

Applying analytical inversion and 4D-Var to estimate sources of methane and air pollutants

Zhen Qu

North Carolina State University

zqu5@ncsu.edu

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Bayesian inference of emissions

Minimize cost Function:

$$J(x) = \underbrace{\frac{1}{2} (x - x_a)^T \mathbf{S}_a^{-1} (x - x_a)}_{\text{Prior Term}} + \underbrace{\frac{1}{2} \gamma (\mathbf{y} - \mathcal{H}x)^T \mathbf{S}_o^{-1} (\mathbf{y} - \mathcal{H}x)}_{\text{Observational Term}}$$

Solutions:

1. **Analytical solution** (linear model, $\mathcal{H} \rightarrow \mathbf{K}$):

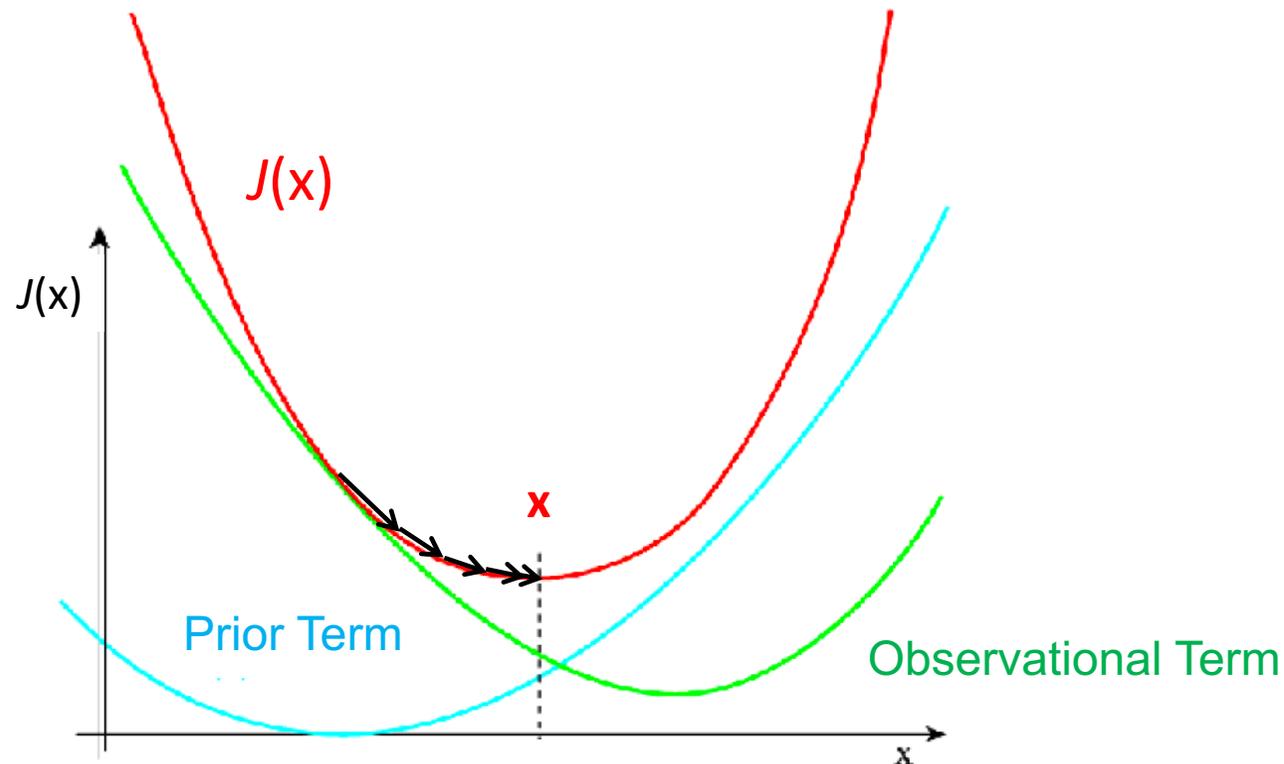
$$\hat{x} = x_a + (\gamma \mathbf{K}^T \mathbf{S}_o^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1} \gamma \mathbf{K}^T \mathbf{S}_o^{-1} (\mathbf{y} - \mathbf{K}x_a)$$

$$\hat{\mathbf{S}} = (\gamma \mathbf{K}^T \mathbf{S}_o^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1}$$

$$\mathbf{A} = \mathbf{I} - \hat{\mathbf{S}} \mathbf{S}_a^{-1}$$

2. **4D variational method (4D-Var):**

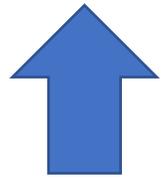
- Non-linear model – seeks a solution iteratively
- Adjoint model calculates the sensitivity of cost function with respect to state vector



