Motivation and research questions

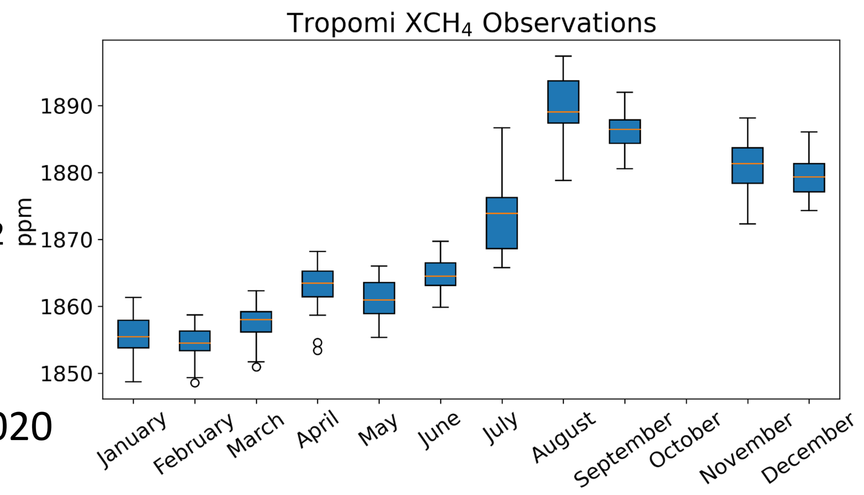
Despite various efforts to reduce methane emissions, their global levels have continued to rise in recent years, and the exact causes of the increase are not very well understood. The scarceness of surface network of observation stations make it very challenging to estimate the methane fluxes, especially for regions like Indian subcontinent. The major objectives for this study is as follows:

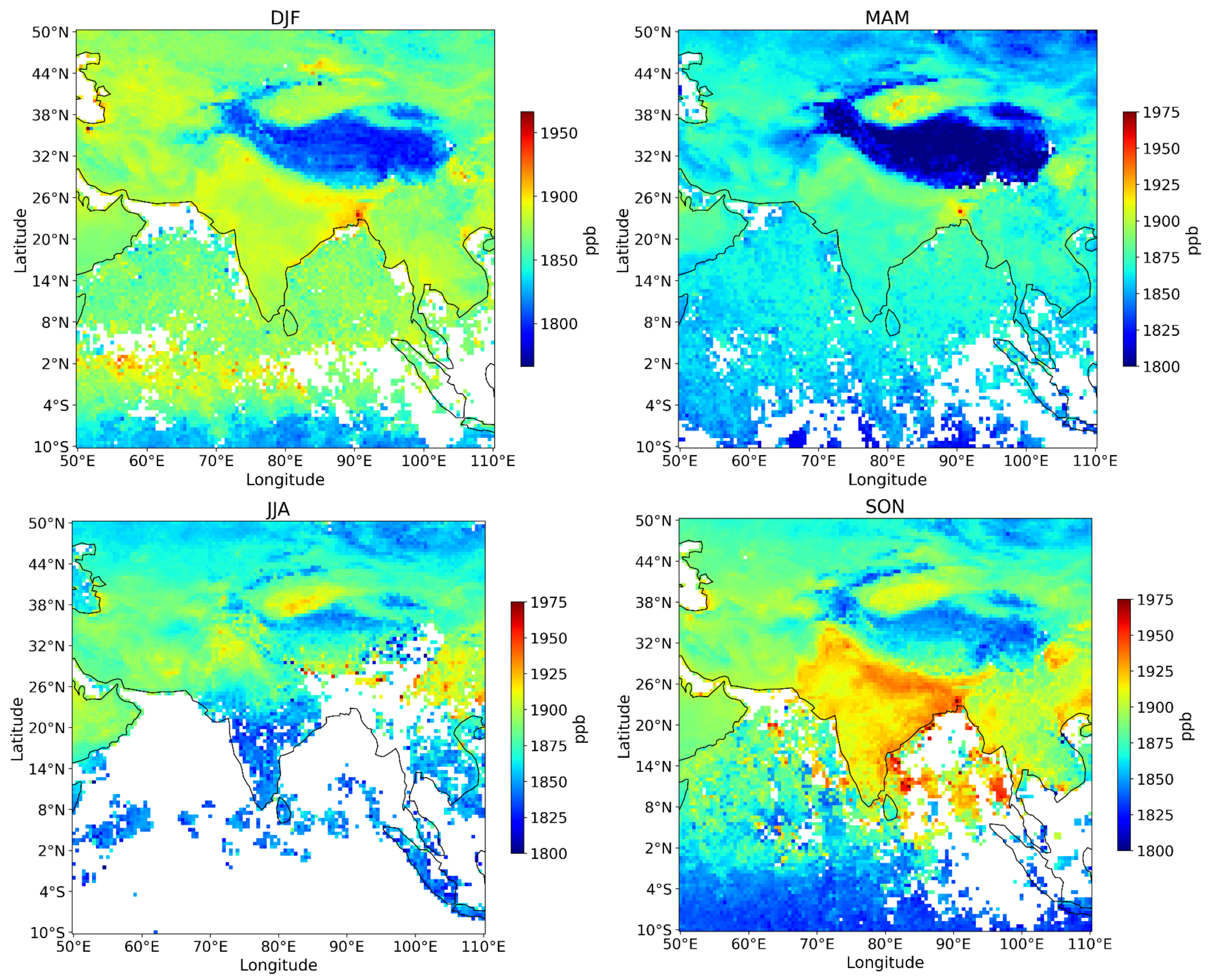
1. Use the high resolution, wide-area observations from the Tropomi instrument to study the CH_4 distribution over Indian subcontinent.
2. Estimate the enhancements in CH_4 concentrations due to emissions.
3. Quantify the CH_4 fluxes and the concentrations through inverse modeling using the constraint provided by the Tropomi column observations.

