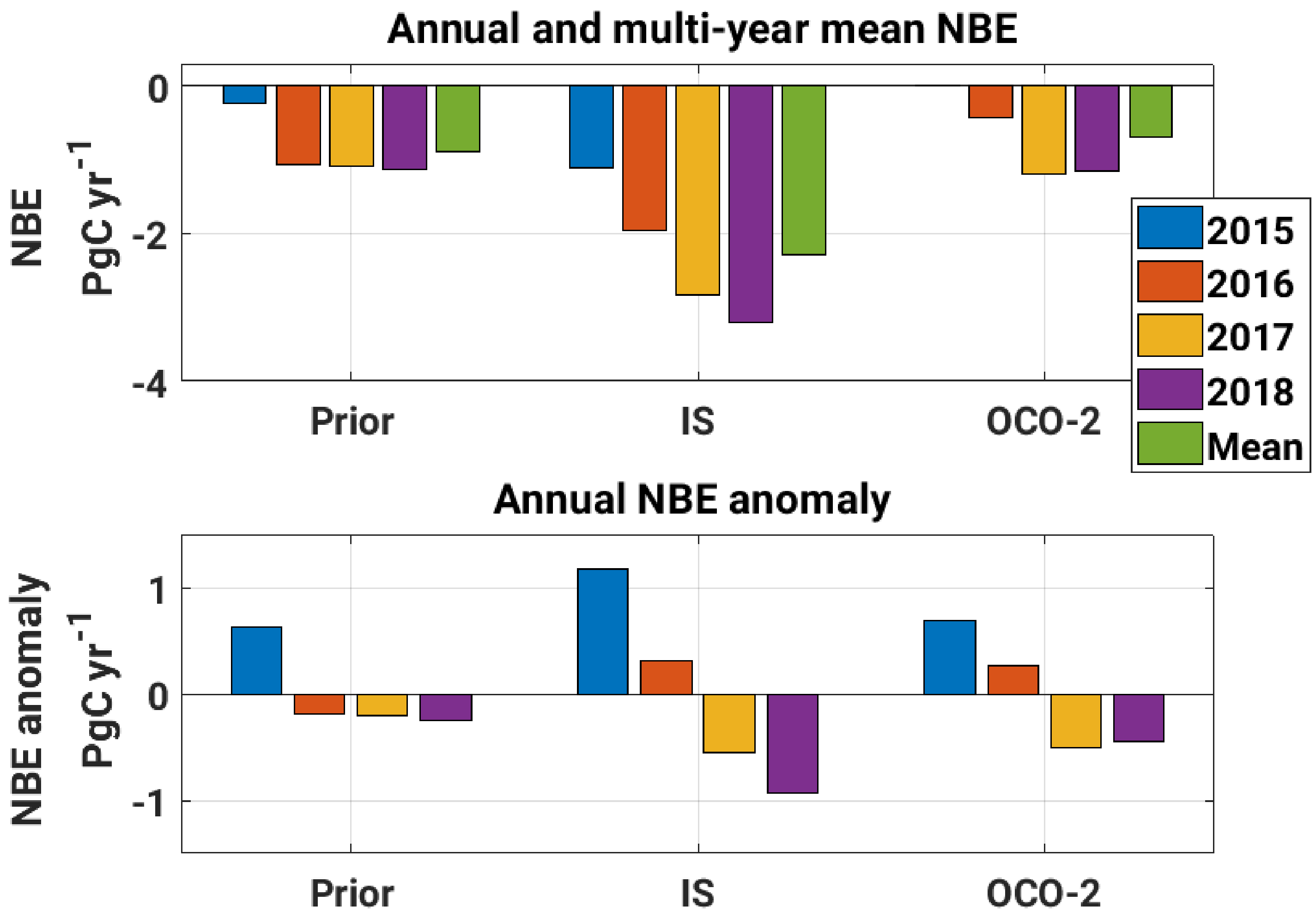
- Spatiotemporal gradients in atmospheric CO_2 mixing ratios are used to estimate "top-down" CO_2 fluxes.
- We assimilate OCO-2 XCO_2 data and global in situ measurements to infer CO_2 surface flux using the GEOS-Chem 4D-Var data assimilation system.