1. Analytical Inversion of Methane

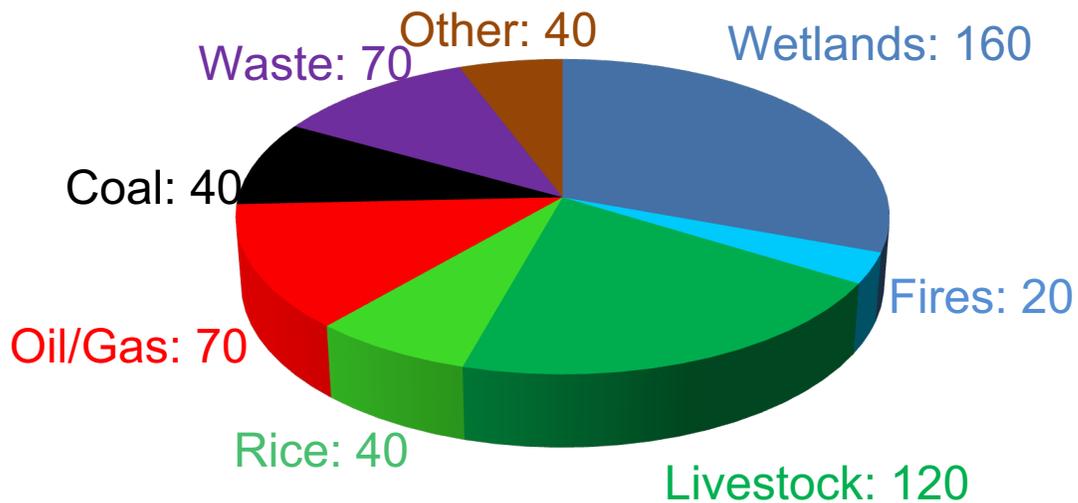


Global Methane Burden Is Balanced by the Sources and Sinks ⁴



Sources

Emission
 $560 \pm 60 \text{ Tg a}^{-1}$



Sinks

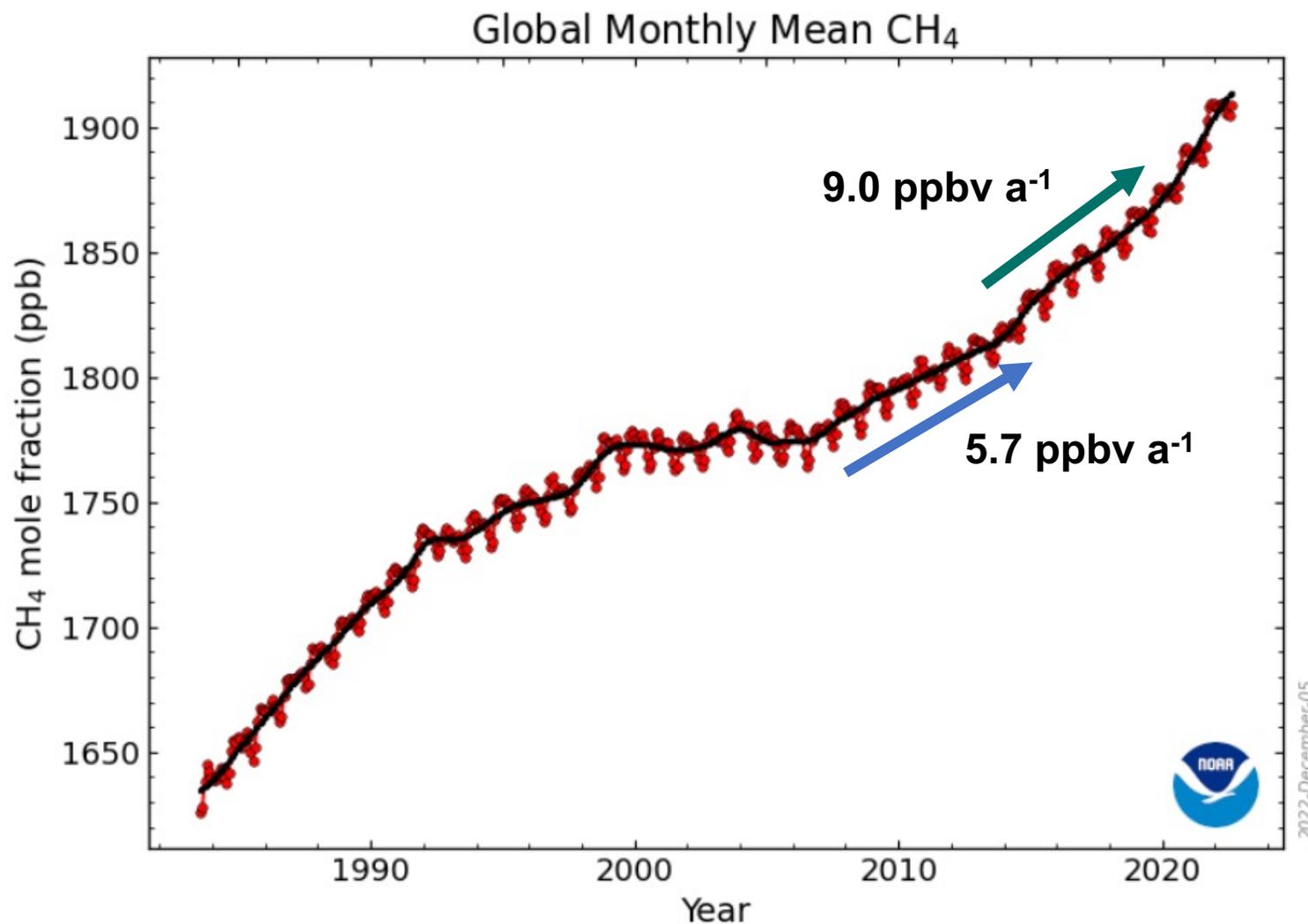
Mainly through reactions with OH:



From prescribed full-chemistry simulation

Sources – Sinks = Imbalance  Growth of CH₄ concentration

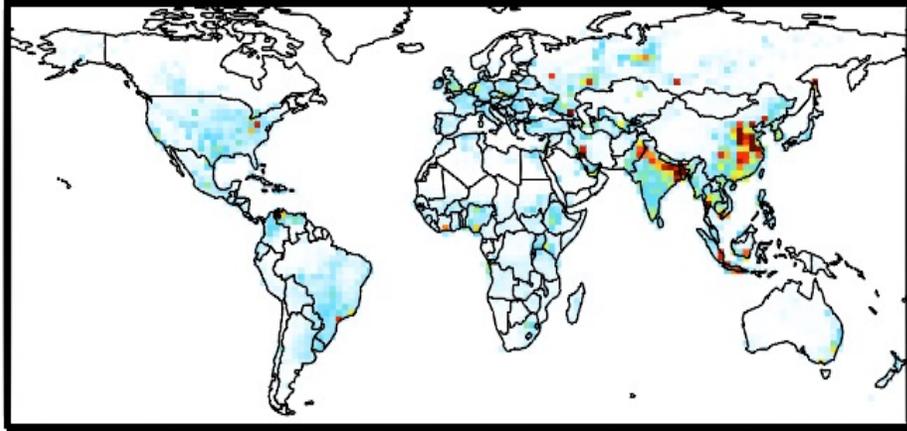
Global Methane Concentration Surge in 2020 & 2021



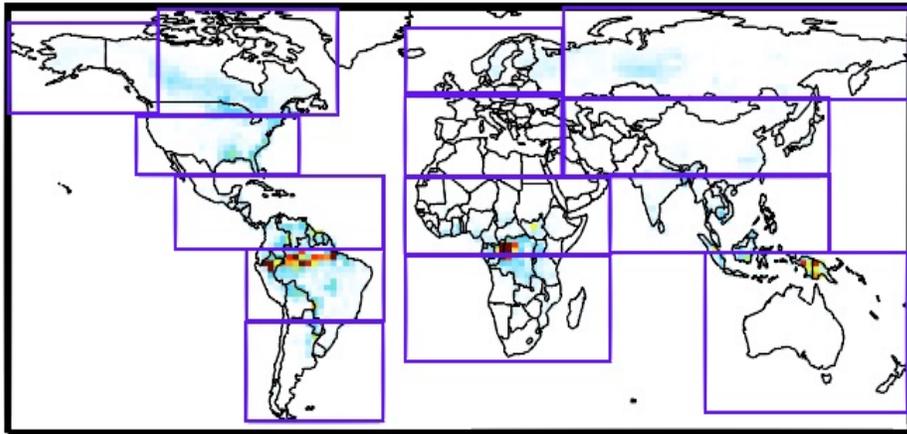
Record high annual increase of 14.7 ppbv in 2020 and 16.0 ppbv in 2021.