Tropomi Column Observations[1]

- Orbiting in a low-earth sun synchronous polar orbit with a swath of 2600 km.
- Gives a daily global coverage at a spatial resolution of 7x7 km²

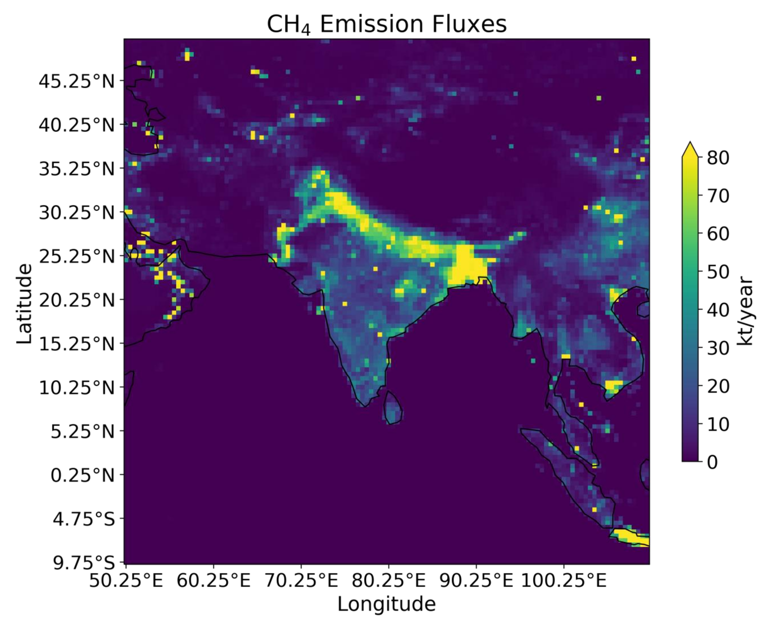
Bottom fig. shows the seasonal mean XCH_4 concentrations for 2020

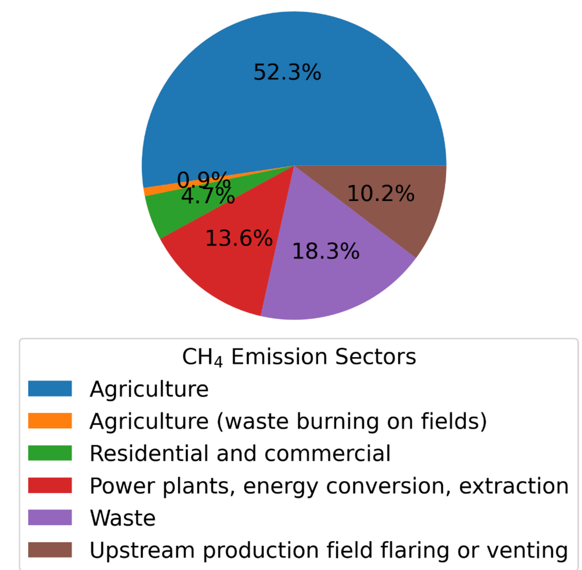




Prior Methane Emissions

The a-priori emissions of methane fluxes are taken from Eclipse Inventory of IIASA available at a resolution of 0.5x0.5 degrees.