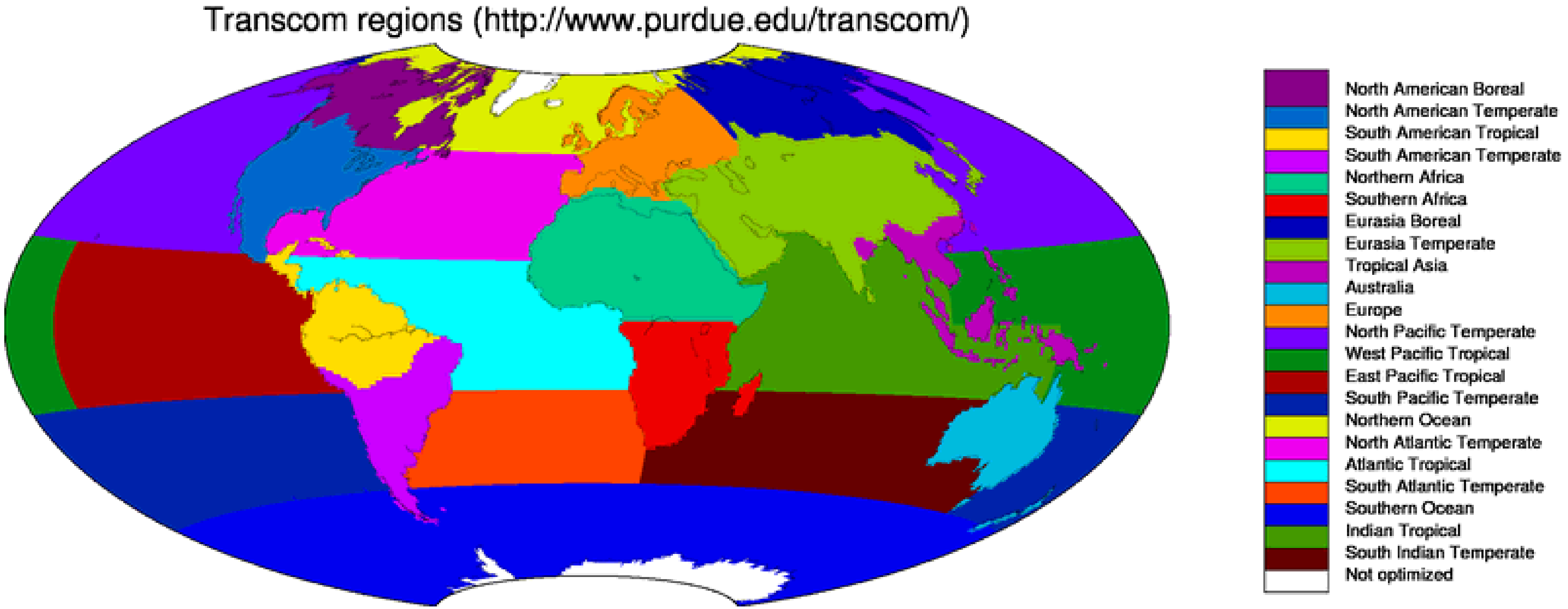
OCO-2 optimized global terrestrial biospheric CO_2 fluxes: NASA Ames Research Center (ARC) global model

Net Biome Exchange (NBE = NEE + unoptimized Biomass Burning Emissions (BBE))

- OCO-2 and IS observations produced global land CO_2 sinks for 2015-2018.
- Annual NBE anomaly signals varied between years, with positive anomaly values for 2015-2016 and negative anomaly values for 2017-2018.
- The higher NBE anomaly values for 2015-2016 reflects the impact of the 2014-2016 El Niño event which led to reduced CO_2 uptake in the tropics.



Insights into regional CO_2 fluxes using OCO-2



- **Top-down emission studies have typically focused on latitudinal or large region constraints.**
- **Recent goal of OCO-2 is to determine spatial scales that MIP fluxes are robust.**
- **NASA ARC model and the L4 MIP fluxes have been used in recent regional subcontinental studies.**