Analytical Inversion Simultaneously Estimates the Sources and Sinks of CH₄

Prior non-wetland emissions



Prior wetland emissions



$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x} - \mathbf{x}_a)^T \mathbf{S}_a^{-1}(\mathbf{x} - \mathbf{x}_a) + \frac{1}{2}\gamma(\mathbf{y} - \mathbf{K}\mathbf{x})^T \mathbf{S}_o^{-1}(\mathbf{y} - \mathbf{K}\mathbf{x})$$

- Prior estimates:
EDGARv4.3.2 as global default;
EPA greenhouse inventory for CONUS;
oil, gas, and coal from GFEI;
wetland from WetCHARTs
- \mathbf{x} : 4020 non-wetland emission, 12 x 14 wetland emissions, 2 hemispheric OH concentrations
- \mathbf{K} : sensitivity of each observation to 4190 state vector elements
- \mathbf{S}_o include both satellite and model errors



Changes in CH₄ Sources and Sinks in 2019-2020

Methane growth rate:

$$\frac{dm}{dt} = E - km - L$$

m = methane mass

E = emission

k = OH loss rate constant

L = minor losses (strat, Cl. Dep)

Acceleration of growth rate:

$$\frac{d^2m}{dt^2} = \frac{dE}{dt} - k \frac{dm}{dt} - m \frac{dk}{dt} - \frac{dL}{dt}$$

Forcing away from steady state:

$$F = \frac{dE}{dt} - m \frac{dk}{dt} = 36 \text{ Tg a}^{-1}$$



Sources

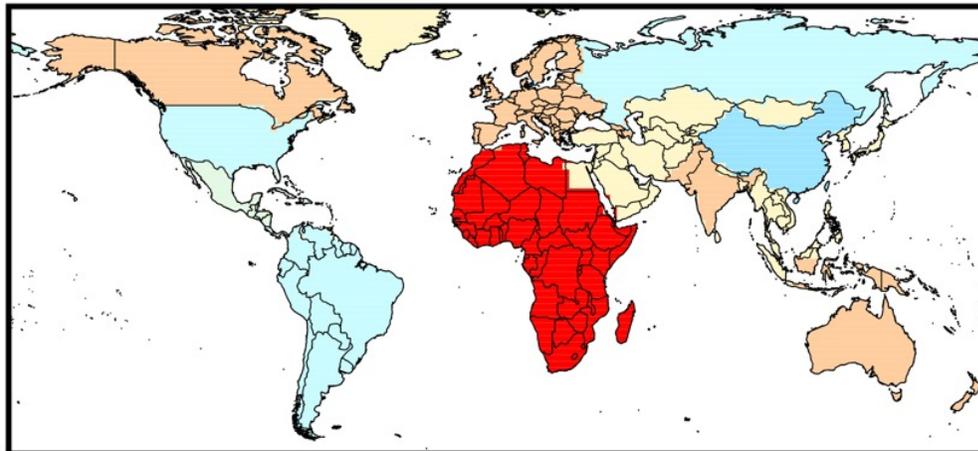
+ 31 Tg a⁻¹ (86%)



Sinks

- 5 Tg a⁻¹ (14%)

2020-2019 change in emissions [Tg a⁻¹]



Global mean OH reduce by 1.2%

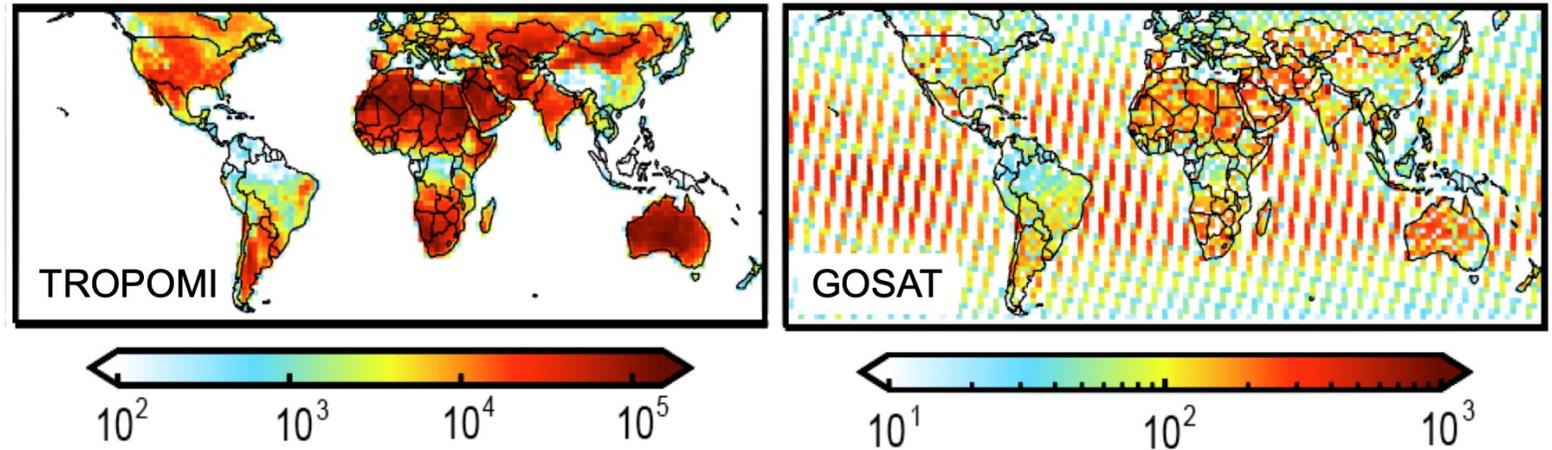
African wetlands drive 50% of the surge; independent evidence from inundation data

9-member inversion ensemble: + 30 ± 5.5 Tg a⁻¹ (82% ± 18%)

(Qu et al., 2022)