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Using Satellite Column Observations Towards Constraining the GHG Budget over India

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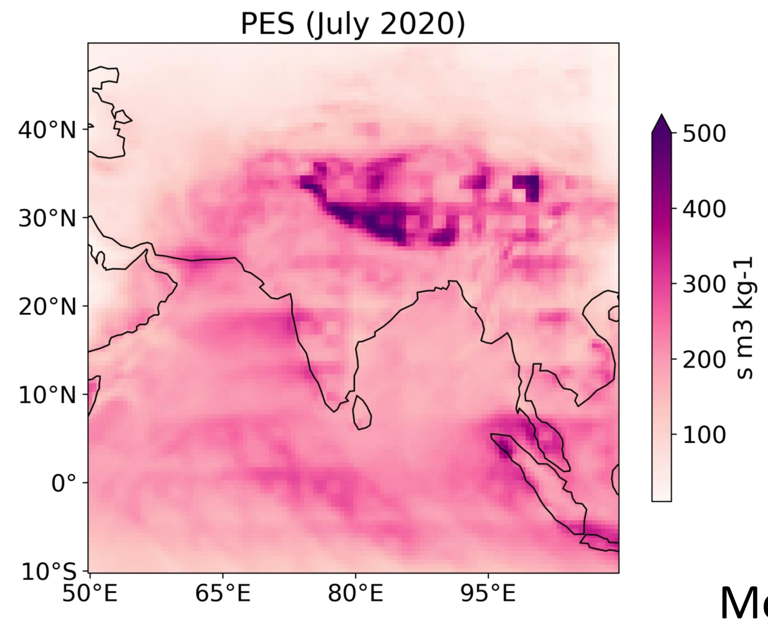
Methodology

Lagrangian model: Flexpart[2]

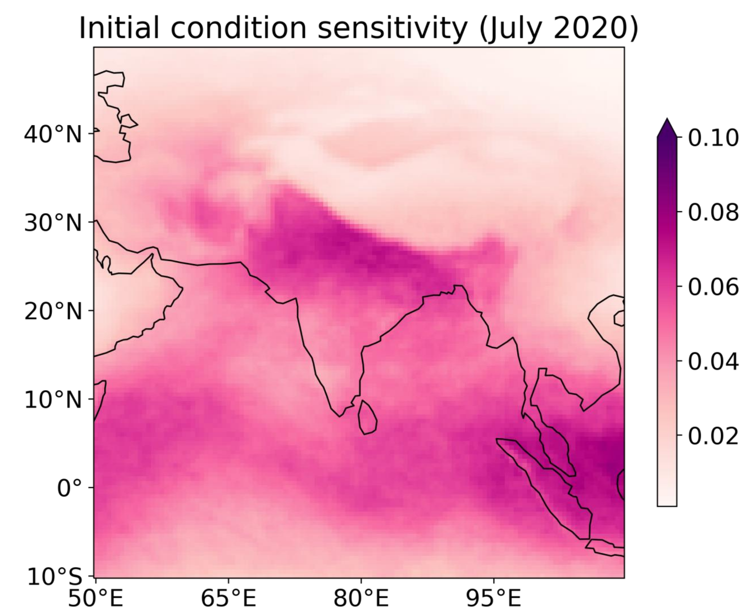
- Meteorology from ERA5 at 0.5 degree resolution
- Number of particles released: 10,000 (linearly decreases with height)
- Traced backward for 4 days

Computes:

- Potential Emission Sensitivity[3] (H)