1. Regional Carbon Cycle: South Asian terrestrial biospheric CO_2 fluxes

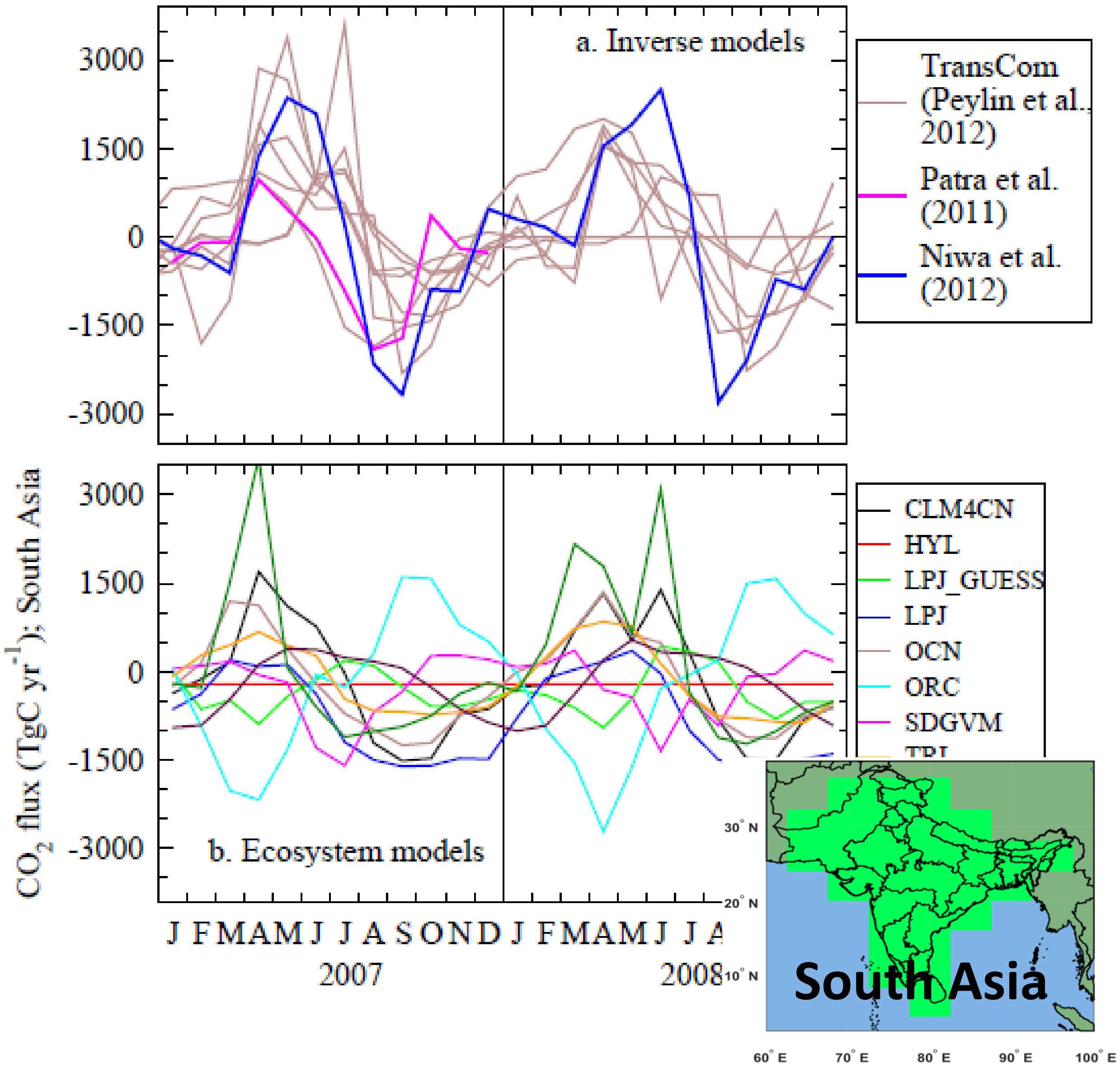
- ➢ **Unique region with distinct Asian monsoonal weather systems, uncertain impacts from ENSO cycling, and steadily-increasing fossil fuel CO_2 emissions.**

- ➢ **South Asia is a region with sparse in situ observations which impedes the accurate quantification of regional CO_2 fluxes.**

