Benchmarking USA Methane Gridded Inventories With Satellite Based Emissions

Presenting: John Worden

NASA Jet Propulsion Laboratory
John Worden
Sudhanshu Pandey
Anthony Bloom
Shuang Ma
Kevin Bowman
Hannah Nesser

NOAA
Brian McDonald

Harvard
Daniel Jacob
Daniel Varon
Lucas Estrada

NCSU
Zhen Qu

SRON
Bram Maasakkers

This work directly supported by NASA CMS funding and builds on work supported by NASA ROSES ACMAP, IDS, CCE, AIST and Aura programs

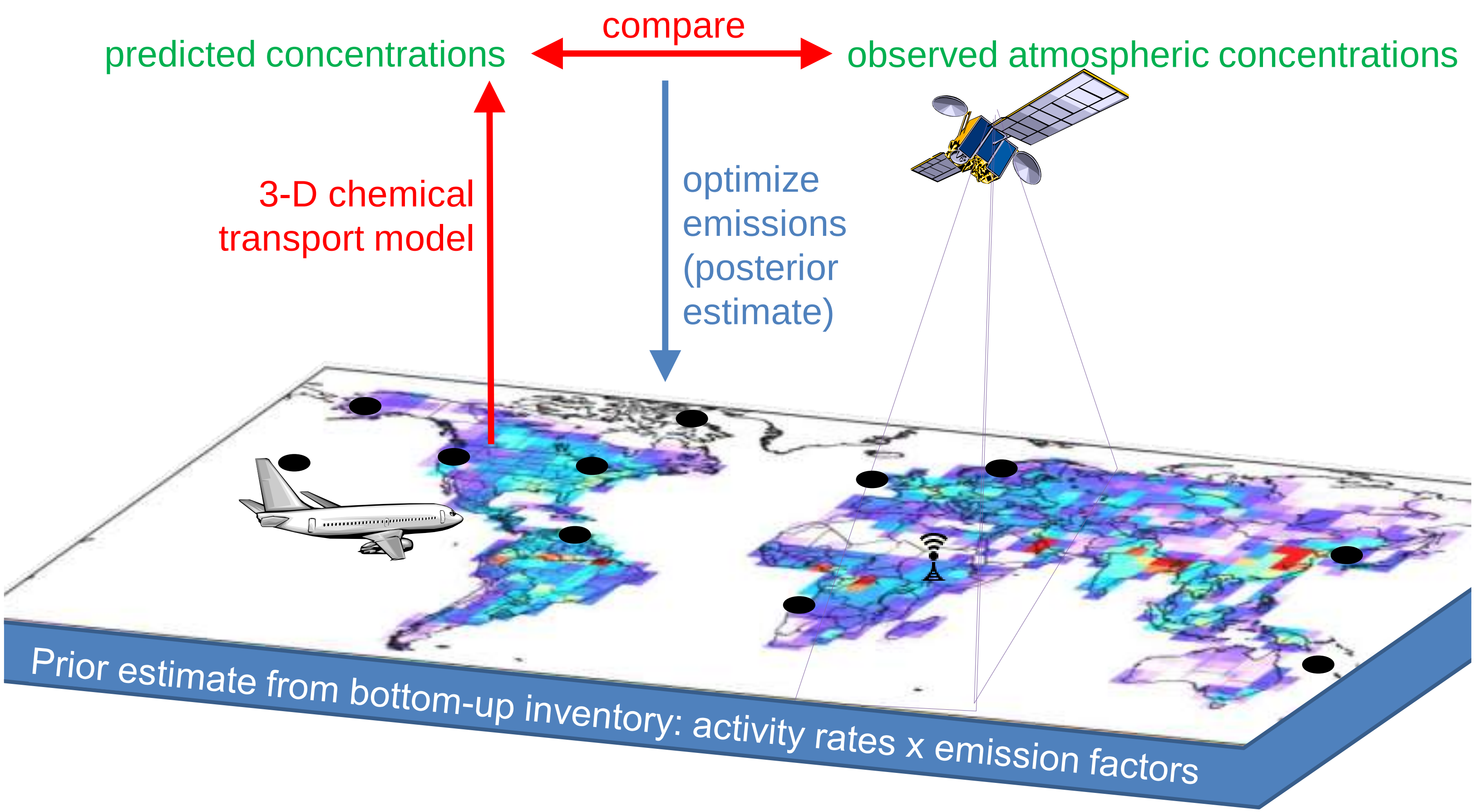
Background: Bottom-up models offer transparent, source-level estimates of methane emissions used for mitigation planning—but these are often inconsistent with top-down atmospheric observations, which capture integrated signals with regionally variable sensitivity and can relate atmospheric growth rate back to regionally varying emissions.

