

# DEEP NEURAL NETWORK FRAMEWORK FOR INVERTING REMOTELY SENSED CO<sub>2</sub> MEASUREMENTS

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ICLR 2025



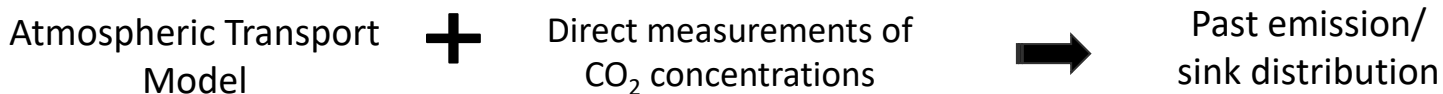
# Outline

- **Introduction**
  - Flux calculation of carbon
- **Proposed method**
  - DL based inversion
- **Results and discussion**
  - Validation challenges
  - Observation
- **Future work**

# Flux calculations

## Estimating Surface Emission/Sink Distribution of CO<sub>2</sub>

- **Bottom-up Methods**  
Inventory of individual sources, activity data & emission factors.
- **Top-down Methods**  
Measurements of atmospheric concentrations of the gas, and physics based inversion



e.g. Data assimilation methods: Ensemble Kalman Filter, 4-D Variational Methods

# Flux calculations pros and cons

## Data Assimilation Methods

- computationally expensive
- require expertise in complex numerical code
- numerical errors, errors from parametrizations

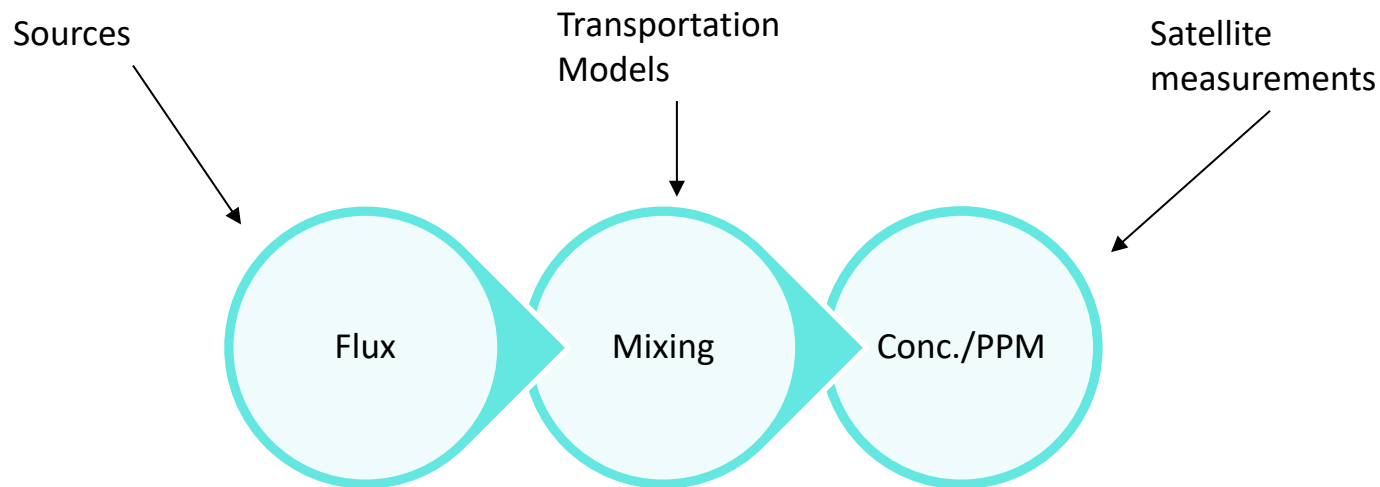
## Advantages of Deep Learning Methods

- Learning non-linearities,
- Ease of implementation, less requirement of domain expertise
- Scalability and Parallelizability