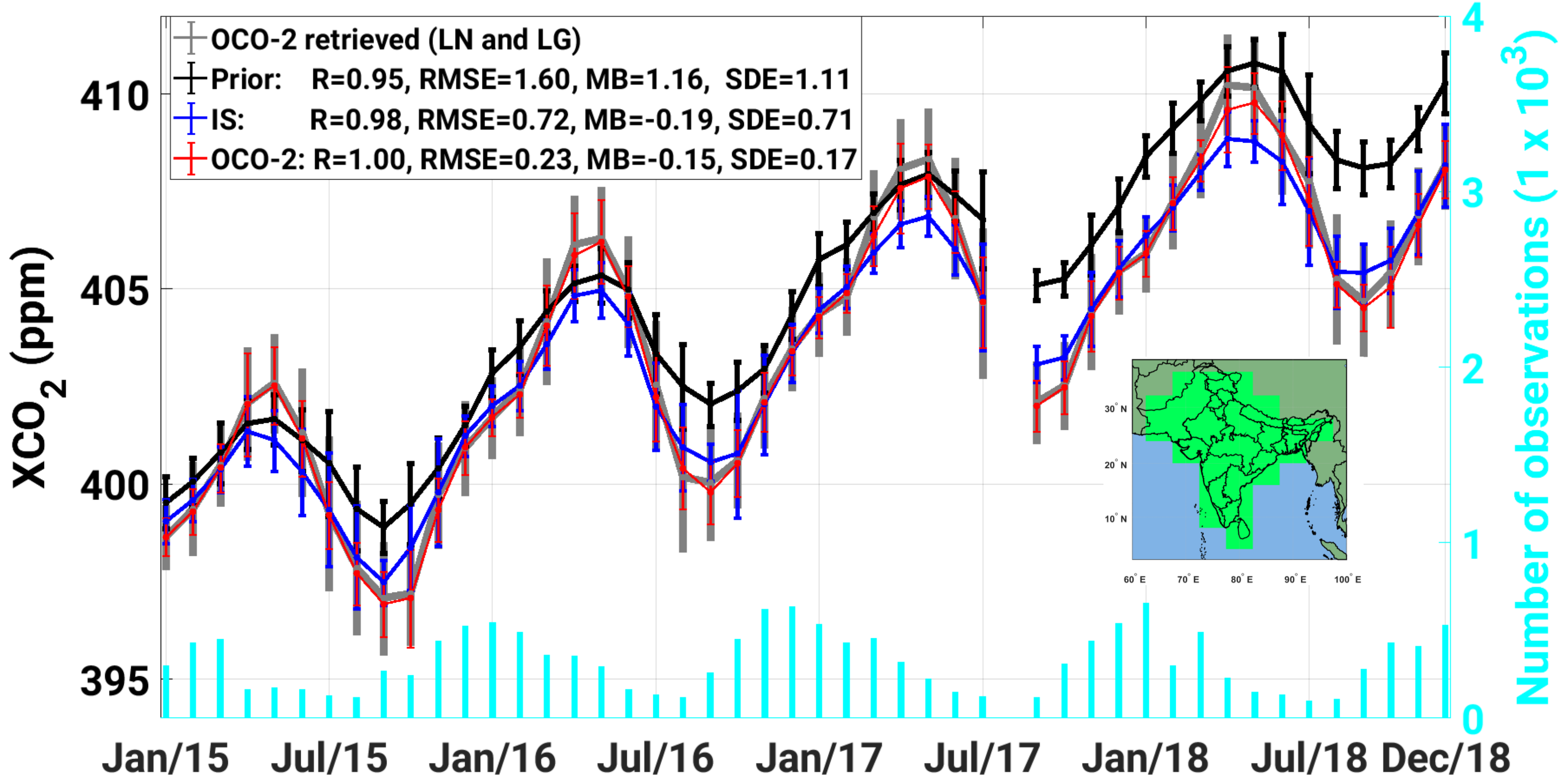
- ➢ **NEE flux estimates from "top-down" and "bottom-up" biosphere models have large uncertainty in this region.**

✓ **Satellite XCO_2 data can compensate for the lack of regional in situ observations to help constrain South Asian NEE estimates.**