Challenge: Different spatio-temporal scales and uncertainty structures between methods make direct comparison difficult, challenging the use of atmospheric data to evaluate activity model emissions and their associated uncertainties.

Approach: We apply an optimal estimation-based comparison framework to identify where atmospheric data contain independent information and to account for inversion method and prior assumptions when comparing with activity-based emissions.

Questions: How can we compare and benchmark atmospheric based emissions to activity based gridded inventories? Which methane emission sectors and location have significant uncertainty? Are emissions changing?

General description of how atmospheric data are used to infer emissions



Inversion and Sectoral Attribution Steps

1) Use optimal estimation to Invert GOSAT XCH4 data to obtain fluxes (Zhang et al. 2022; Qu et al. in review)
Priors and state vector for Inversion:
Wetlands (month, region) (from Bloom et al. 2017)
Anthropogenic Fluxes (yearly from 2010 to 2022, 5x4 degrees)

- Includes Updated fossil emissions based on reports to UNFCCC (Scarpelli et al. 2022)
- Edgar 4.3 for all other emissions

OH Lifetime (year)

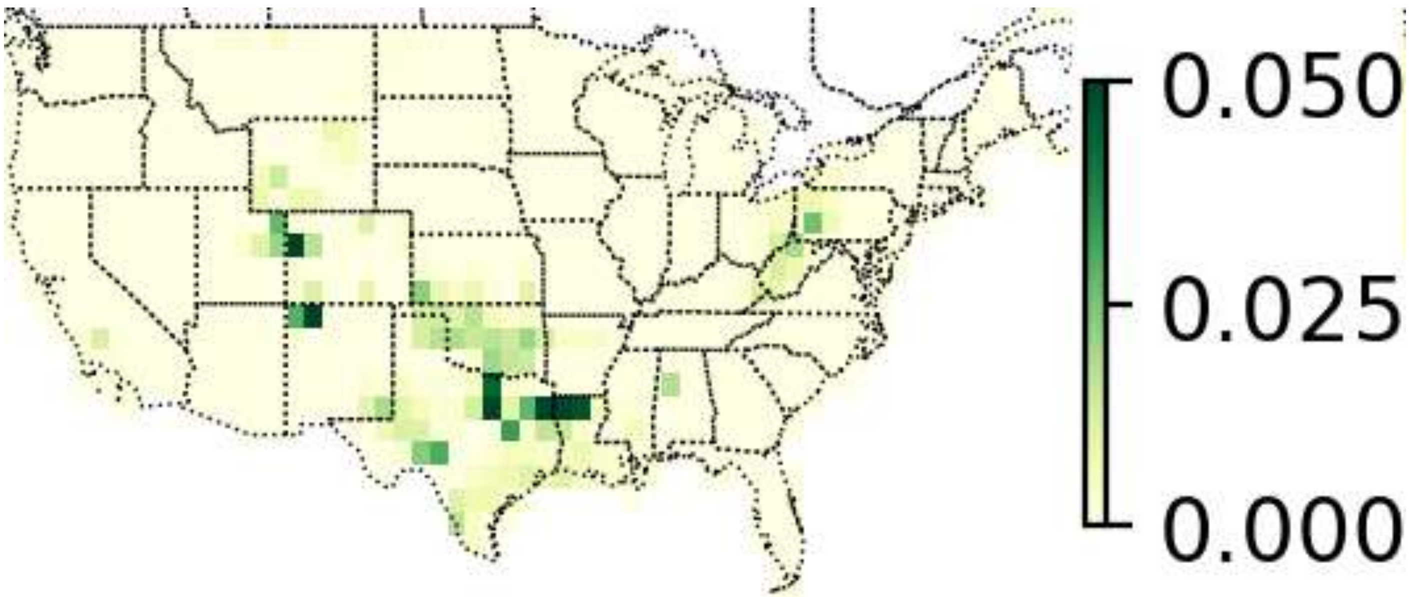
2) Bayesian projection of Anthropogenic fluxes at 5x4 degree to emissions by sector at one degree (Cusworth et al. 2021; Worden et al. 2022,2023)