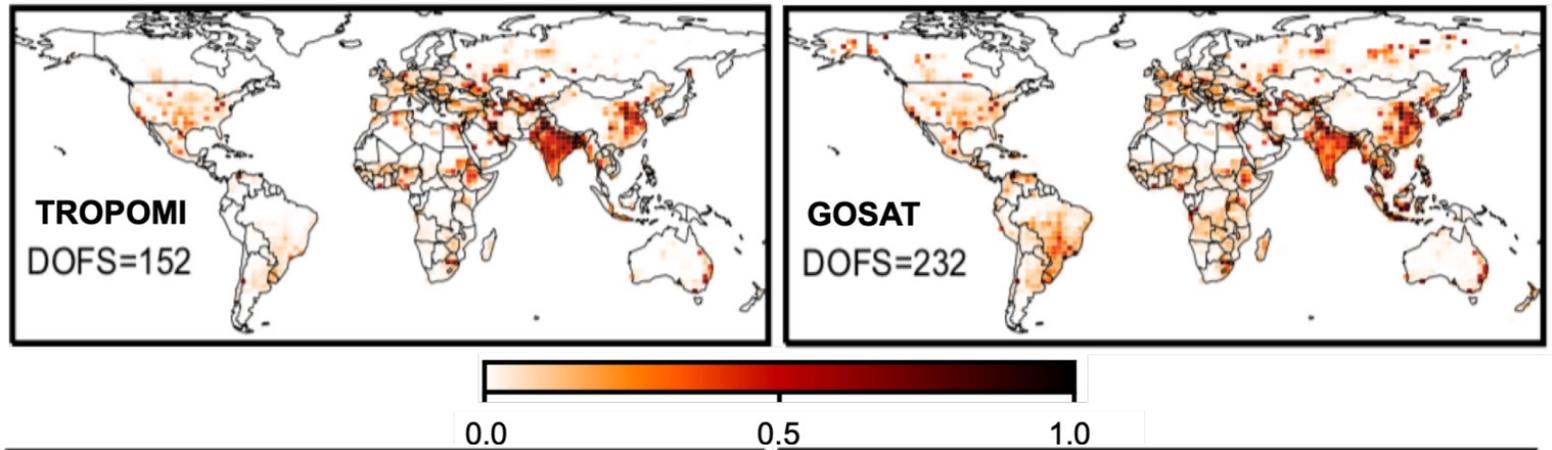
Analytical Inversion: Compare Observations from Different Instruments

of observations

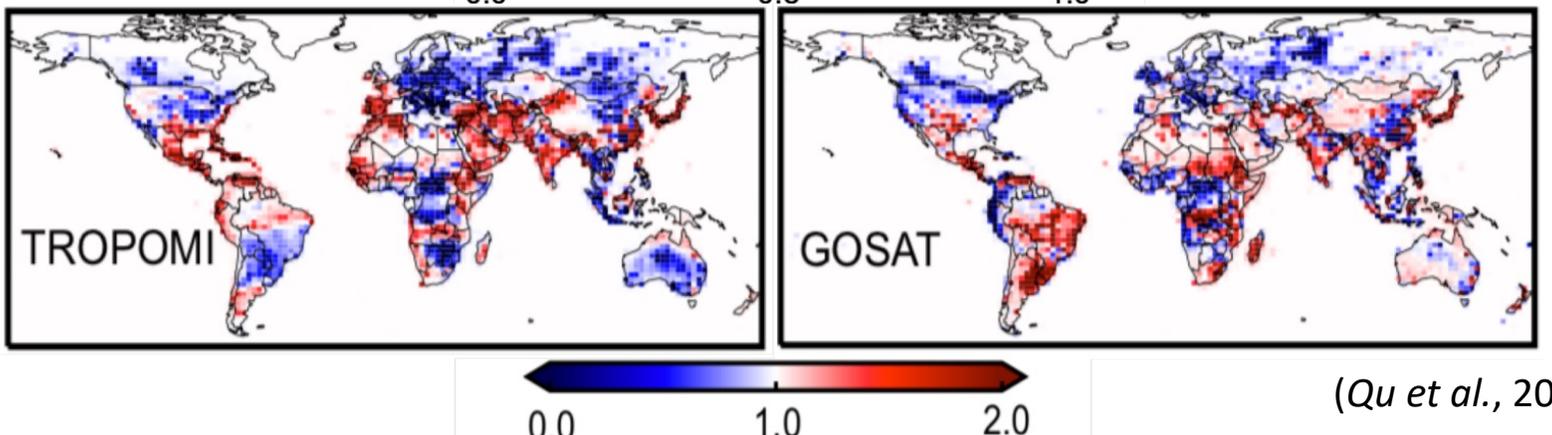


Averaging kernel (A)

Degrees of freedom for signal (DOFS): $\text{trace}(A)$



Posterior / prior



Other Applications of CH₄ Analytical Inversions

Complementarity of GOSAT and in-situ observations

Integrated Methane Inversion cloud-based facility

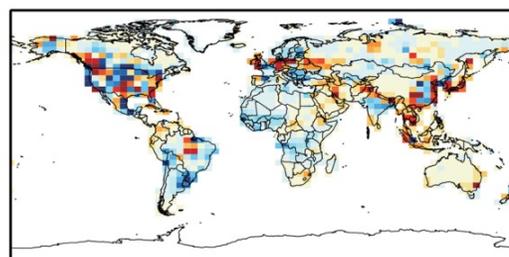
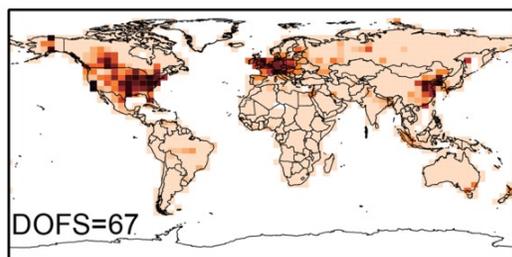
Anthropogenic methane emission trends in 2010-2017

Averaging kernel sensitivities

Posterior trends [a⁻¹]

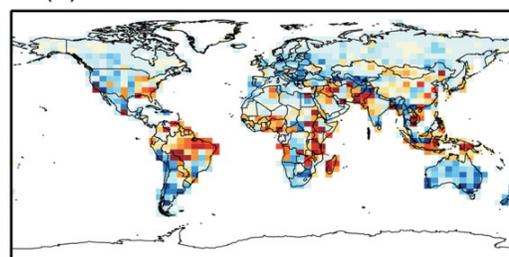
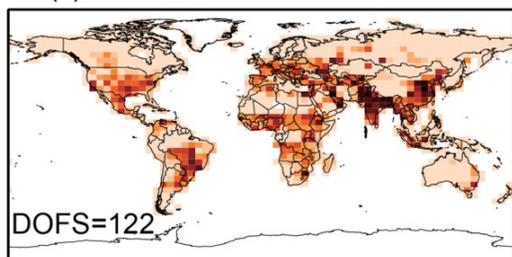
(a)