Patra et al., 2013, ACP



Larger seasonal cycle of CO_2 over South Asia

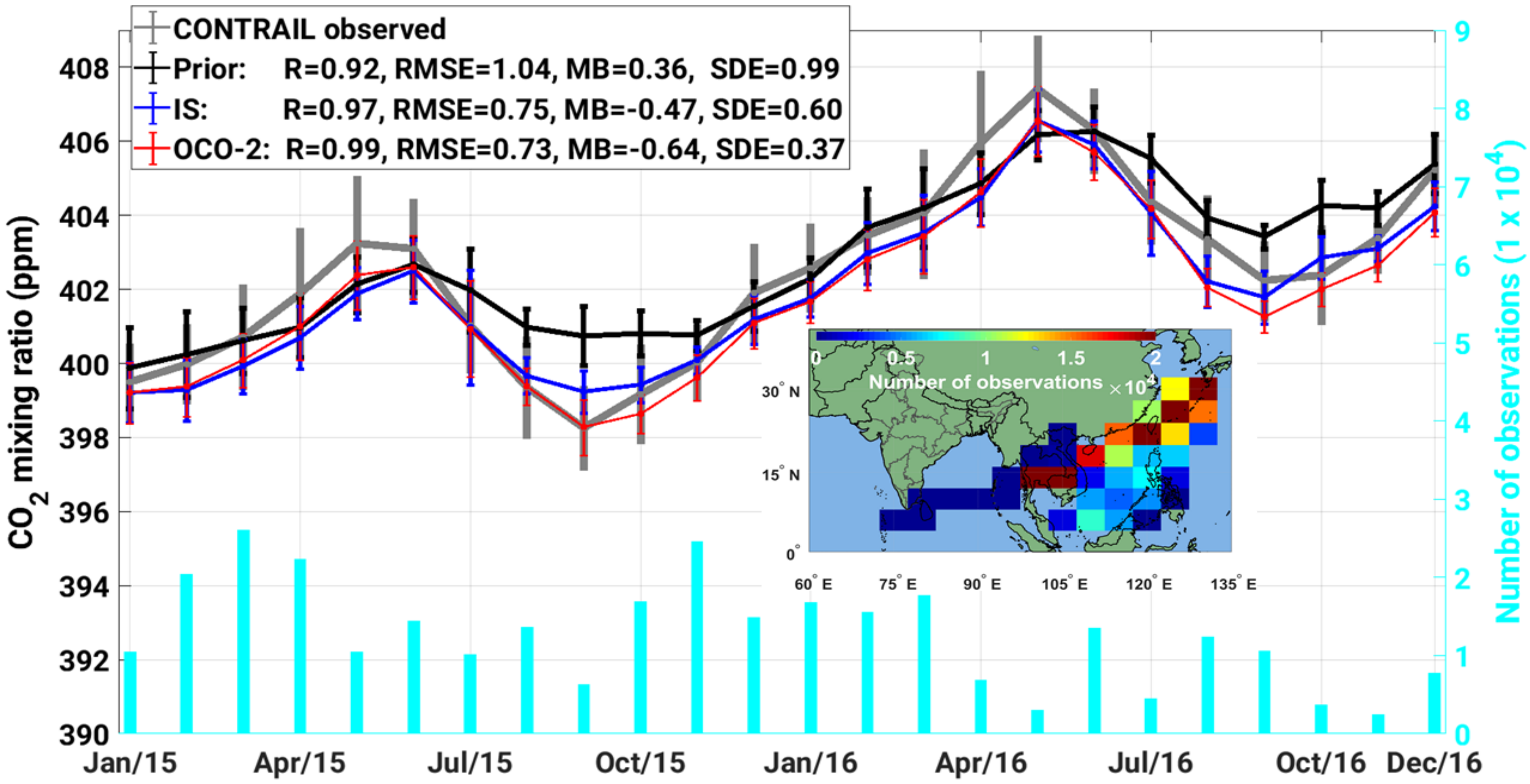


Philip et al., 2022, JGR

OCO-2 retrieved XCO_2 (LN + LG) versus model simulated prior and posterior XCO_2 averaged over South Asia.

- **The seasonal cycle of OCO-2 XCO_2 is larger than simulated XCO_2 using prior fluxes.**
- **Posterior XCO_2 estimated when assimilating OCO-2 data better reproduces OCO-2 retrieved XCO_2.**