State vector: Livestock, waste, rice, and fires (1x1 degree, annual, EDGAR 5.0), coal, oil, gas (1x1 degree, annual, UNFCCC reports for 2016; Scarpelli et al. 2020)

Bayesian / Optimal Estimation approach provides the covariances, averaging kernels, and ancillary data such as the priors needed to account for variable information content for the purpose of inventories to satellite based estimates

Averaging Kernel describes where observing system does and does not have information

Diagonal of Averaging Kernel Matrix for oil + gas + coal emissions
DOFS ~1.6 means GOSAT data can constrain total emissions + some spatial information



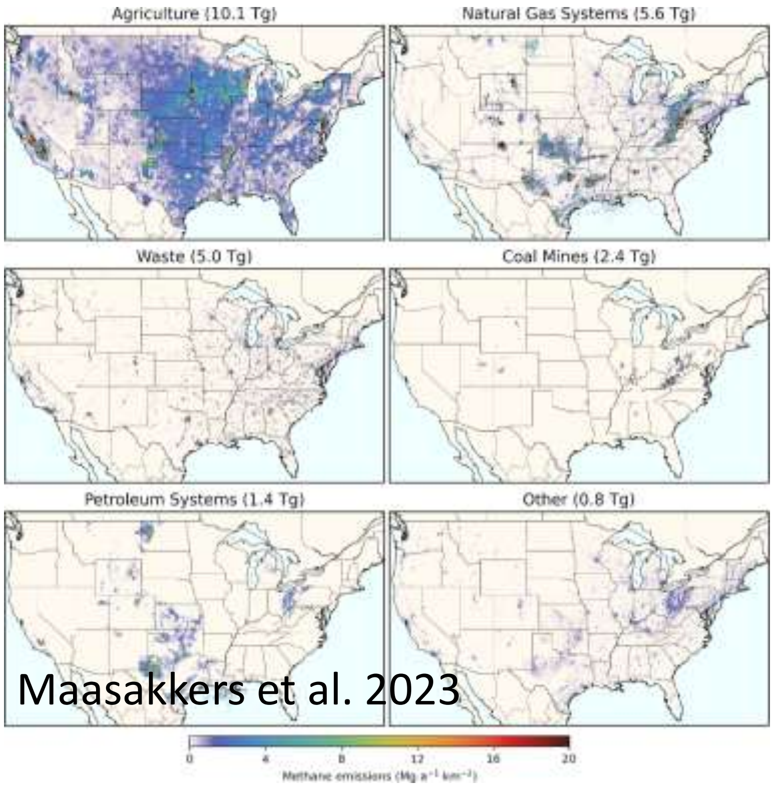
The averaging kernel matrix is used to construct the “Inversion Operator”: needed to account for variable information content (prior uncertainties, and sensitivity of observing system to emissions)

$$\hat{\mathbf{z}} = \mathbf{z}_A + \mathbf{A}(\mathbf{z} - \mathbf{z}_A)$$

The estimate depends on the “true emissions” projected through the prior and averaging kernel (+ uncertainties)

If A ~ 0 (no sensitivity) then the estimate reflects the prior
If A ~ I (perfect system) than the estimate reflects the true emissions

How to compare GOSAT based emissions to gridded inventory?



Maasakkers et al. 2023

Step 1: Integrate inventory (typically at 0.1x0.1 degree) to emissions at 1x1 degree degrees

Step 2: Project inventory through inversion (or observation) operator to remove effect of prior and account for observing system sensitivity and inversion constraints

$$\hat{\mathbf{z}}_i = \mathbf{z}_{\mathrm{A}} + \mathbf{A}(\mathbf{z}_i - \mathbf{z}_A)$$

- Project inventory through inversion operator

$$\hat{\mathbf{z}} - \hat{\mathbf{z}}_i = \mathbf{A}\boldsymbol{\delta}_i + \mathbf{G}\mathbf{n} + \boldsymbol{\delta}_{\mathbf{m}}$$

- Subtract adjusted inventory from estimate to remove effect of a priori on comparison

