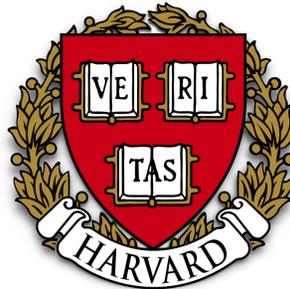


# Reconciling satellite and in-situ estimates of North American methane emissions during the unconventional gas boom of 2009–2012

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**Joshua Benmergui**

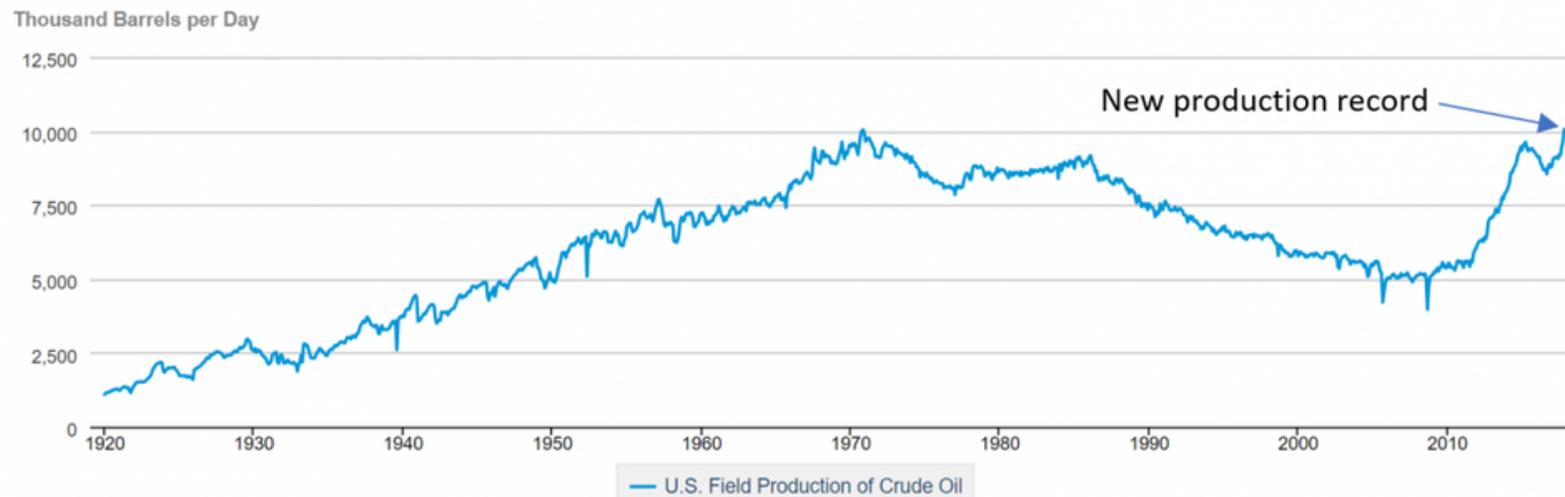
John A. Paulson School of Engineering and Applied Sciences  
Harvard University

With Data, Code, and Input from:

Arlyn E. Andrews, Kirk W. Thoning, Michael Trudeau, Anna M. Michalak, Vineet Yadav,  
Scot M. Miller, Edward J. Dlugokencky, Lori Bruhwiler, Kenneth A. Masarie,  
Douglas E.J. Worthy, Colm Sweeney, Marc L. Fischer, Thomas Nehrkorn,  
Marikate E. Mountain, and Steven C. Wofsy

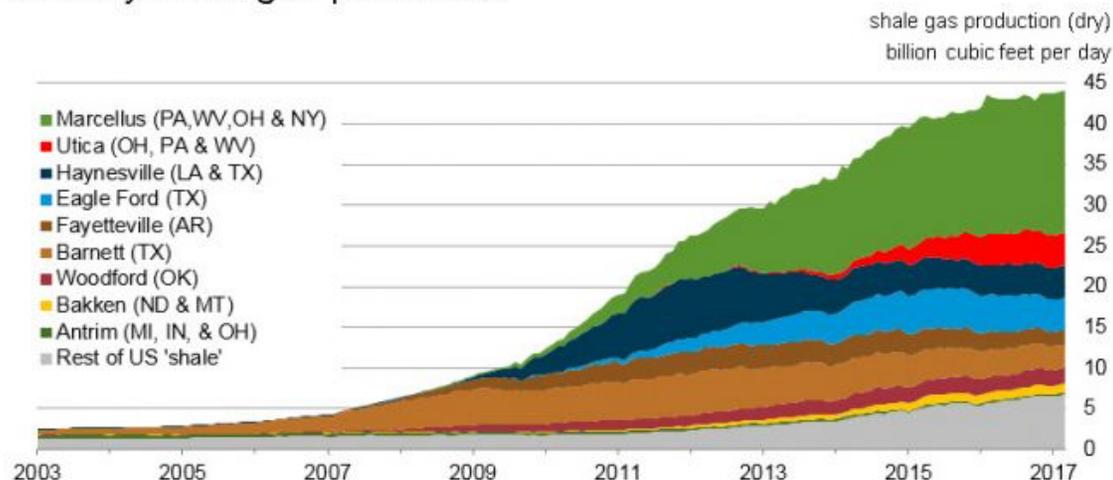
The US experienced the “shale gas revolution” 2007-2015 due to a combination of horizontal drilling and hydraulic fracturing. Was this accompanied by significantly increased methane emissions?