**Can we use deep learning to invert the concentrations?**

# Intuition



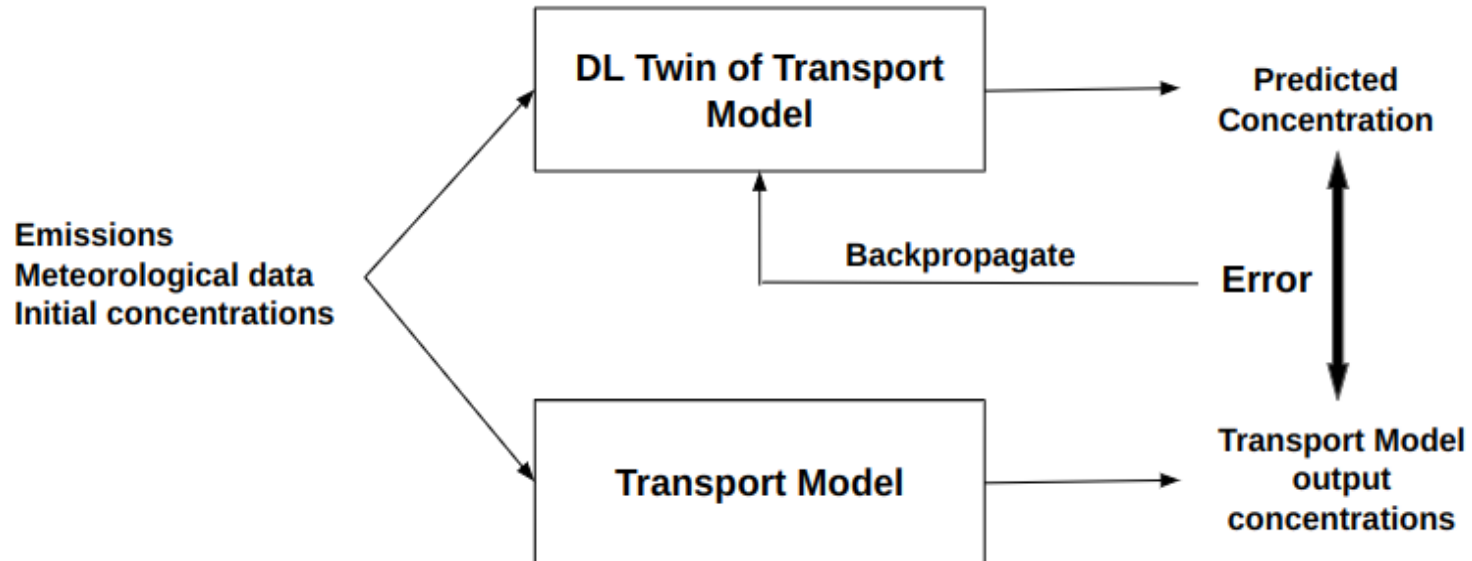
## Unified network doing double duty

DL for twin for transportation

DL for flux correction based on the consistency of the measurements and model output