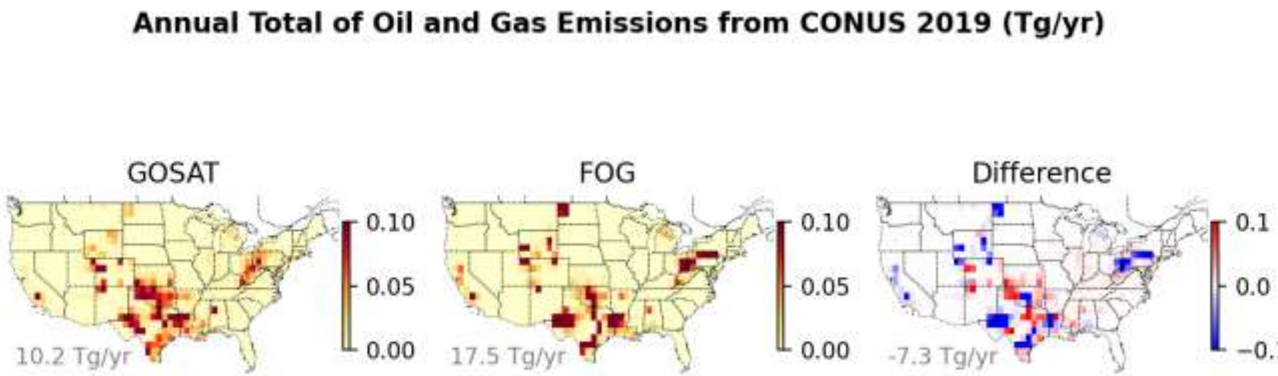
$$E||\hat{\mathbf{z}} - \hat{\mathbf{z}}_i|| = \mathbf{A}\mathbf{S}_{\mathbf{i}}\mathbf{A}^{\mathbf{T}} + \mathbf{S}_{\mathbf{n}} + \mathbf{S}_{\mathbf{m}}$$

- Uncertainties now depend on inventory, measurement, and model error

$$\mathbf{S}_{\mathbf{i}} + \mathbf{S}_{\mathbf{n}} + \mathbf{S}_{\mathbf{m}} + (\mathbf{I}\text{-}\mathbf{A})\mathbf{S}_{\mathbf{A}}(\mathbf{I}\text{-}\mathbf{A})^{\mathbf{T}}$$

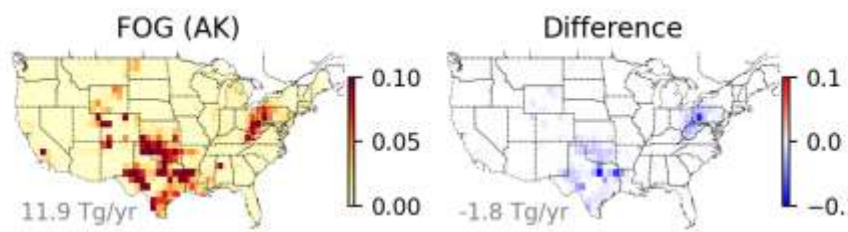
- Uncertainties without first projecting inventory through inversion operator are much much larger

Comparison of GOSAT Based Fossil Emissions to NOAA FOG emissions with and without inversion operator



No Use of Observation Operator

$$\boldsymbol{Uncertainties} \sim \mathbf{S_i} + \mathbf{S_n} + \mathbf{S_m} + \mathbf{(I\text{-}A)S_A(I\text{-}A)^T}$$