U.S. Field Production of Crude Oil

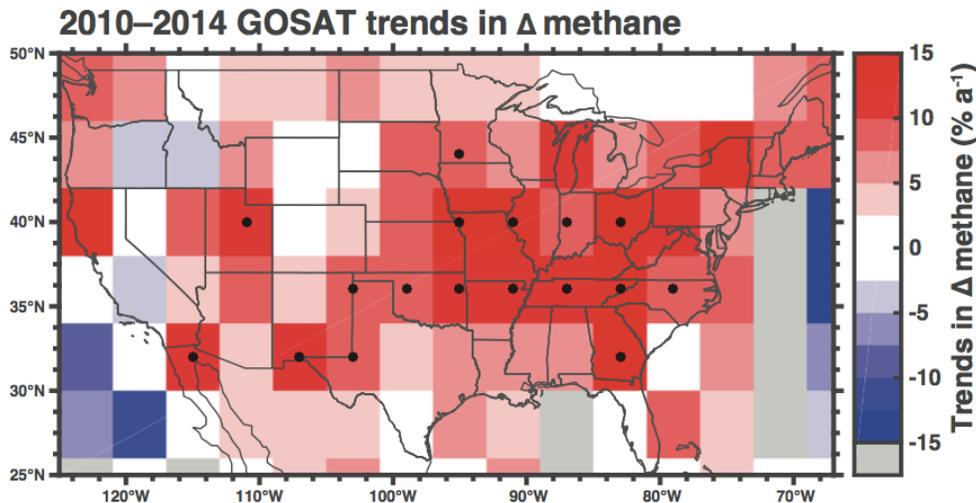
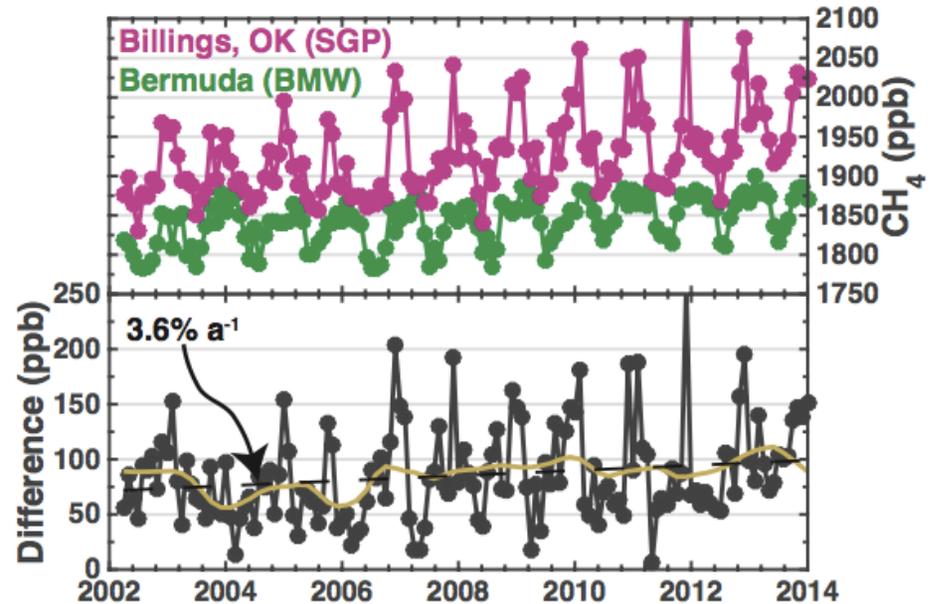
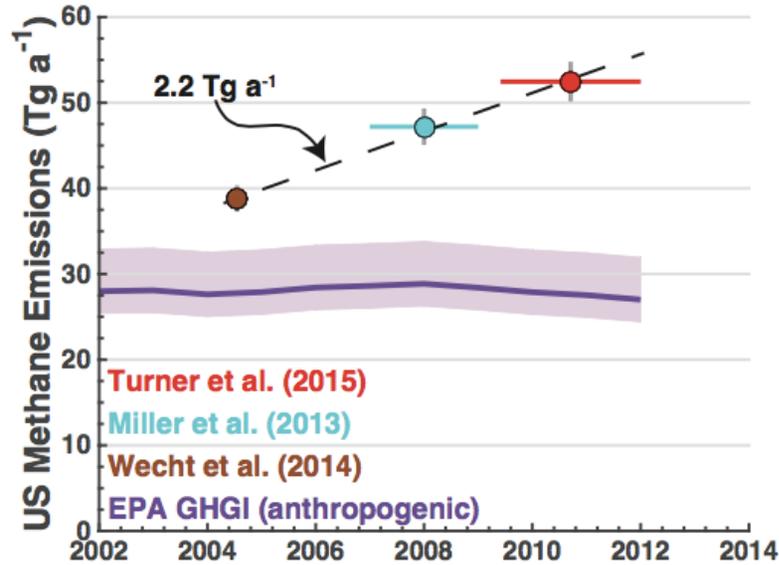


eia Source: U.S. Energy Information Administration

U.S. dry shale gas production



Turner et al. (2016) suggested a 30% increase in US emissions 2004-2014.



If this trend is correct, it would account for 30-60% of the renewed global trend

But Bruhwiler et al., (2017) made several poignant critiques.

In order to carefully assess trends in US methane emissions:

- a consistent inversion framework should be used to compare different periods (and data types).
- boundary conditions should be constructed in a way that avoids aliasing emissions trends.
- The seasonal sampling bias of GOSAT should be considered.

Here, we perform an analysis aimed at satisfying these points.

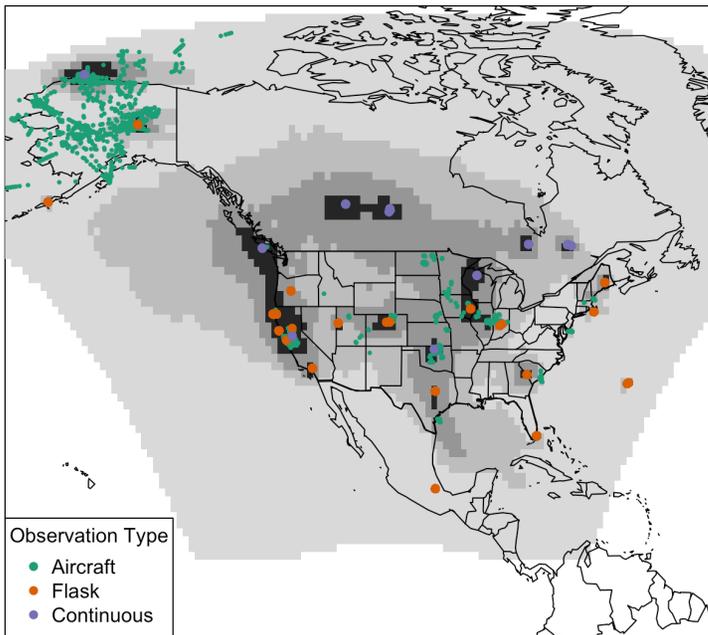
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# We analyzed observations using the CarbonTracker-Lagrange CH<sub>4</sub> inverse modeling system.

- 10 day back trajectories through 10km WRF fields (AER)
- GOSAT influence simulated with 23 levels weighted by pressure, averaging kernel, and water vapour
- Daily resolved geostatistical inverse model

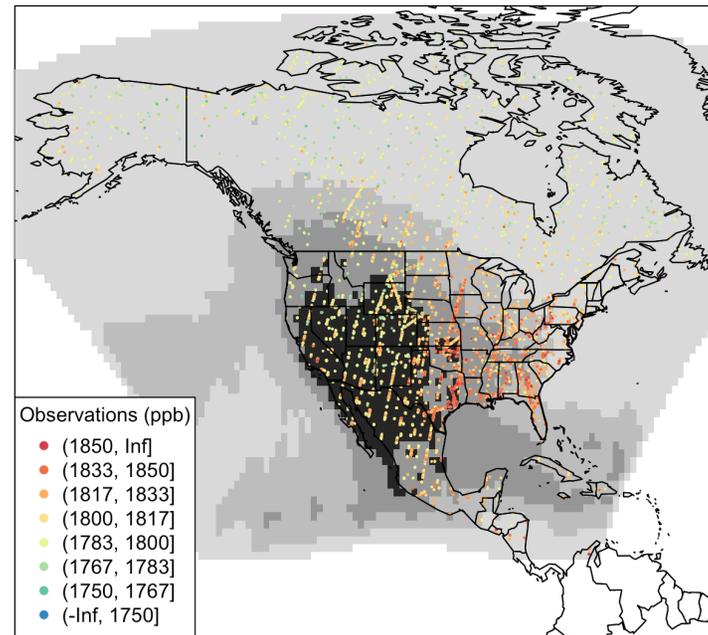
## In-Situ, Flask, Aircraft (NOAA Obspack)



### Surface observations selected:

- 11am - 3pm
- longer time series
- no complex terrain

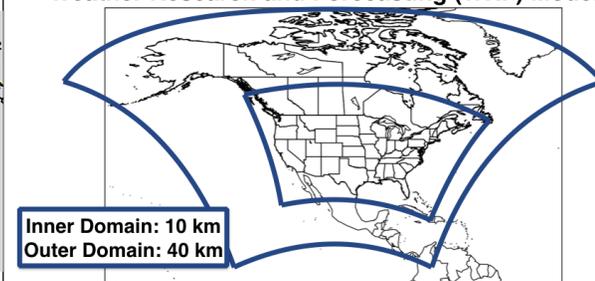
## GOSAT RemoteC Proxy 2.3.7



### GOSAT observations selected:

- Passed all quality flags
- No glint

## Weather Research and Forecasting (WRF) Model



Optimized and run by AER  
Thomas Nehkorn and Marikate Mountain



### Contours Contain X% of Footprint



Our inversion system minimizes the geostatistical cost function:

$$p(\mathbf{s}, \boldsymbol{\beta} | \mathbf{z}) \propto \exp \left[ -\frac{1}{2} (\mathbf{z} - \mathbf{H}\mathbf{s}) \mathbf{R}^{-1} (\mathbf{z} - \mathbf{H}\mathbf{s}) - \frac{1}{2} (\mathbf{s} - \mathbf{X}\boldsymbol{\beta}) \mathbf{Q}^{-1} (\mathbf{s} - \mathbf{X}\boldsymbol{\beta}) \right]$$

observational constraint

prior information

Jacobian

model-data mismatch error covariance

drift coefficients

prior error covariance

observations (background corrected)

emissions state vector

matrix of predictors

(Michalak et al., 2004)

We solve a linear model of prior information.  
This ensures that the prior is not influencing the trend.