(b)



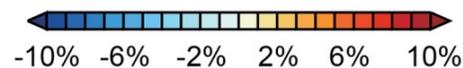
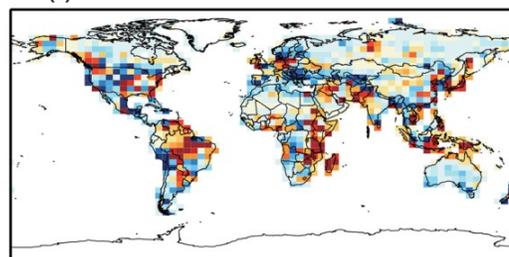
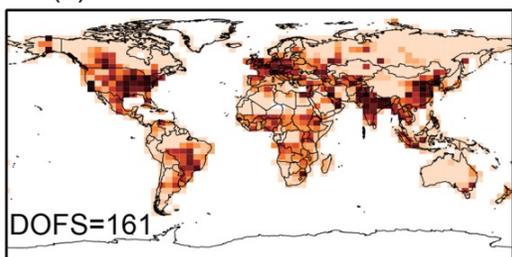
(c)

(d)



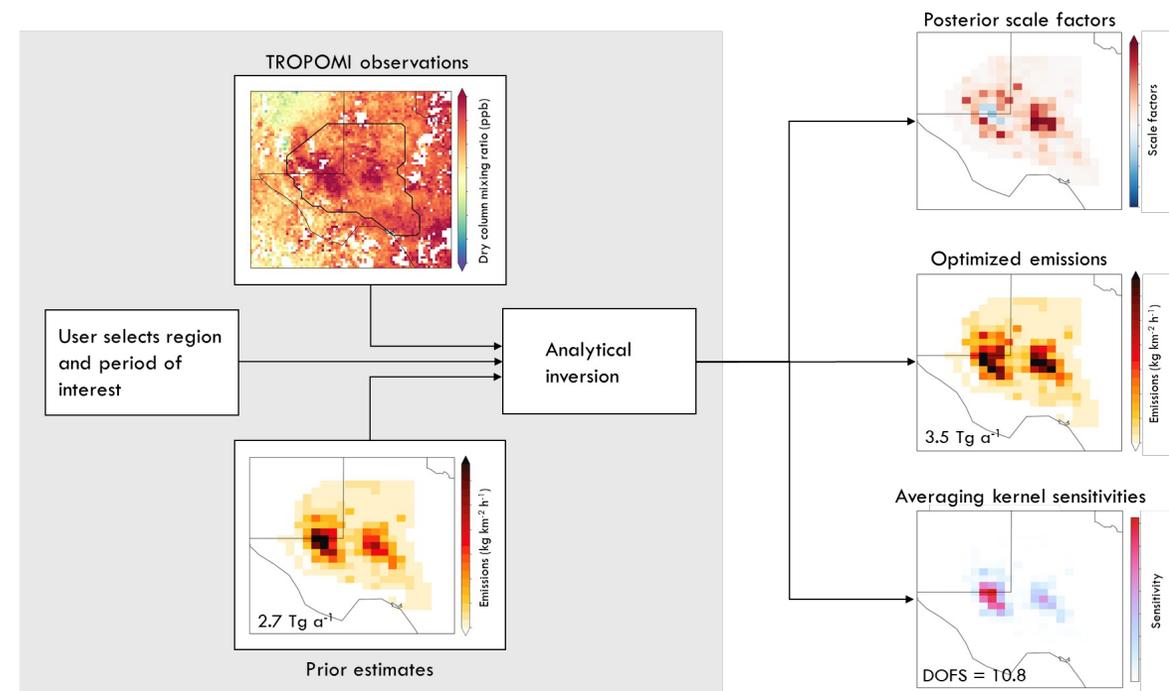
(e)

(f)



(Lu et al., 2021)

- 0.25° or 0.5° resolution
- TROPOMI data and GEOS-Chem on AWS



(Varon et al., 2022)

in-situ-only
inversion

GOSAT-only
inversion

GOSAT + in situ
inversion



Summary

- Analytical inversion: forward model is linear; can easily quantify information content and generate an ensemble of inversions
- The largest increases of methane emissions over 2010-2021 are from Africa and South America.
- Emissions from Africa, South America, and Equatorial Asia drives the methane surge in 2020 and 2021.

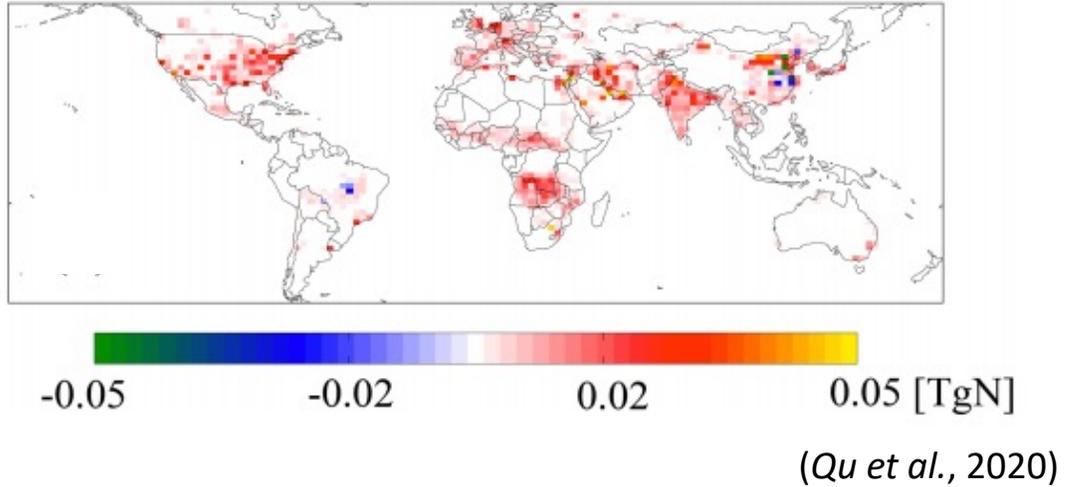
2. Quantifying NO_x , SO_2 , and CO Emissions using 4D-Var