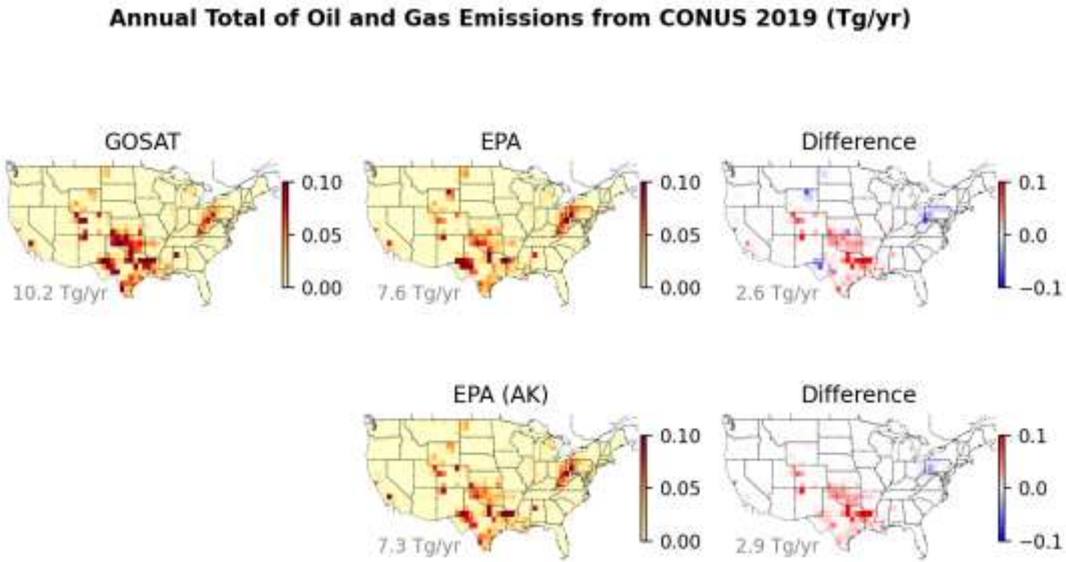


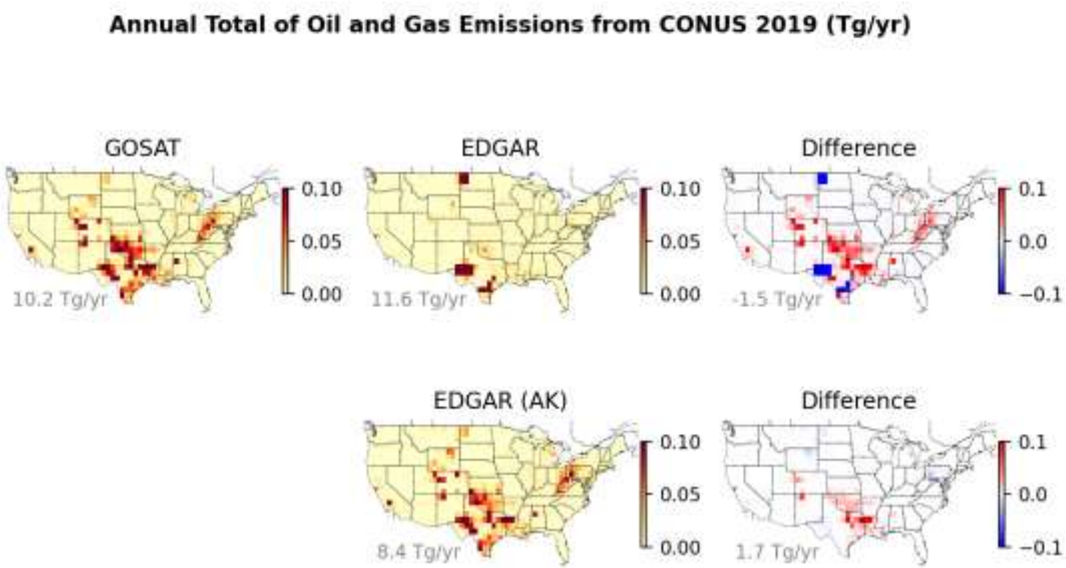
Observation Operator Applied

$$\boldsymbol{Uncertainties} \sim \mathbf{S_n} + \mathbf{S_m} + \mathbf{AS_iA^T}$$

FOG inventories are based on aircraft data involving multiple tracers (measured CH_4/NOx + bottom-up NOx)
(Francoeur et al. 2021; *Environmental Science & Technology)*

Comparison of GOSAT Based Gas Emissions to EPA and EDGAR emissions with and without inversion operator