We use the L-BFGS-B algorithm to solve the emissions under the constraint that they are non-negative.

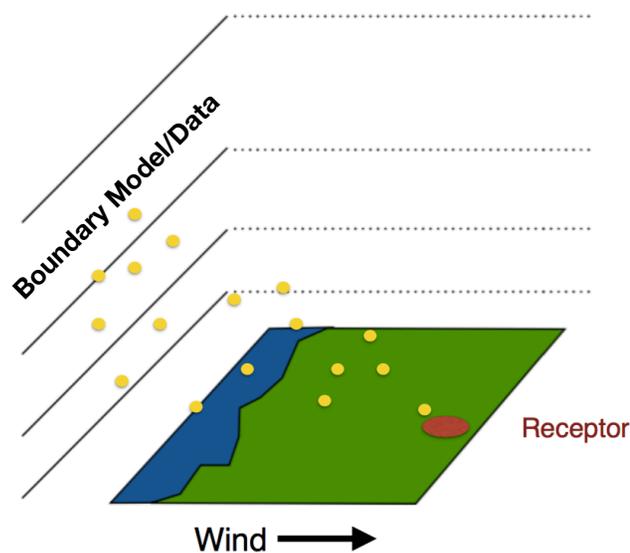
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Background concentrations are usually evaluated in one of the following ways:

## Empirical/model offline model

Use separate data/model at the inversion system boundary

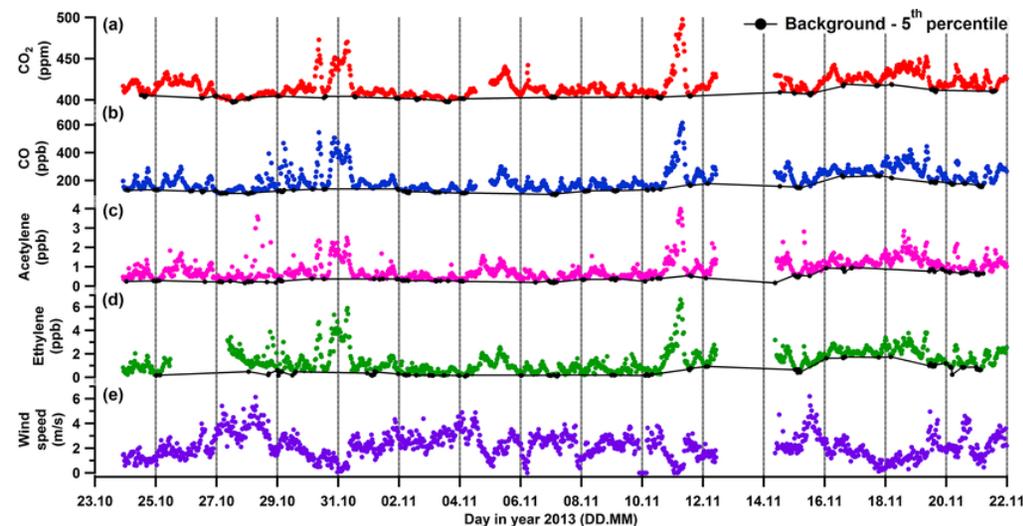


Works great for surface data  
GOSAT mean enhancement for USA is 11ppb  
Stratospheric errors/biases are problematic

## Statistical

Use the clean-air data as background concentrations

Example: Ammoura et al., 2015



GOSAT would need to be binned spatially  
Many regions have no clean air (e.g. Texas)

We created a hybrid method

The background is estimated using a *quantile regression*.

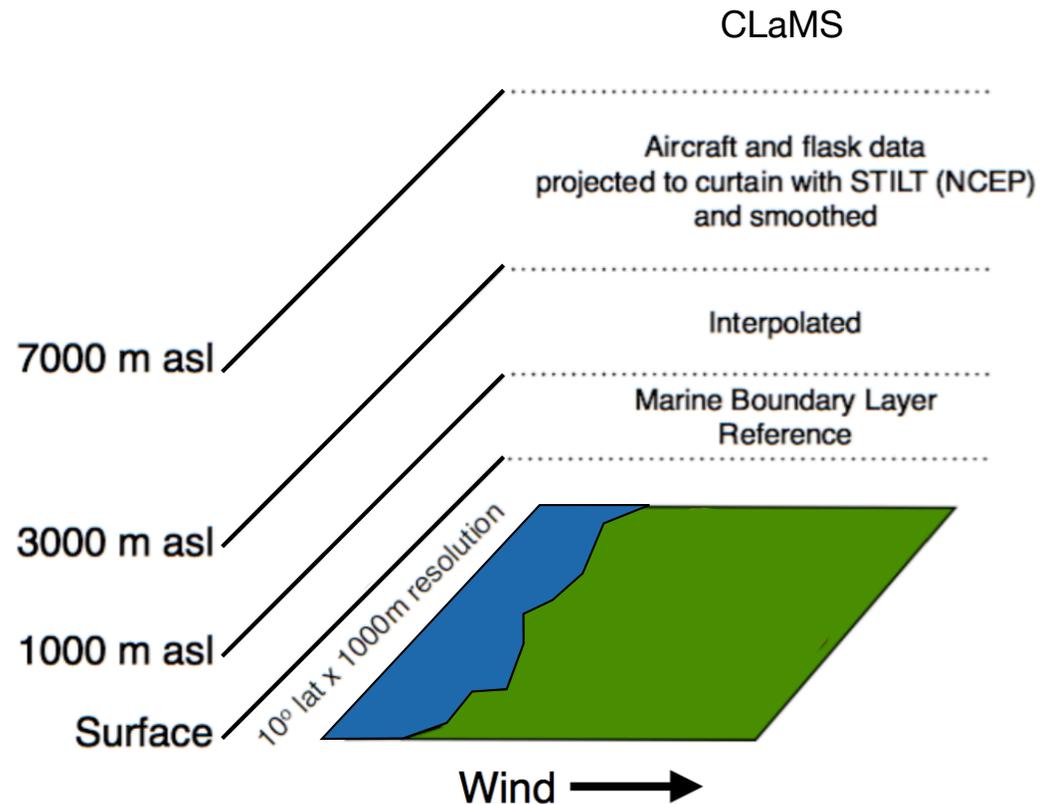
A quantile regression is a linear model of data, but instead of predicting the mean, it predicts a quantile  $q$ .