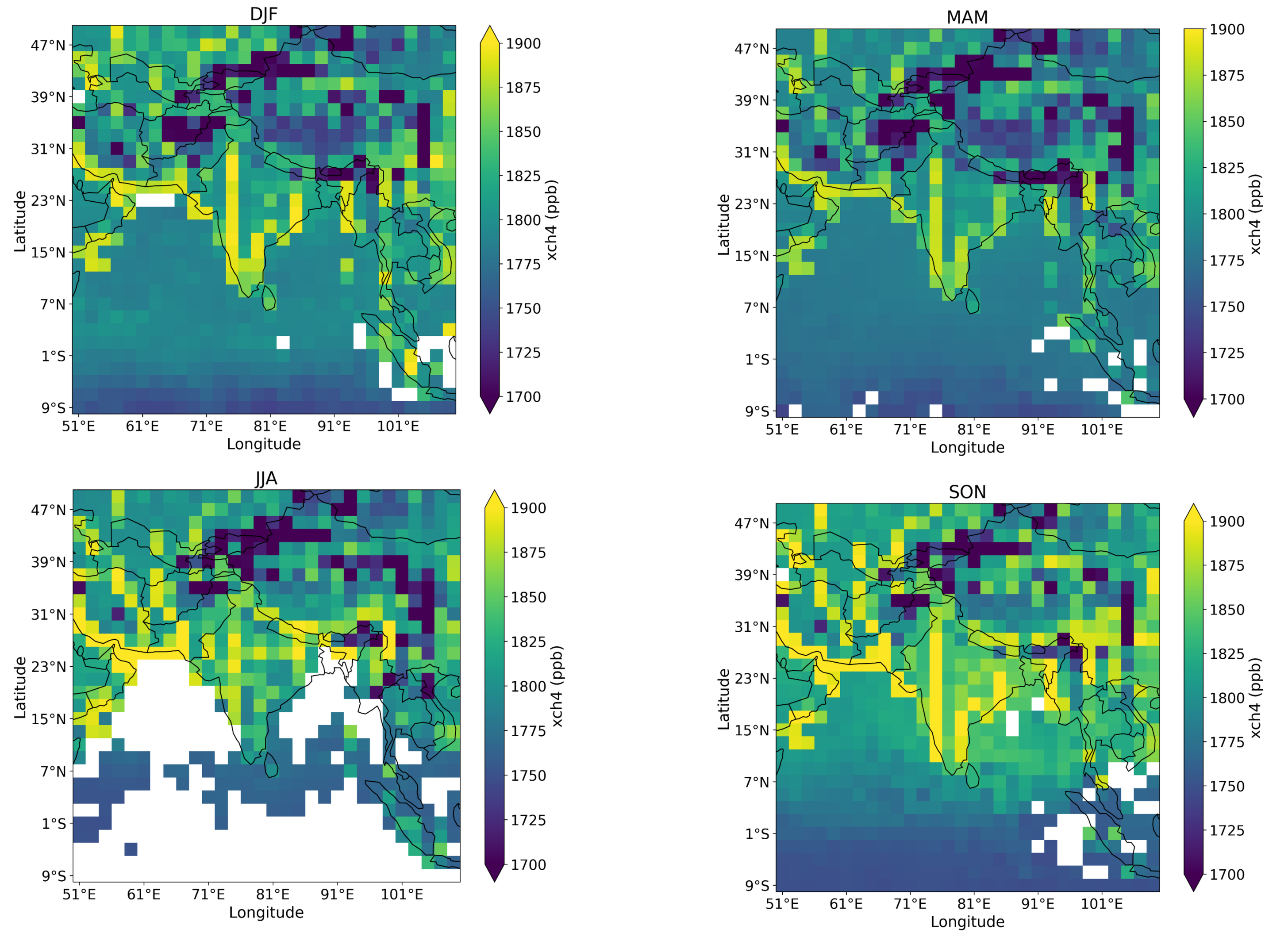
- Initial Condition Sensitivity (H^{ini})



Model Concentration: $y_{model} = \mathbf{H}\mathbf{x}_b + \mathbf{H}^{ini}\mathbf{y}^{ini}$