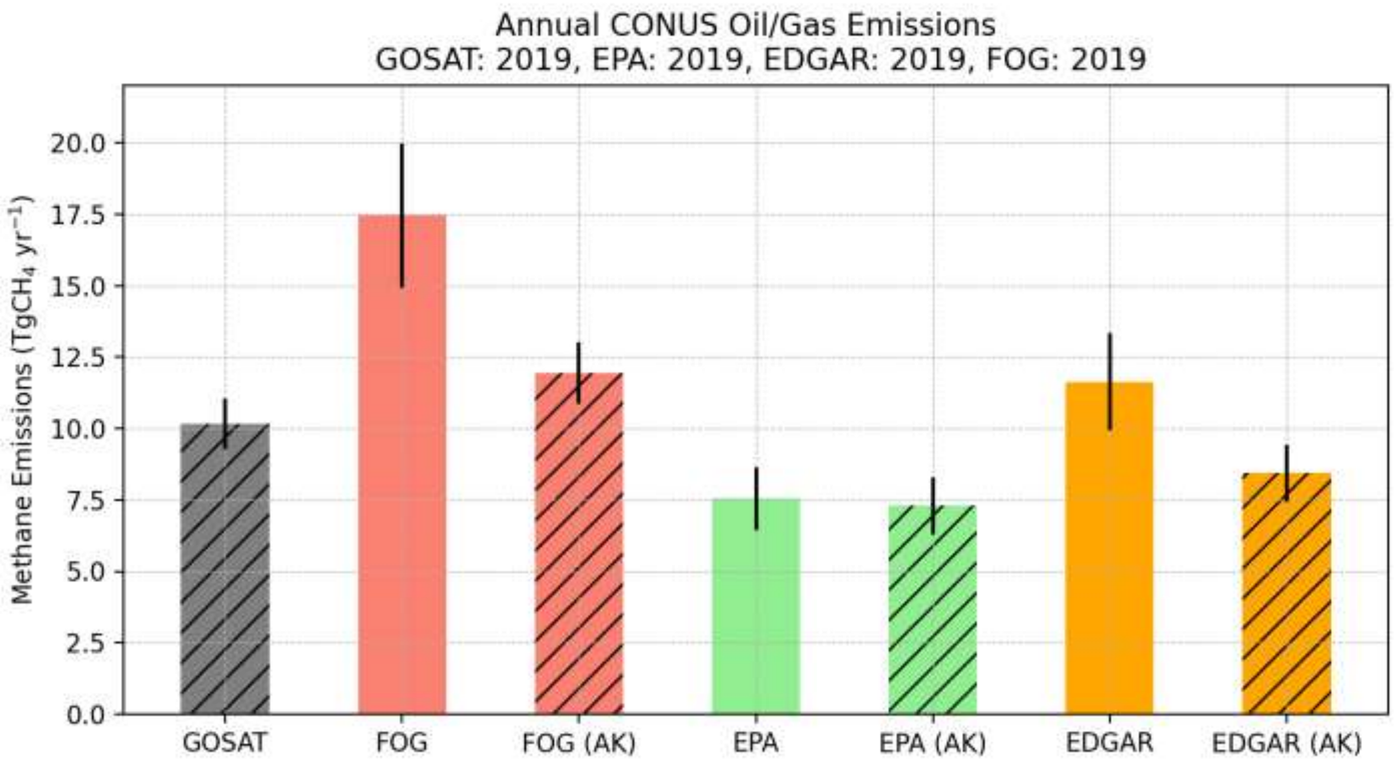


Largest differences in Oklahoma, Texas, and Louisiana, even after applying inversion operator