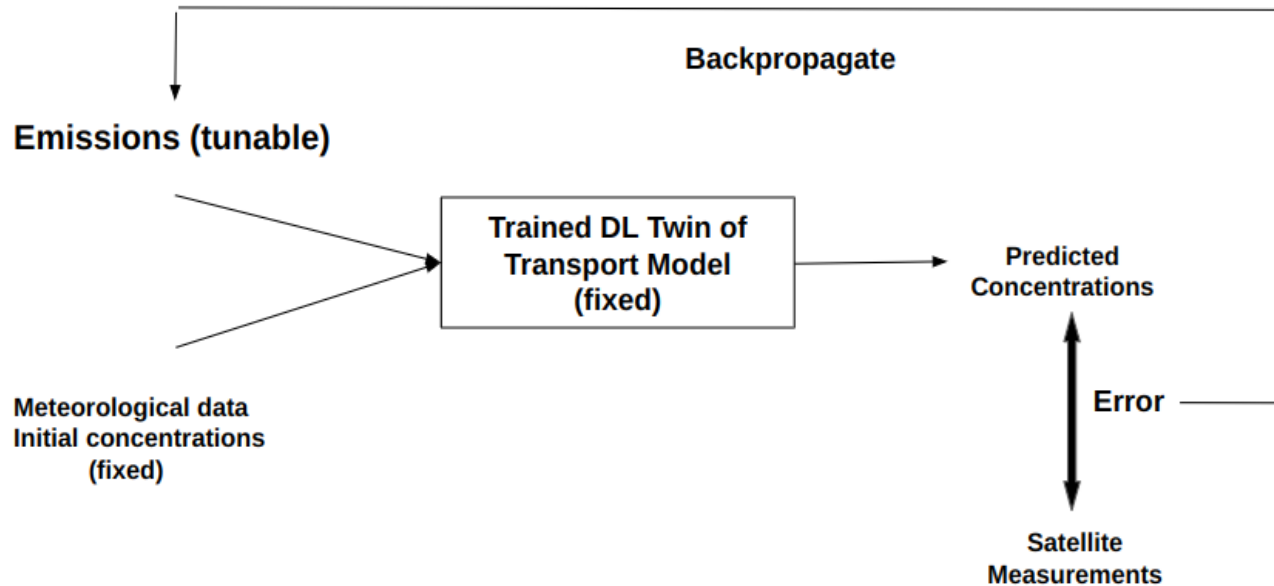
# Digital twin for transportation

Part 1: Take Numerical Transport Model → Train its Deep Learning Twin/Surrogate



# Deep network for inversion

Part 2: DL Twin Model + Satellite Concentration Measurements → Corrected Emissions



# Digital twin training

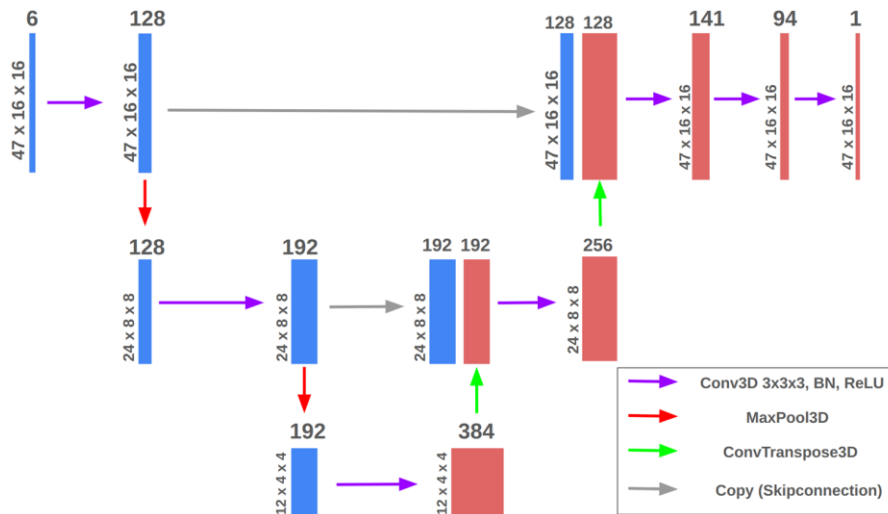
## Training Data Generation

Emissions (fossil fuels ...)  
+ Initial Concentrations  
+ Meteorological Data (NASA)



Numerical Model: GEOS-Chem

Daily Average Concentrations (PPM)



Input: Emissions, Initial Concentrations, Winds, P, T

Output: 1-day concentration change (ppm)

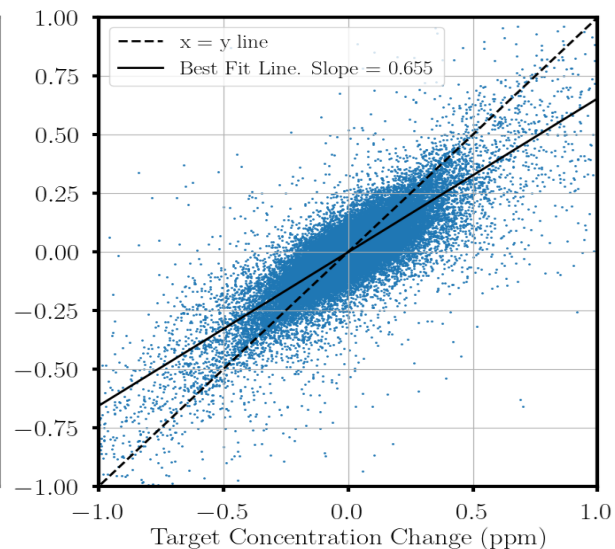
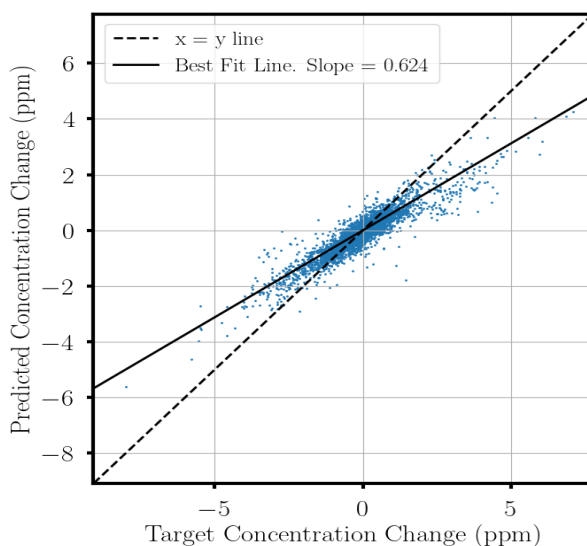
Grid:  $4^\circ \times 5^\circ$  (Asia)