The quantile regression minimizes:

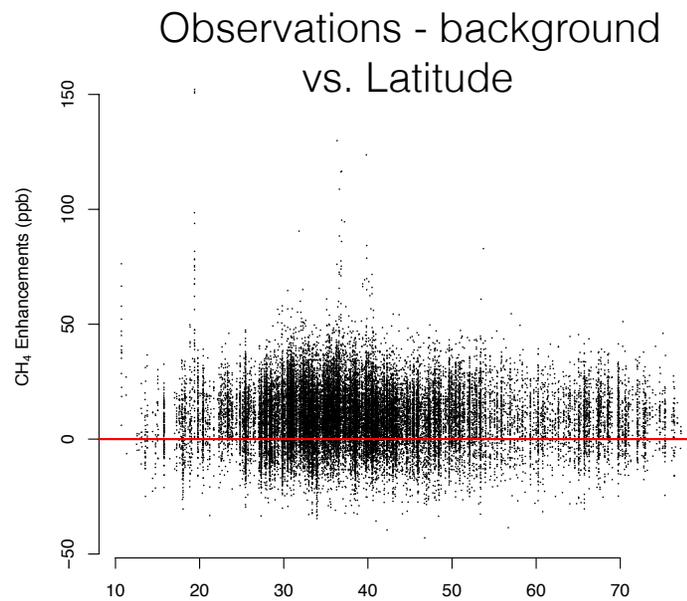
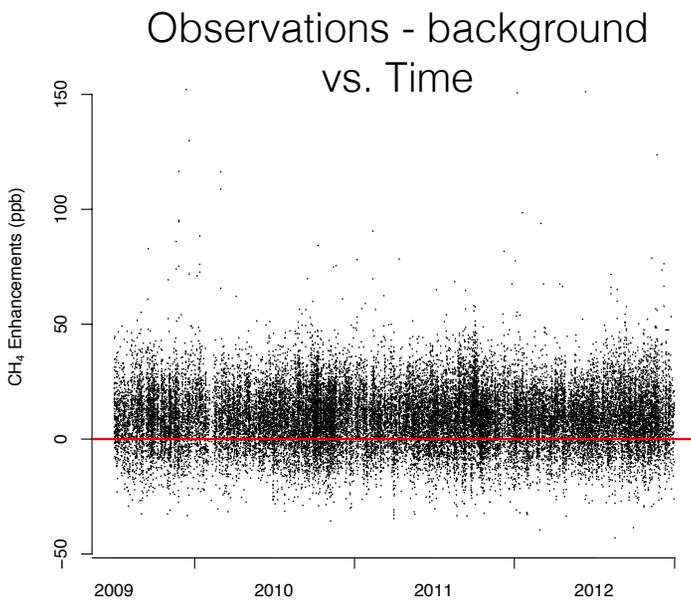
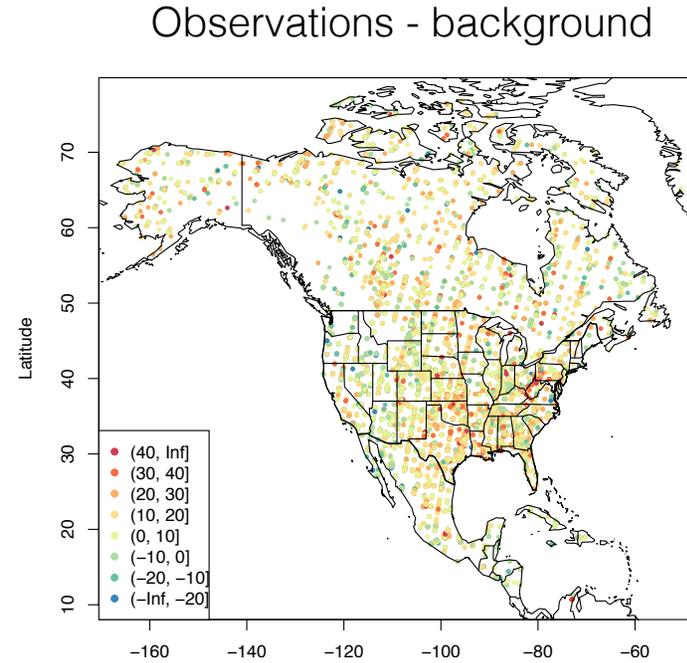
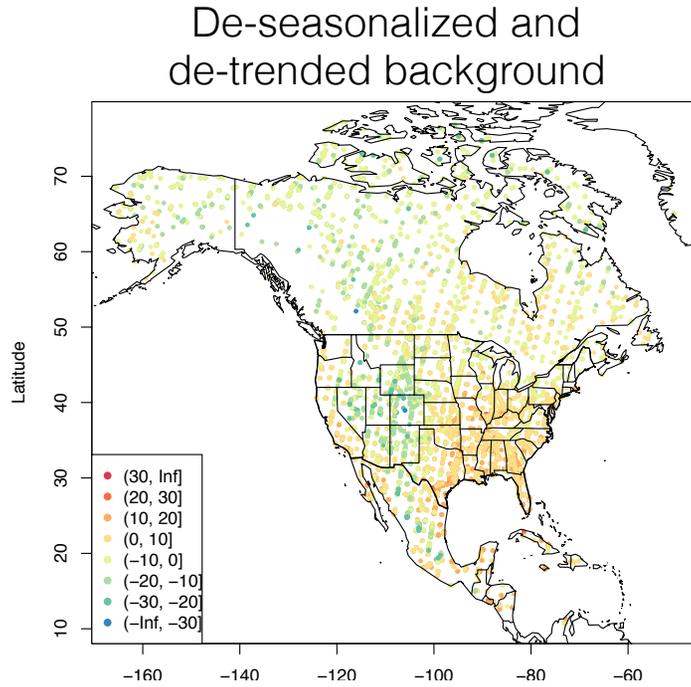
$$Q(\beta_q) = \sum_{i|y_i < x_i\beta} q|y_i - x_i\beta| + \sum_{i|y_i \geq x_i\beta} (1 - q)|y_i - x_i\beta|$$

## Our Variables:

- $x_2$  Stratospheric contribution from CLaMS
- $x_1$  Tropospheric contribution from NOAA Marine Boundary Reference/ Aircraft and Flask
- $x_0$  Intercept



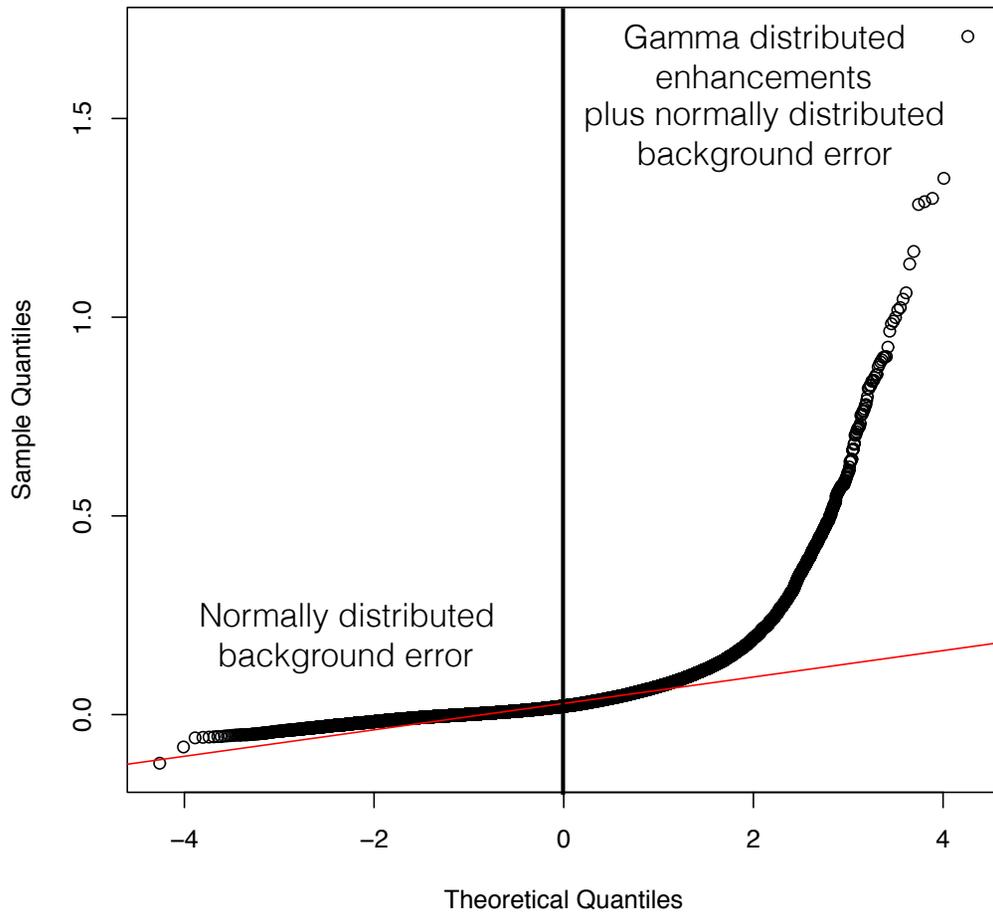
# The quantile regression produces a clear signal, and has good residuals in time and latitude