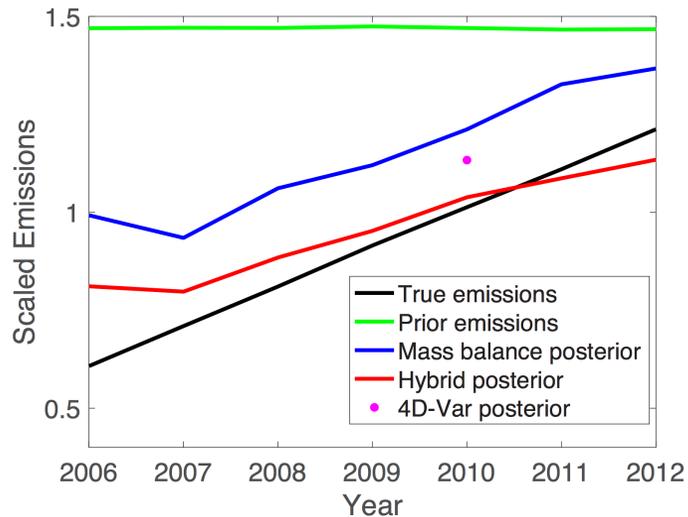
Previous Applications of 4D-Var

Improve spatial distribution:

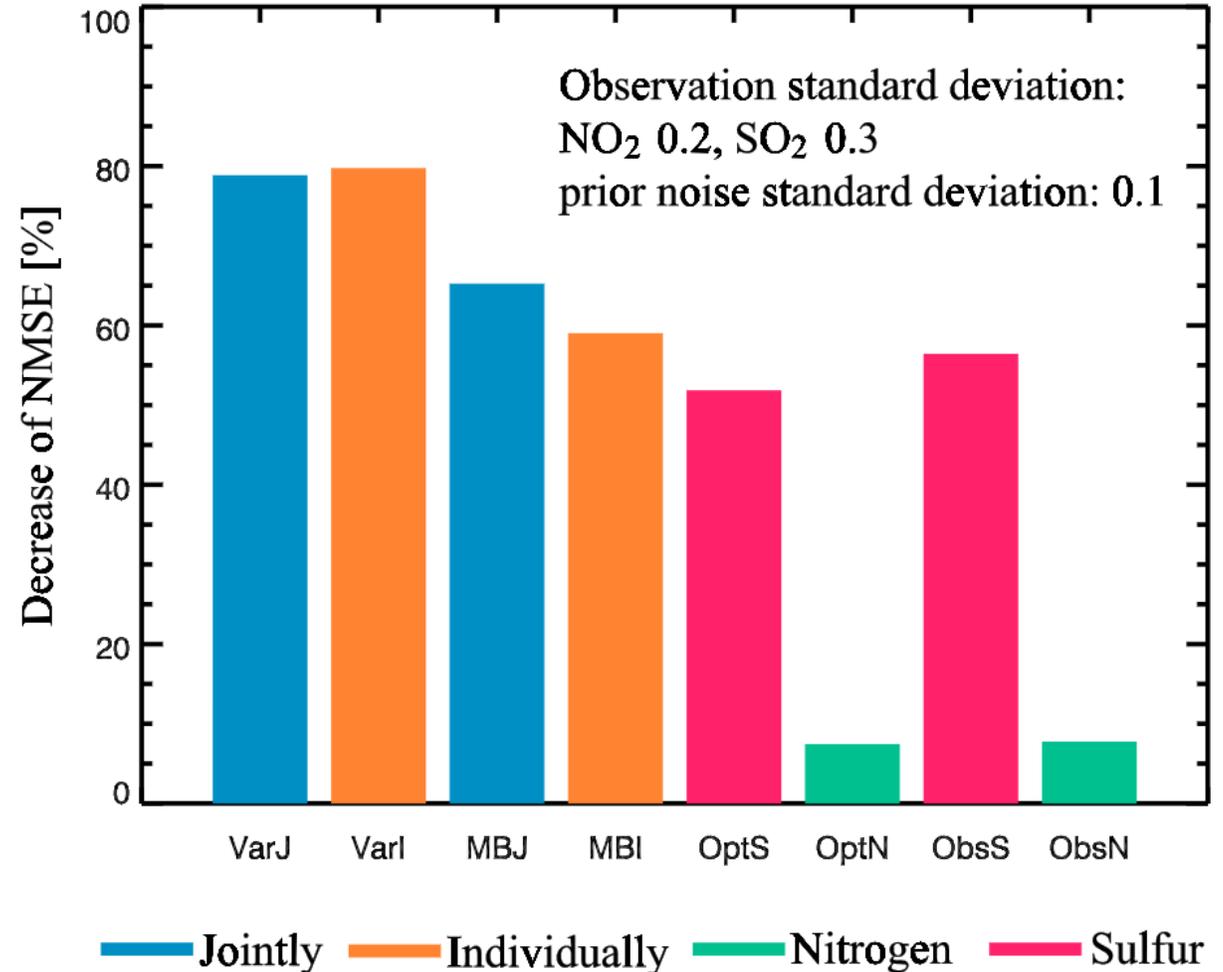
NO_x emissions (Top-down – HTAP, 2010)



Combined w/ mass balance for trend:



Address the impact of chemical interactions:



Limitations in Previous Top-down Estimates

Cannot...