Model Size: 7.6 Million parameters

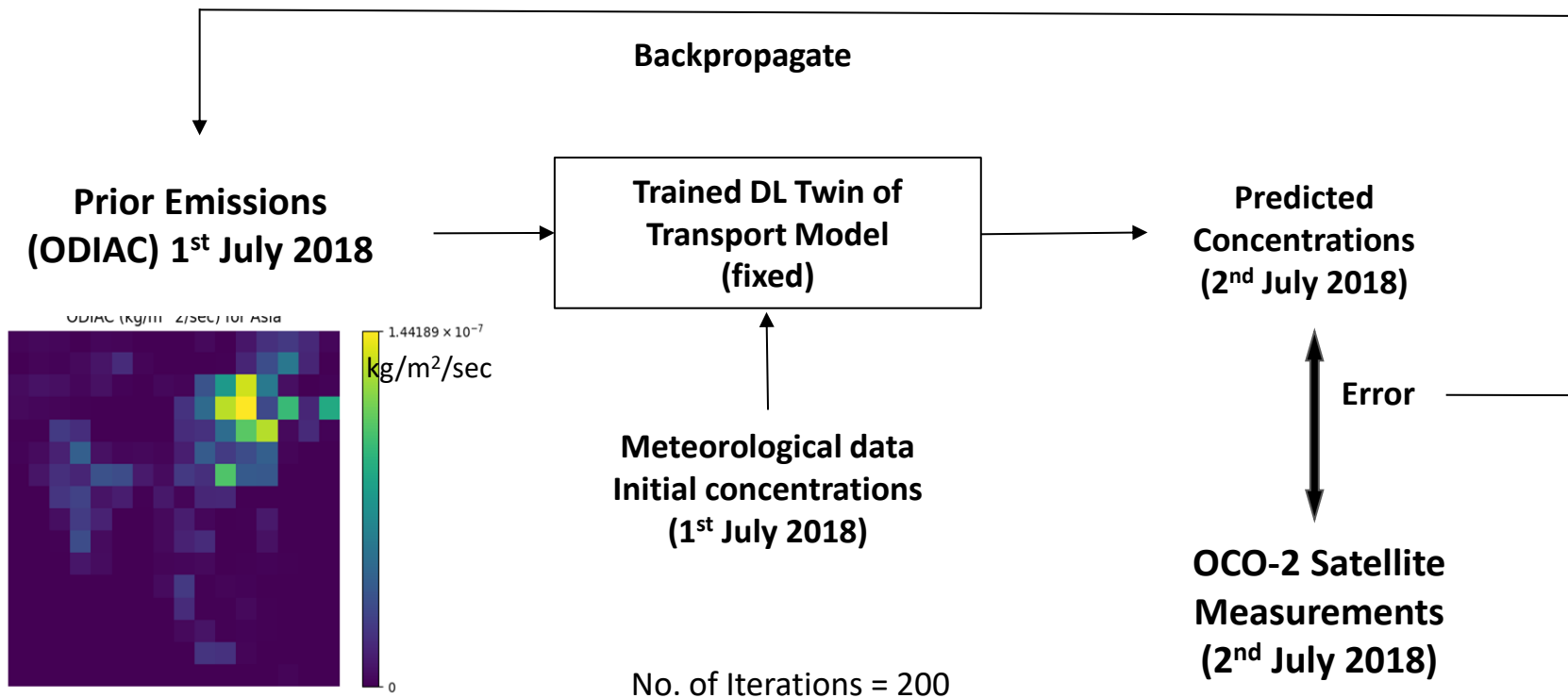
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	Concentrations	Change in Concentrations
Percentage Error (Loss x 100)	0.045%	47.9%
Pearson Correlation Coeff.	0.996	0.885
Coeff. Of Determination	0.992	0.751