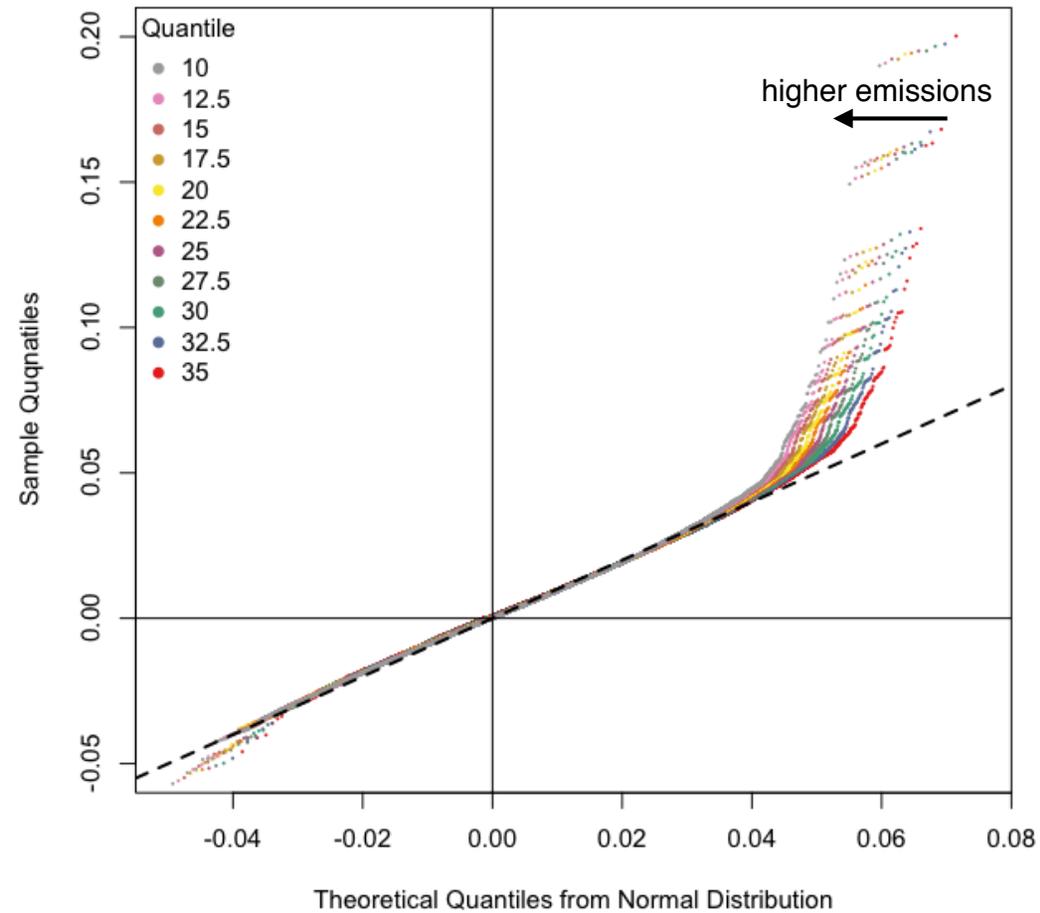
The positive skewness of the distribution of observations gives the strength of the signal.

## Q-Q plots

### Obstack



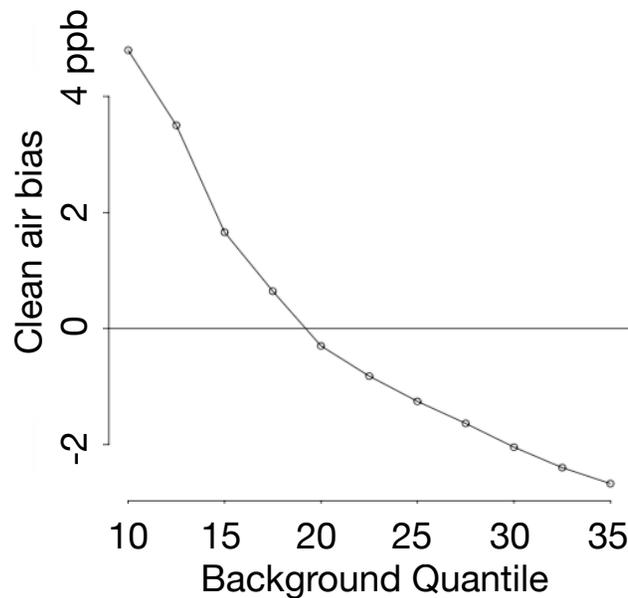
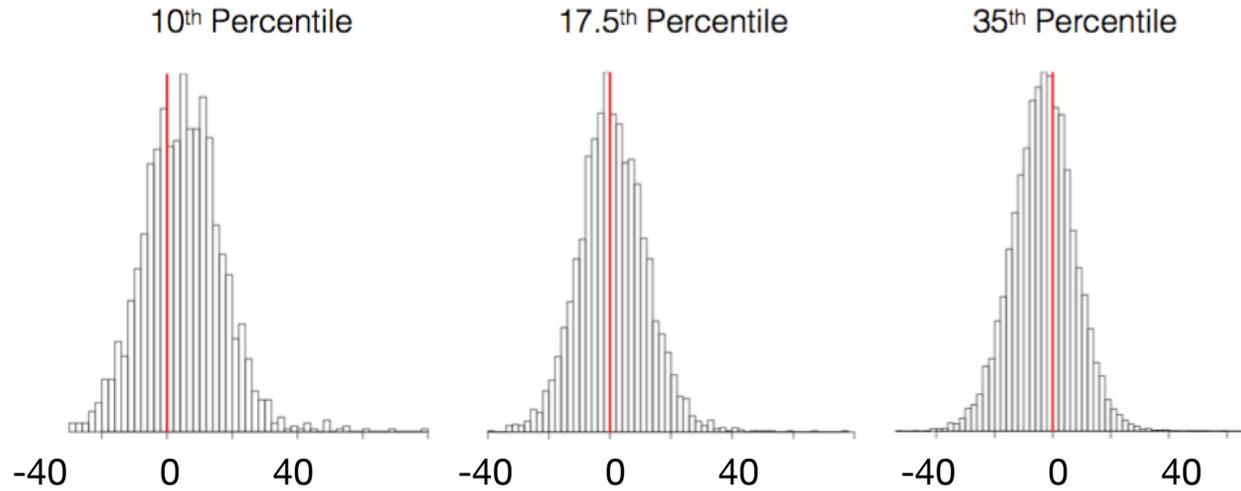
### GOSAT



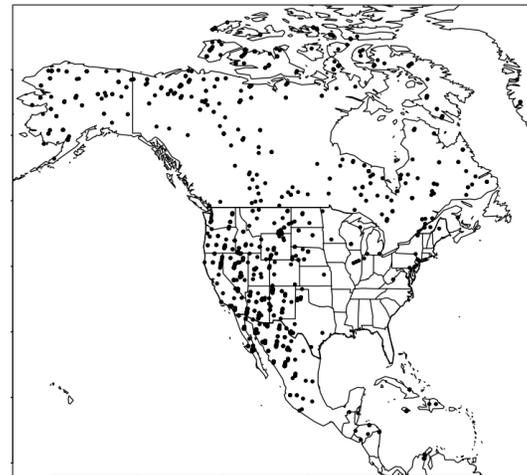
But how do we decide which quantile to use?