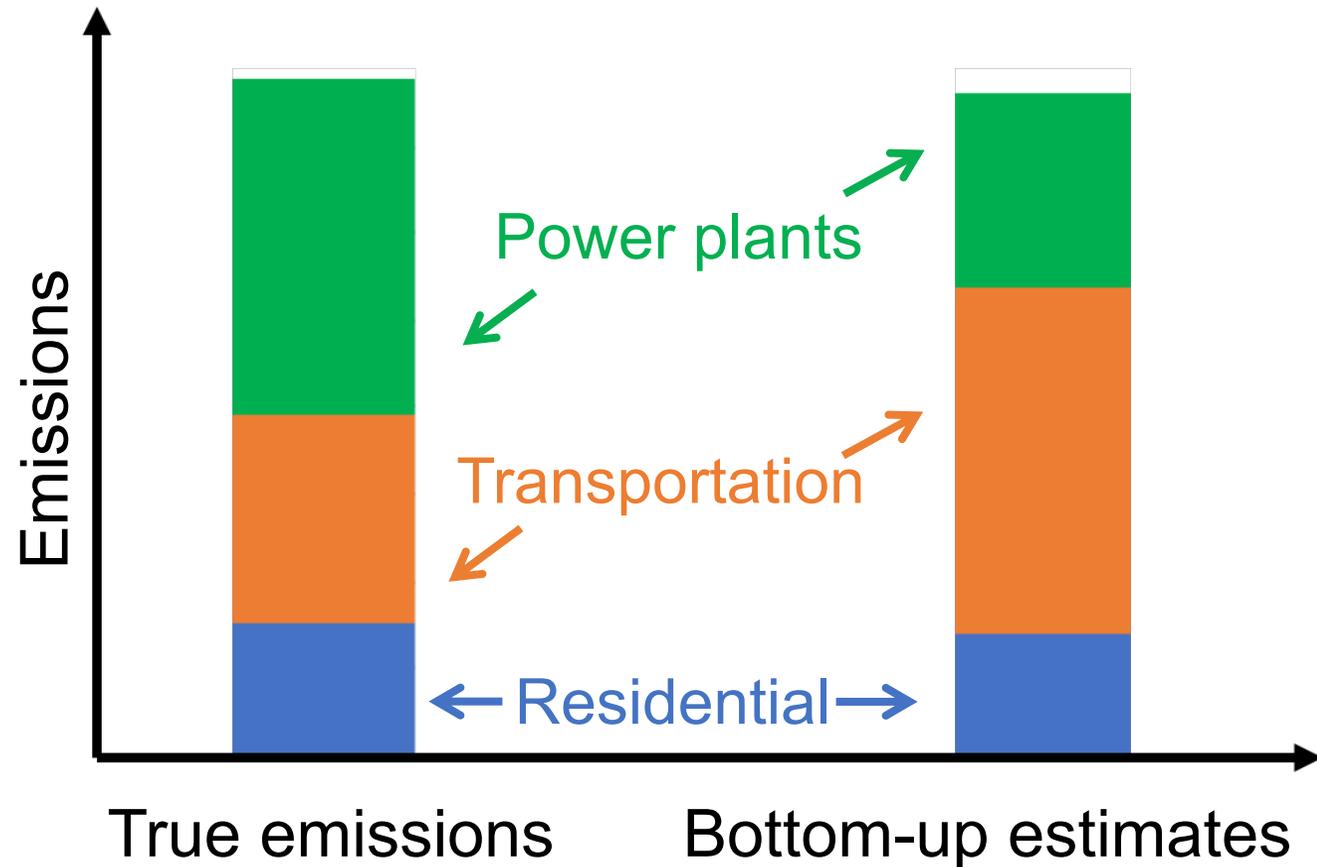
1. optimize sectoral profiles
2. separate errors from emission factor & activity rates

$E = \text{species emission factor} \times \text{activity}$

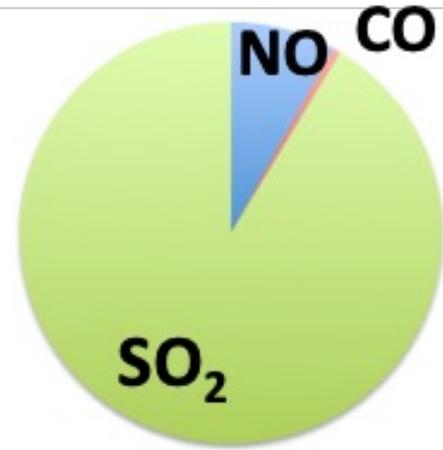
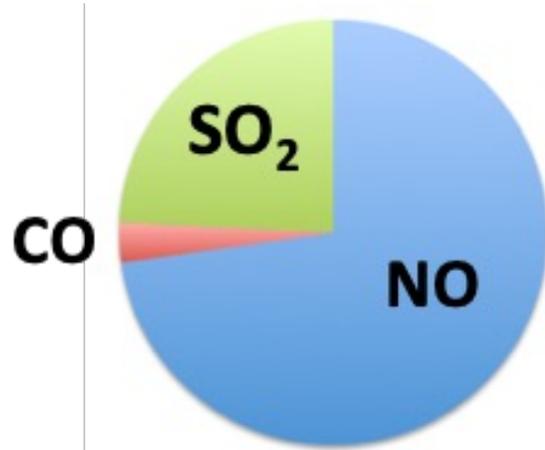
↑ optimize ↑

New sector-based inversion

Similar total emissions, different profiles



Unique Emission Profile for Each Source



Formulation of a sector-based inversion

Species-based inversion:

$$E_l = \sigma_l \sum_{k=1}^7 A_{a,k} F_{a,k,l} = \sigma_l E_{a,l}$$

l : species
 k : sector

$$J_1(\sigma_{k,l}) = J_0 + \frac{1}{2} \gamma_{r1} \sum_{l=1}^3 (\sigma_l - \sigma_{a,l})^T \mathbf{S}_{a,l}^{-1} (\sigma_l - \sigma_{a,l})$$

Sector-based inversion:

$$E_{k,l} = \sigma_k A_{a,k} \sigma_{m,l} F_{a,m,l}$$

$$J_2(\sigma_k, \sigma_{m,l}) = J_0 + \frac{1}{2} \gamma_{r2} \sum_{k=1}^7 (\sigma_k - \sigma_{a,k})^T \mathbf{S}_{a,k}^{-1} (\sigma_k - \sigma_{a,k}) \quad \text{activity rates in sector } k$$

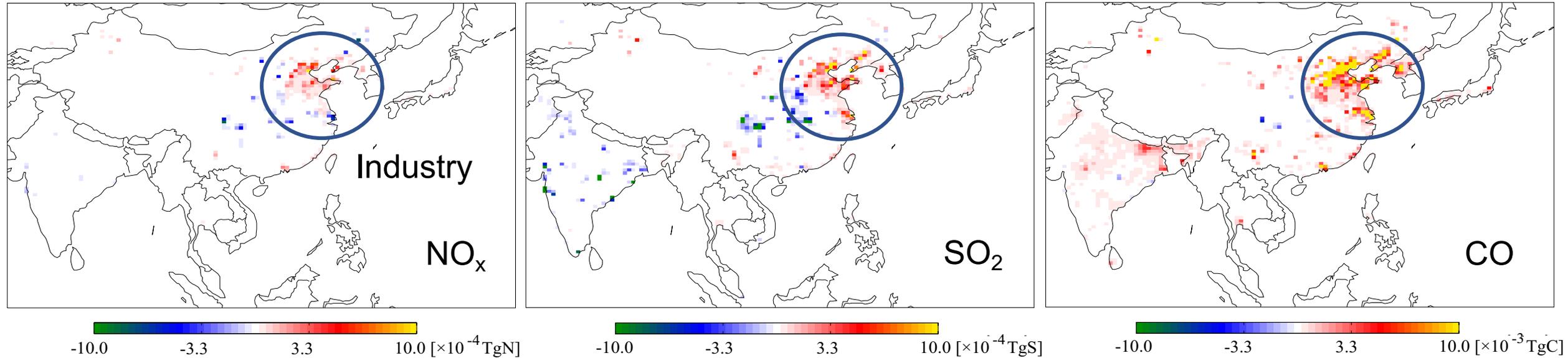
emission factor for species l in sector m

$$+ \frac{1}{2} \gamma_{r2} \sum_{m=1}^3 \sum_{l=1}^3 (\sigma_{m,l} - \sigma_{a,m,l})^T \mathbf{S}_{a,m,l}^{-1} (\sigma_{m,l} - \sigma_{a,m,l}).$$