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# Inversion

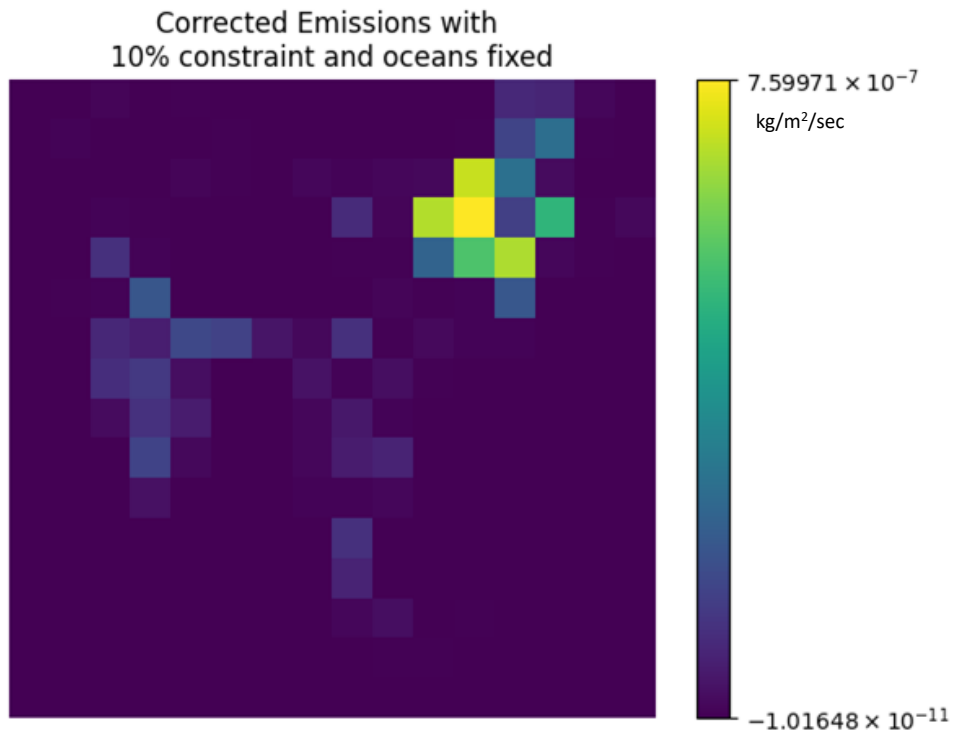


# Validations challenges

- EDGAR (Emissions Database for Global Atmospheric Research) report and, ODIAC data
  - Based on the inventory data
  - Emissions because of antropogenic activities (fossile fuel burning)
- **ODIAC (prior) and EDGAR account only for antropogenic emissions.** But satellite measurements are affected by all sources.
- Small to negligible differences in fluxes for short time span

# Validation

- Predict the daily averages using the input condition as per the ODIAC and aggregate for a year
- Total emissions for 2018 according to **EDGAR report** : (17.811 Gt) Gt
- Total emissions of the region (extrapolated to the whole year) increase from (prior) 19.6 Gt to 60.2 Gt