# The correct quantile predicts clean air observations without bias

Look at observations with <1.5ppb enhancement.  
Subtract the enhancement and calculate the mean.

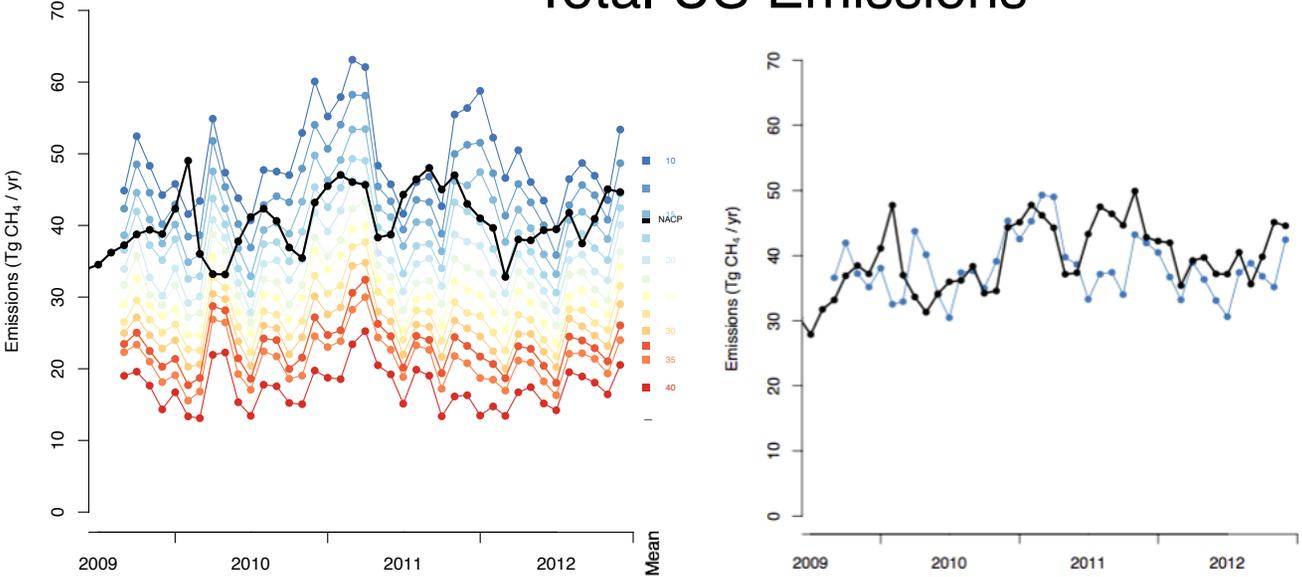


### Clean Air Observations



# We find independent agreement between posterior emissions using GOSAT and Obstack data

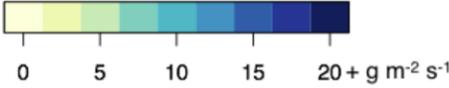
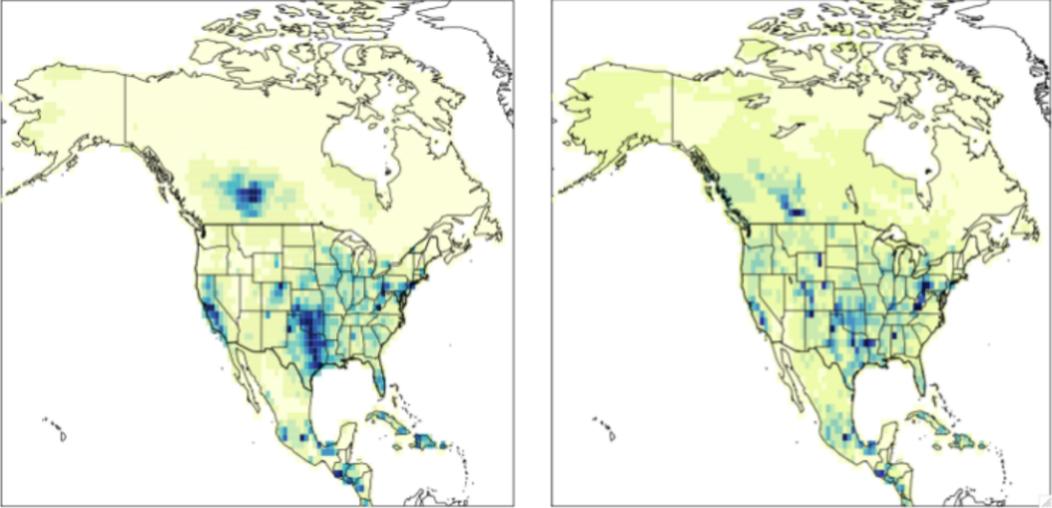
## Total US Emissions



Black: Obstack: 41 ± 2 Tg/yr  
Colors: GOSAT: 40 ± 3 Tg/yr

Obstack

GOSAT



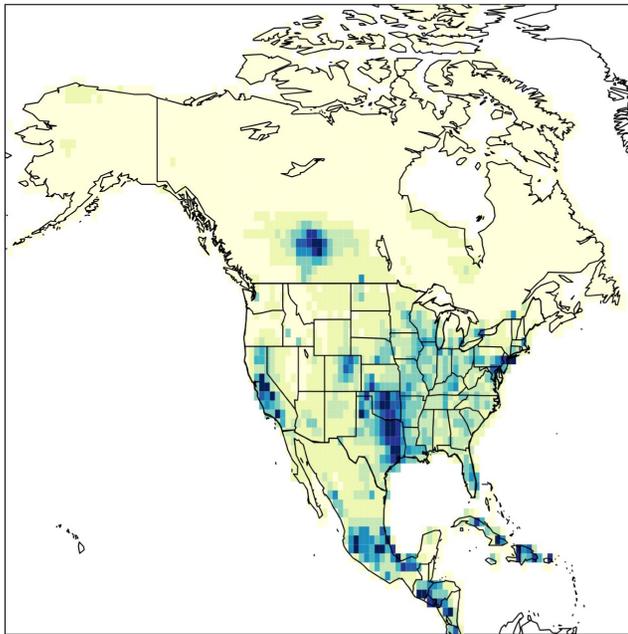
In order to carefully assess trends in US methane emissions:

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# Does the seasonality of GOSAT sampling produce a bias?

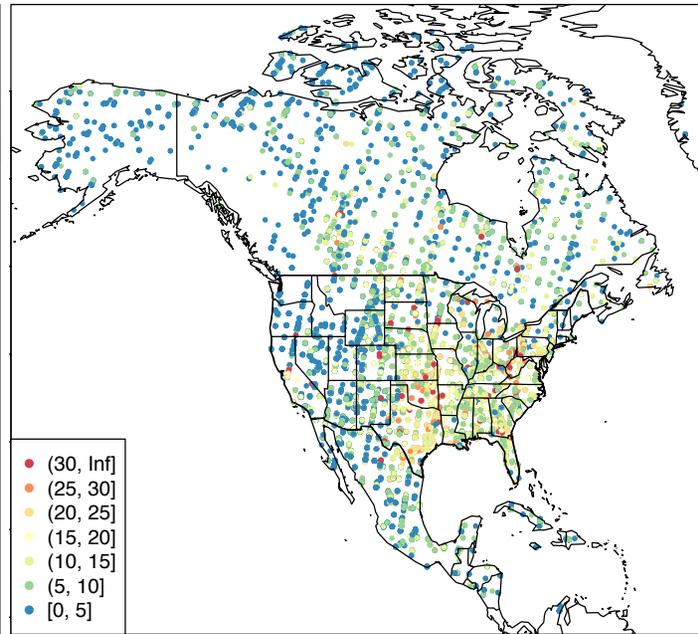
We run an OSSE inversion using the GOSAT footprints, with perfect transport and backgrounds, and target emissions given by the posterior of the NACP inversion.