Posterior CO_2 better capturing seasonality of CONTRAIL observations

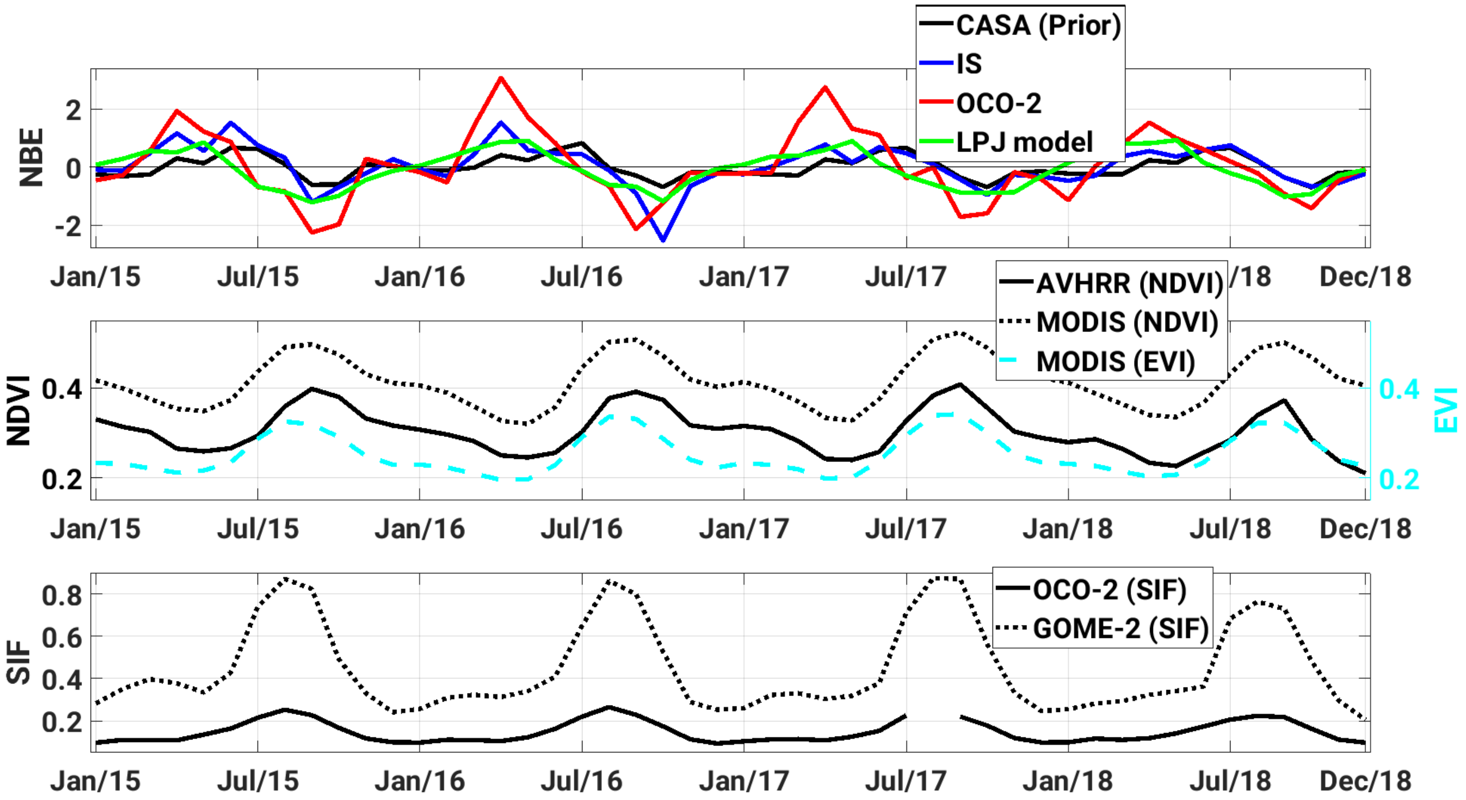


Monthly averaged CONTRAIL observed and modeled CO_2 mixing ratio (ppm) at altitude range of ~5-13 km near the South Asia region.

Philip et al., 2022, JGR

- **The seasonal pattern of CONTRAIL observations was reproduced by posterior CO_2 constrained by both IS and OCO-2 data (R = 0.97-0.99) better than the prior (R = 0.92).**

OCO-2 optimized fluxes compare better with remote-sensing NEE-proxies



Correlation coefficients (R) between monthly mean NBE (from 2015 to 2018) and remote-sensing NEE-proxies (NDVI, EVI, SIF).

	NDVI (AVHRR)	NDVI (MODIS)	EVI (MODIS)	SIF (GOME-2)	SIF (OCO-2)
Prior	-0.44	-0.39	-0.18	0.06	0.16
IS	-0.56	-0.59	-0.41	-0.14	-0.11
OCO-2	-0.74	-0.85	-0.73	-0.49	-0.47
LPJ	-0.76	-0.92	-0.85	-0.63	-0.60

- **OCO-2 constrained NBE are better correlated with satellite-based NEE-proxies (NDVI, EVI and SIF) compared to prior (CASA) and IS-constrained model simulations.**