# Concluding remarks

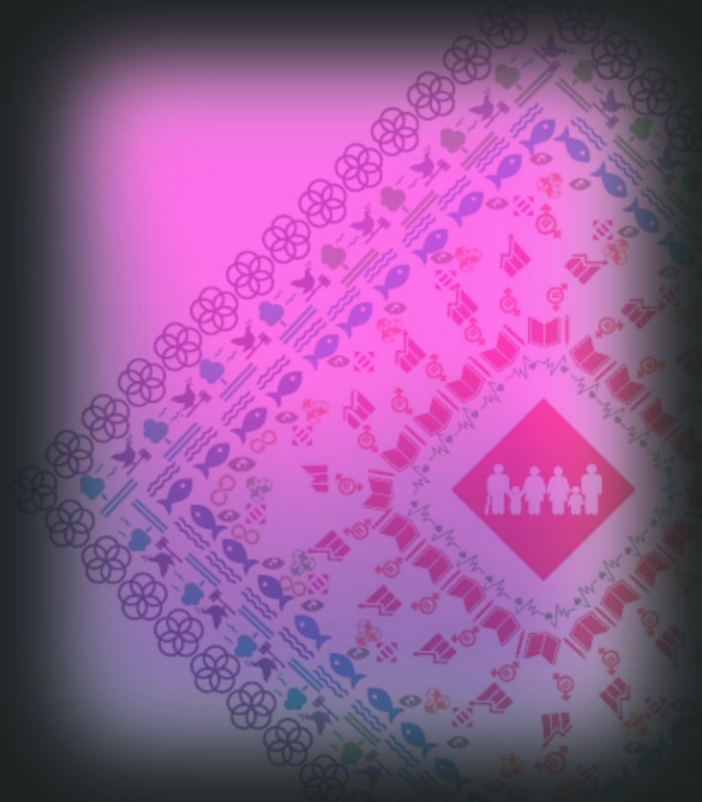
Results are encouraging, however need further investigation

- Building more accurate model using better computing infrastructure
- Incorporating additional complex transportation processes
- Incorporating domain knowledge in the formulations - Considering emission dynamics other sources more constraints and so on

## Key takeaway

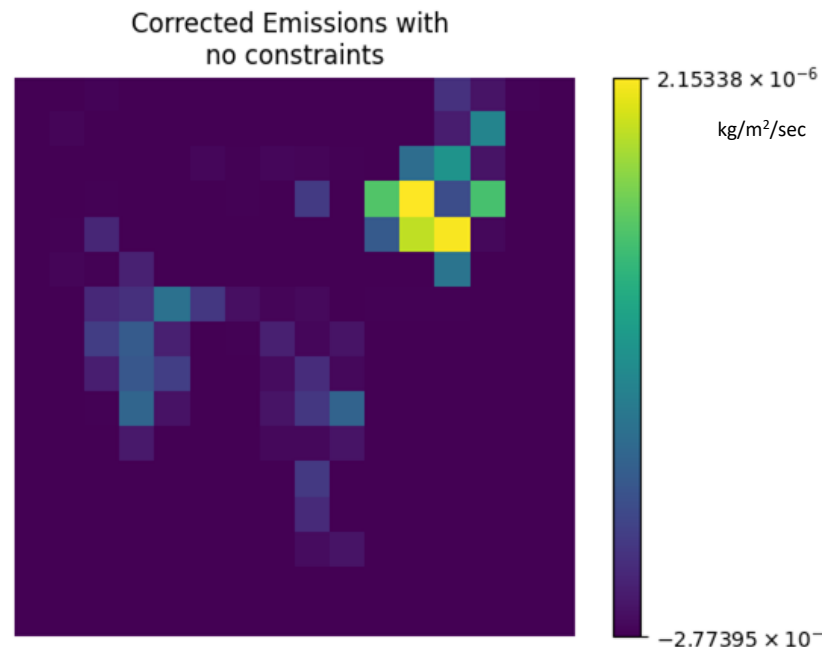
- A unique framework for inversion
- Potential to create most accurate flux data product

Thank You



# Experiment 1 – no constraints on sources and sinks

- After 200 iterations, RMS error with satellite measurements: ~9.14%
- Intensified hotspots in China and India
- Ocean regions turned to sinks
- Total emissions of the region (extrapolated to the whole year) increase from 19.6 Gt (prior) to 185.0 Gt



## Experiment 2 – Fixed ocean emissions

- ODIAC emissions are only terrestrial so we neglect emissions from oceans.
- After 200 iterations, RMS error with satellite measurements:  $\sim 9.14\%$
- Emissions reduce very slightly
- Total emissions of the region (extrapolated to the whole year) increase from 19.6 Gt to 181.0 Gt