Background mole fractions(X_{CAMS})

$$X_{cams} = \sum_i^n [X_{apriori} + a_i\,(X_{model\_i} - X_{apriori\_i})]P_i$$



Summary and Remarks

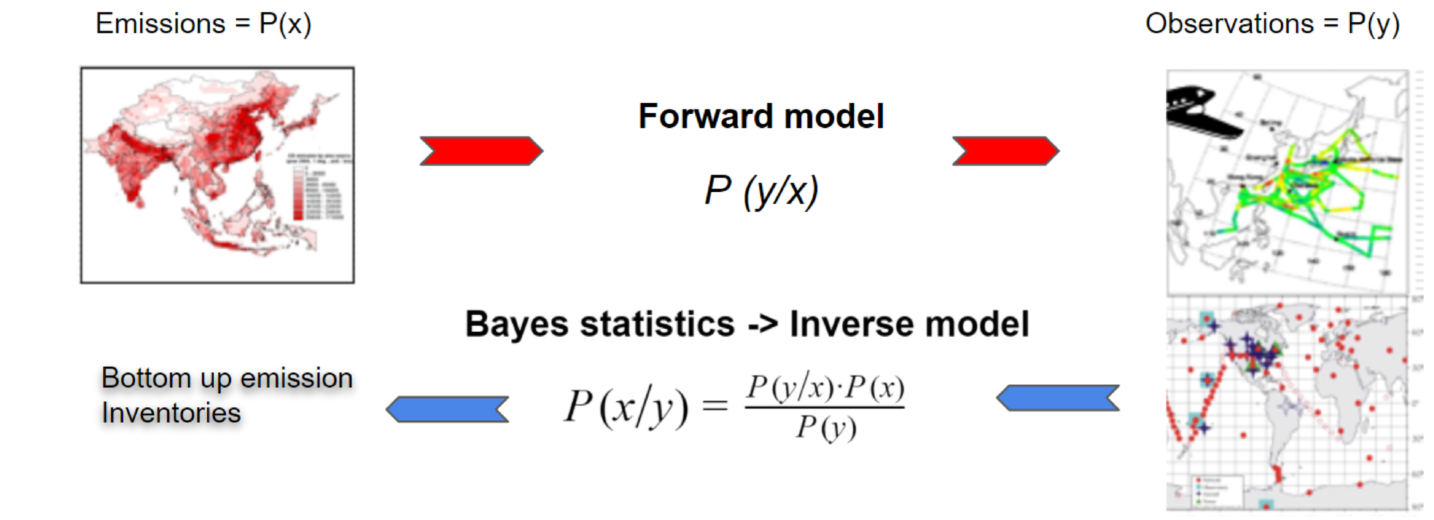
1. CH_4 concentrations are higher over north-eastern and eastern parts of India as seen from the column observations.
2. The methane concentrations are higher towards the post-monsoon and winter seasons
3. Agriculture sector contributes the major source of methane fluxes.
4. The higher CH_4 fluxes over Indo-Gangetic Plain and Bangladesh are primarily due to the rice cultivation[4].
5. The Lagrangian model simulations shows higher sensitivities over the north-eastern parts of India implying the particles reside longer over these area(on July)
6. Column CH_4 mole fractions derived from CAMS(X_{cams}) is biased low on comparison with the Tropomi column mole fractions

Future Work/ Inverse Modeling

Theory

- Bayesian Approach of Inverse Modeling

Assuming normal distribution of emissions and the errors associated, the Bayesian estimate of the true state is the one that maximizes the posterior probability.



$$P(x/y) = \frac{P(y/x)\cdot P(x)}{P(y)}$$

Cost function[5]

- $J(x) = (x - x_b)^T B^{-1} (x - x_b) + (y_o - Hx)^T R^{-1} (y_o - Hx)$

Posterior

- $x_a = x_b + (B^{-1} + H^T R^{-1} H)^{-1} H^T R^{-1} (y_0 - y)$

For Satellites

- $v^{avg} = v^{pri,avg} + \sum_{i=1}^n a_i\,(v_i^{mod} - v_i^{pri})$
- $v^{avg} = v^{pri,avg} - \sum_{i=1}^n a_i v_i^{pri} + H^{col} f + H^{ini,col}\, y^{ini}$

v^{avg} is the total column concentration
$v^{pri,avg}$ is the prior concentration
a_i is the averaging kernel at layer i
v_i^{mod} is the model concentration at layer i
v_i^{pri} is the prior concentration at layer i
n is the number of layers
H^{col} is the sensitivity to fluxes
$H^{ini,col}$ is the sensitivity to background
y^{ini} is the background concentration

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