NACP



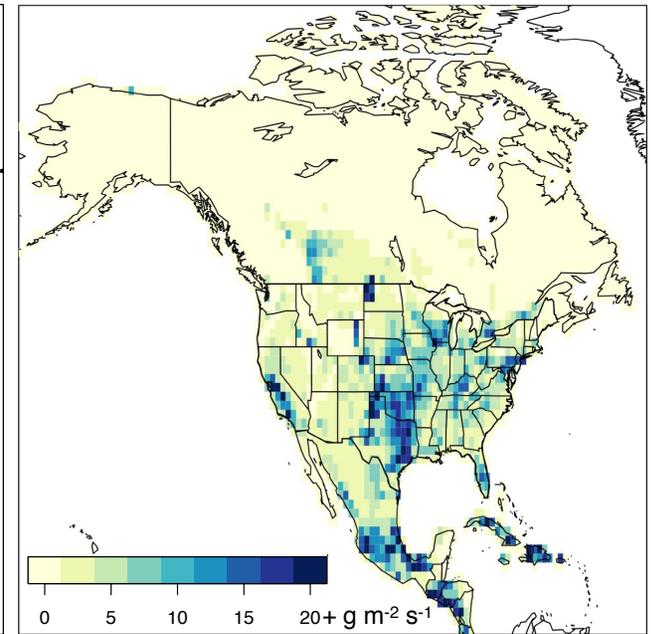
Assume these emissions  
("target")

GOSAT



Simulate these observations

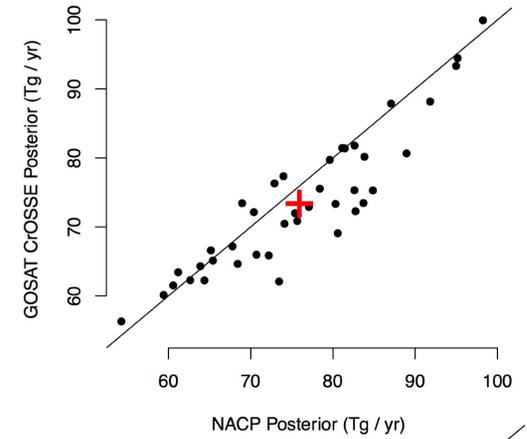
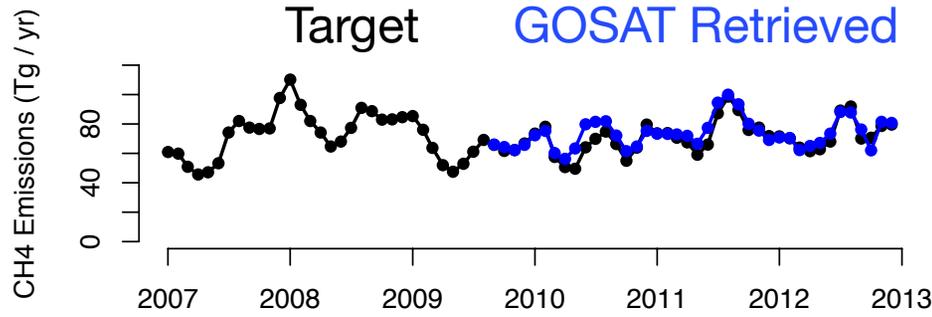
OSSE



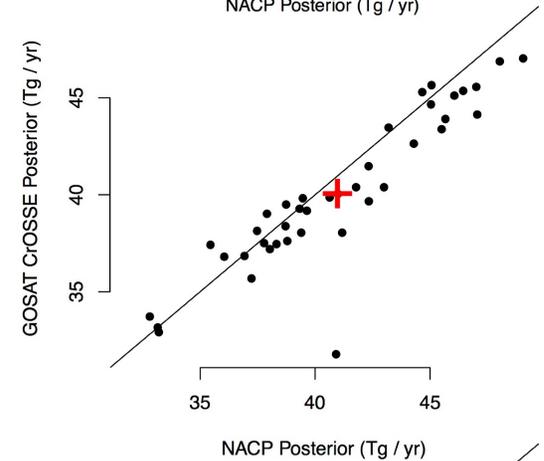
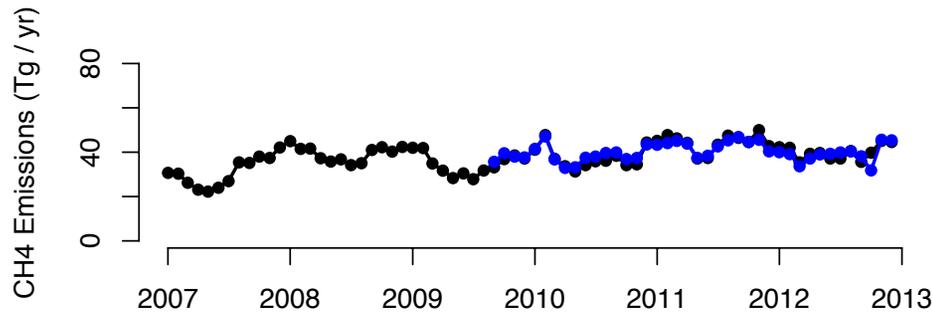
Retrieve these emissions

# GOSAT does a good job of matching the budget

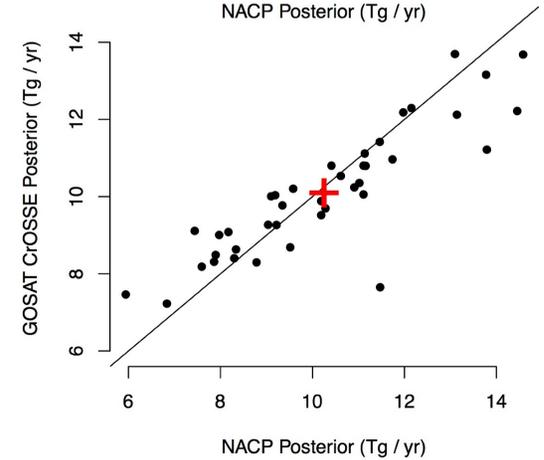
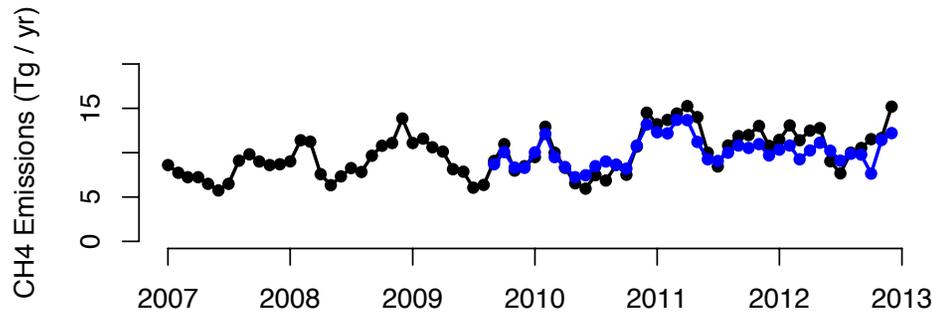
Whole Domain