(Qu et al., 2022)

Sector-based Inversion: Independent Adjustments for Each Source

Emission adjustments (Top-down – bottom-up, Jan, 2010)



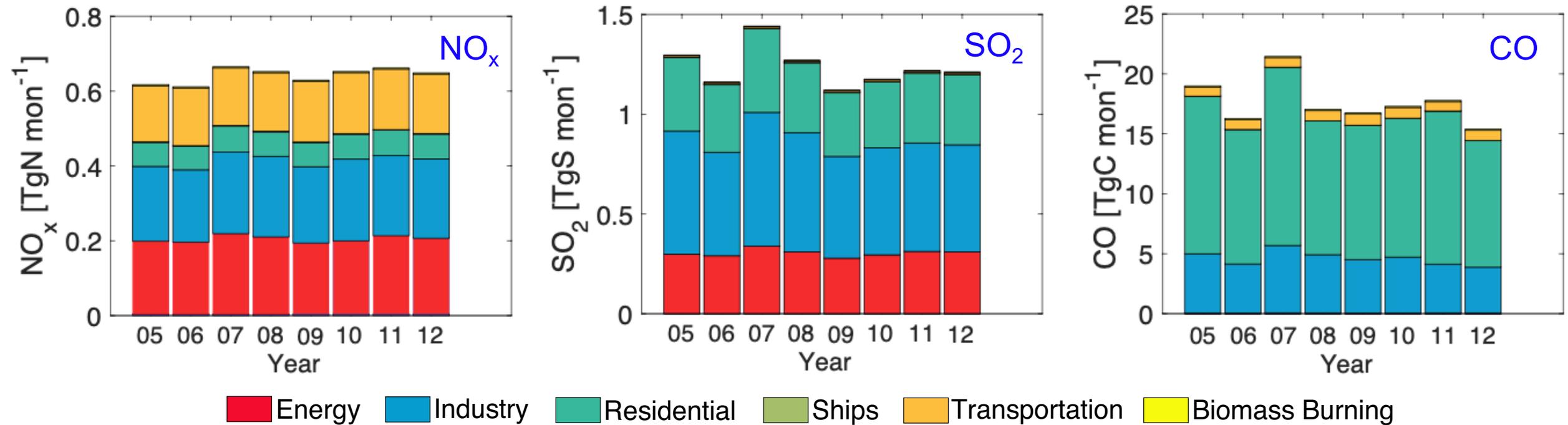
(Qu et al., 2022)

Bottom-up emissions: **overestimate** **underestimate**

$$E = \text{species emission factor} \times \text{activity}$$

How Different Sources Respond to Regulations in China?

Top-down emissions in China (Jan, 2005-2012)

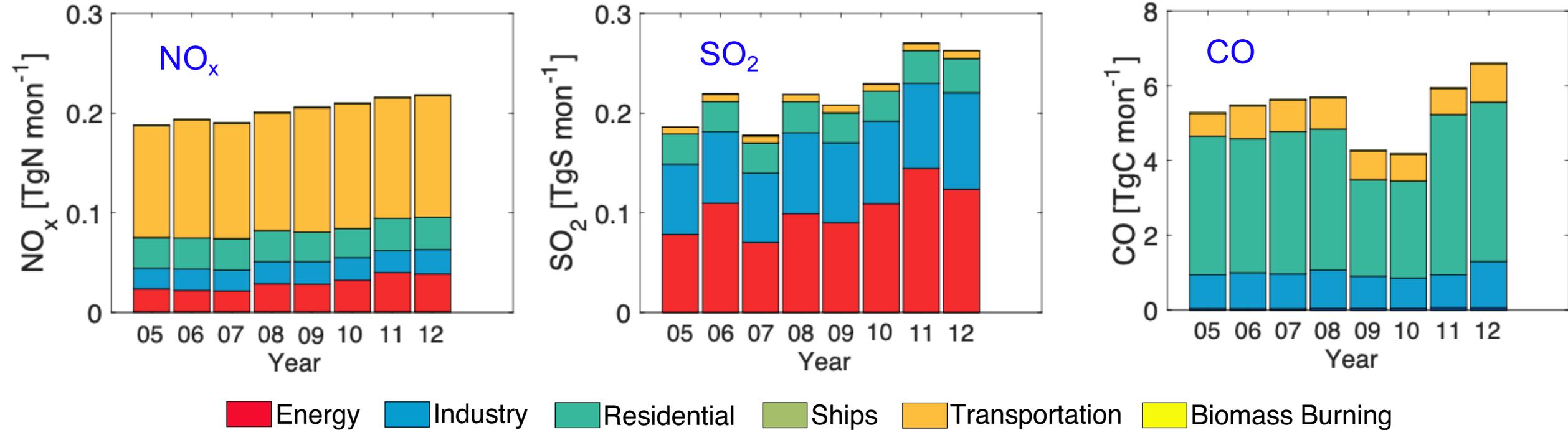


- Industry and energy sectors drive NO_x & SO₂ trends
- Residential and industry sectors drive CO trends

(Qu et al., 2022)

Emissions Continuously Increase in India

Top-down emissions in India (Jan, 2005-2012)



- Energy sector drives NO_x & SO₂ trends
- Residential sector drives CO trends

(Qu et al., 2022)



Summary

- 4D-Var: good for non-linear problems, computational expensive, but can be combined with other methods (e.g., mass balance) to reduce the computational cost.
- Top-down emissions from a newly developed sector-based inversion framework lead to the best agreement with independent surface measurements and provide a new perspective to evaluate bottom-up estimates by activities.