Good agreement in Appalachian region

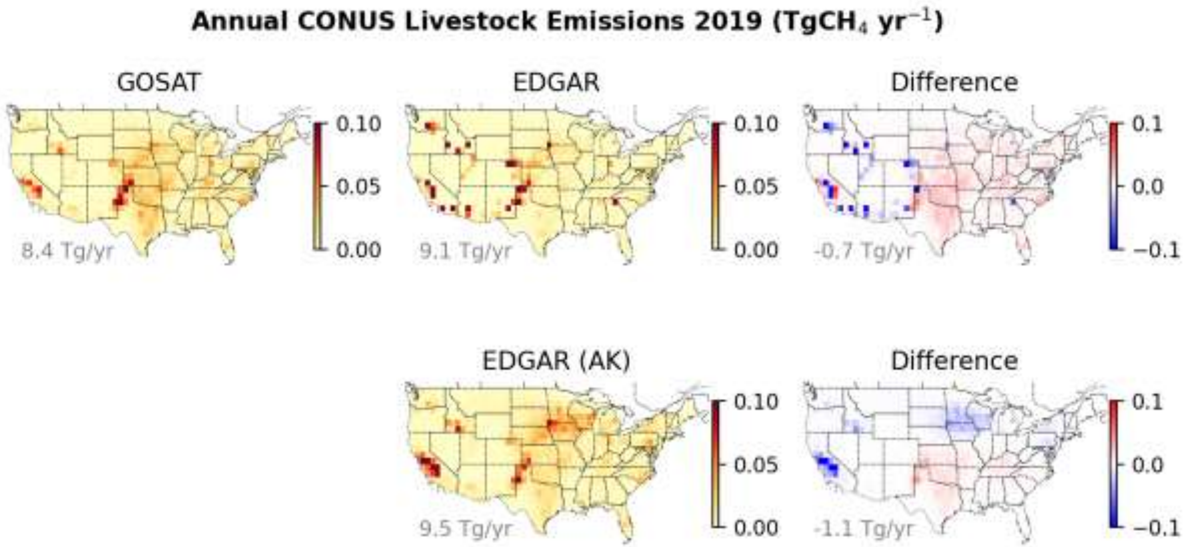
No sensitivity to Bakken emissions (N. Dakota)

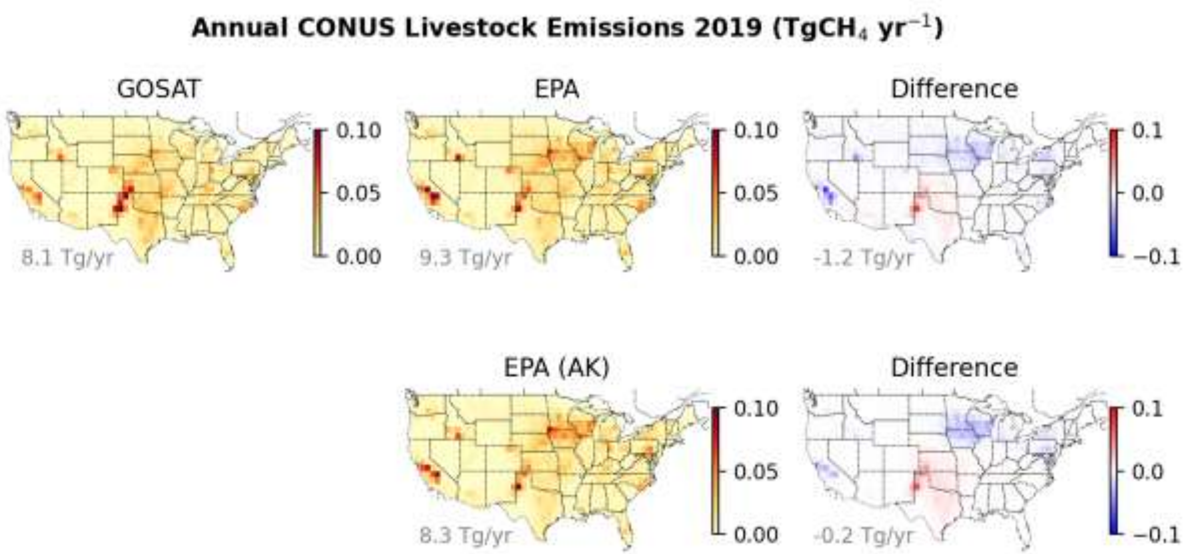
Comparison of GOSAT based fossil emissions with NOAA FOG, EPA, and EDGAR



GOSAT fossil emissions estimates agree best with FOG (atmospheric/activity based inventory) and are inconsistent with EPA (activity based) inventories.