USA

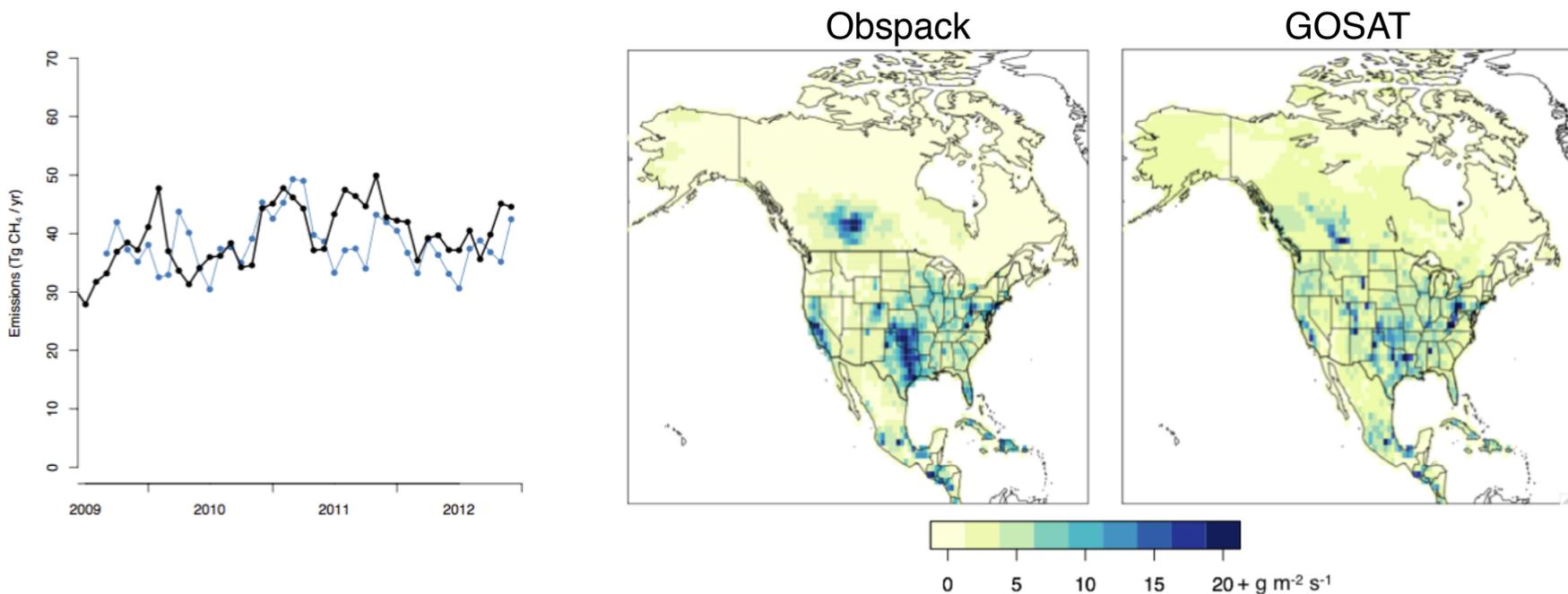


Texas/  
Oklahoma



# Conclusions

- We retrieved US methane emissions from GOSAT and Obstack with good agreement.
- Our inversion system does not produce a significant trend in US methane emissions for 2009 - 2012.
- 2013 and 2014 coming shortly.



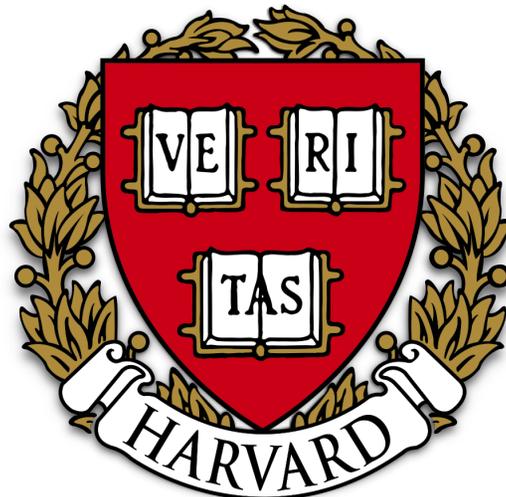


**Thanks!**

**Check out CarbonTracker-Lagrange at  
[esrl.noaa.gov/gmd/ccgg/carbontracker-lagrange/](http://esrl.noaa.gov/gmd/ccgg/carbontracker-lagrange/)**

**And CarbonTracker at:  
[esrl.noaa.gov/gmd/ccgg/carbontracker/](http://esrl.noaa.gov/gmd/ccgg/carbontracker/)**

**Contact me at:  
[benmergui@g.harvard.edu](mailto:benmergui@g.harvard.edu)**



# Error Parameters (Restricted Maximum Likelihood)

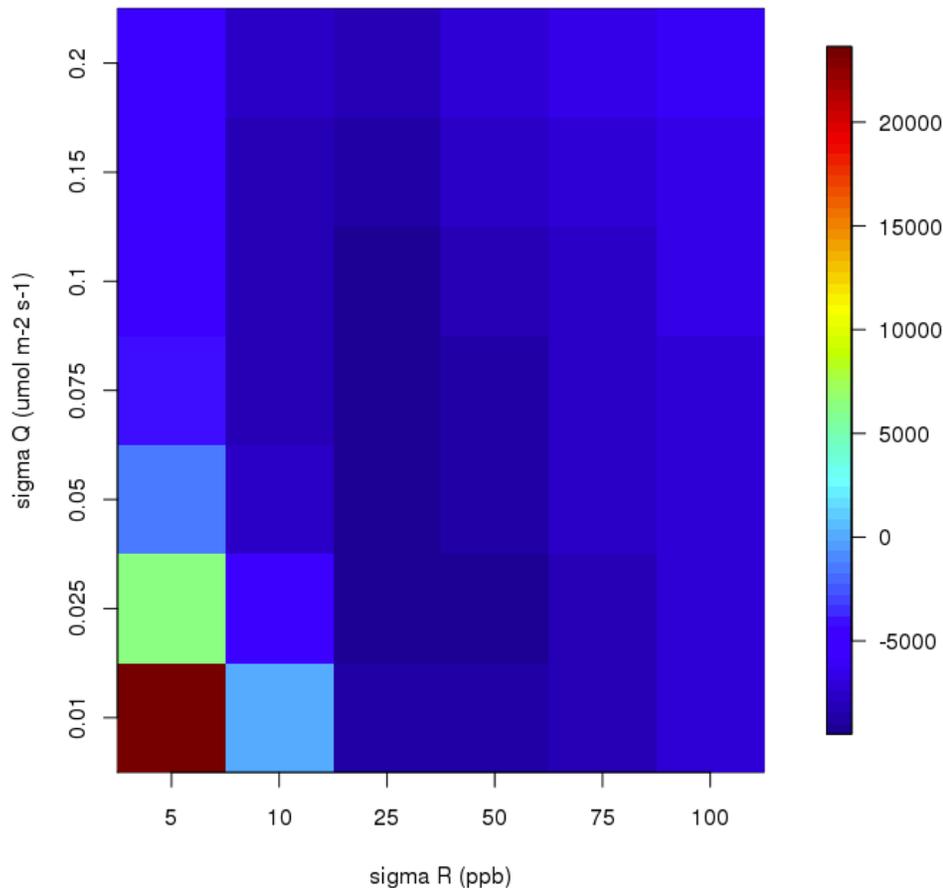
## NACP

$$\sigma_Q = 0.034 \mu\text{mol m}^{-2} \text{s}^{-1}$$

$$\phi_l = 100 \text{ km}$$

$$\phi_t = 30 \text{ days}$$

$$\sigma_R = 30.6 \text{ ppb}$$



## GOSAT

$$\sigma_Q = 0.05 \mu\text{mol m}^{-2} \text{s}^{-1}$$

$$\phi_l = 100 \text{ km}$$

$$\phi_t = 30 \text{ days}$$

$$\sigma_R = 10 \text{ ppb}$$