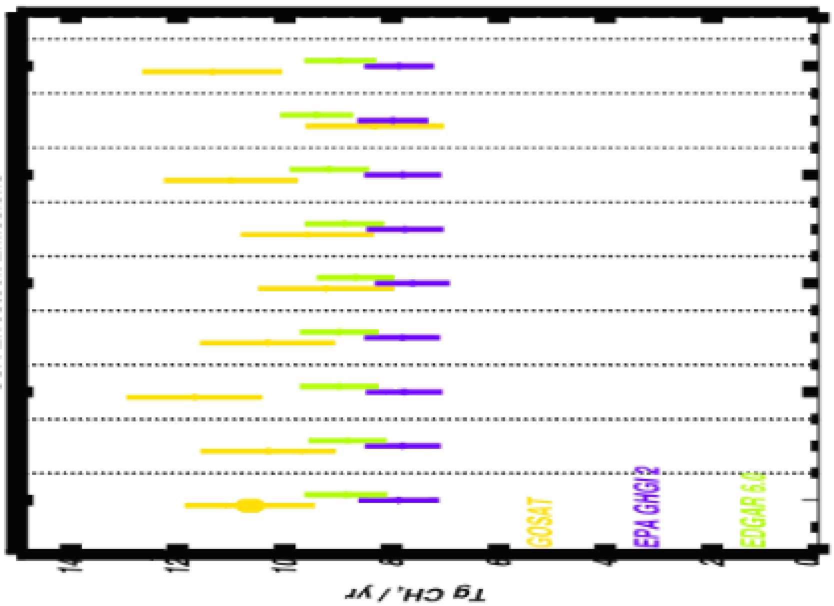
Differences point toward unresolved spurious emissions as a large fraction of the total fosil emissions, consistent with previous results (e.g. Alvarez et al. 2018, Cusworth et al. 2022)

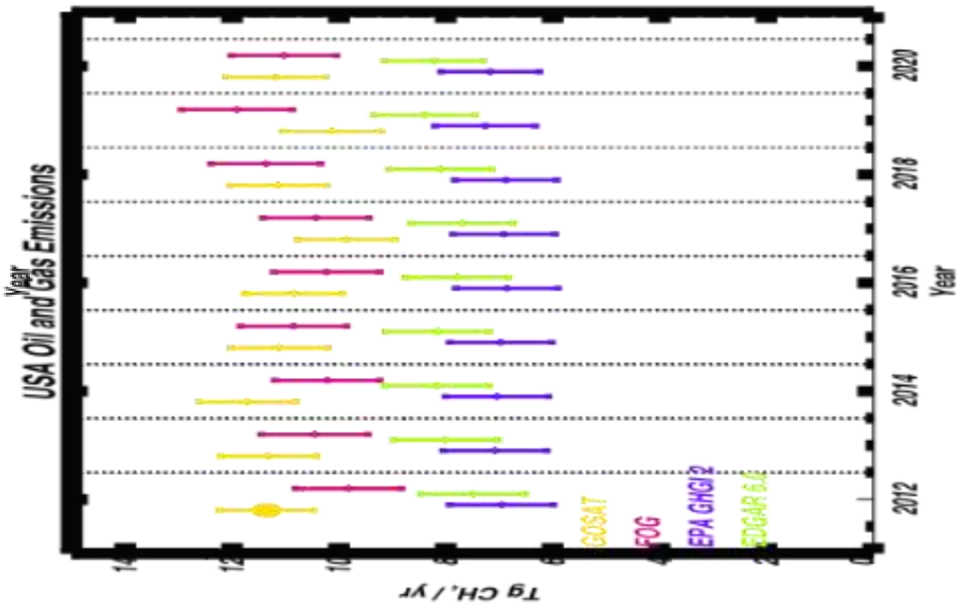




Both EDGAR and EPA livestock emissions show positive biases in the South and negative biases in North and California

Are there any changes in livestock and oil&gas emissions between 2012 and 2020?





We observe no significant change in emissions between 2012 and 2010 for GOSAT, FOG, EPA, and EDGAR estimates of Oil&Gas and Livestock emissions.

Summary

Benchmarking activity-based emissions with atmospheric data requires accounting for the variable information content of satellite observations, which differs by region and emission source.

GOSAT-based estimates for oil and gas align (within uncertainty) with the NOAA-FOG hybrid inventory but diverge from EPA and EDGAR inventories, particularly in Oklahoma, Texas, and Louisiana—highlighting key regions where additional measurements could most reduce uncertainty.

Livestock emissions from activity data appear lower than those inferred from GOSAT; regional differences suggest that environmental factors influence emission ratios relating #livestock to methane emissions.

Neither oil & gas nor livestock emissions show clear trends from 2010 to 2018 across datasets.

Next Steps:
Information content for newer TROPOMI based emissions is much much larger than GOSAT based estimates (~**770 versus ~5 DOFS for USA anthropogenic emissions**, Nesser et al. ACP 2024). (He et al. submitted 2025, East et al. in preparation)