Estimating US methane emissions with GOSAT

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1) **Methane is a potent greenhouse gas**
   - 2nd only to CO₂

2) **Recent trends in atmospheric methane are not well understood**
Global methane emission sources

**Anthropogenic**
- Biomass Burning (5%)
- Landfills (11%)
- Ruminants (13%)
- Rice (4%)
- Permafrost (0.1%)

**Natural**
- Wetlands (32%)
- Fossil Fuels (14%)
- Geologic Hydrates (0.8%)
- Geological (8%)

**Biogenic**
- Freshwater (6%)
- Animals (2%)
- Wildfires (0.4%)
- Termites (2%)

**Thermogenic**

**Pyrogenic**

331 Tg a\(^{-1}\)

347 Tg a\(^{-1}\)

Kirschke et al. (2013)
Methods of estimating methane emissions

**Bottom-up**

Cattle Density

$\text{CH}_4$ $\times$

= Global map of cattle emissions

**Top-down**

Satellites provide dense spatial coverage but have large uncertainties
Methane retrievals from low Earth orbit

Satellites Retrieving Methane:

**Thermal IR**
- AIRS, TES, IASI, CrIS

**Shortwave IR**
- SCIAMACHY
- GOSAT
- TROPOMI


**SWIR**
- column average
- day only
- land only

**TIR**
- upper troposphere
- day + night
- land + ocean

Atmospheric CH$_4$
Methane retrievals from low Earth orbit

Satellites Retrieving Methane:

- **Thermal IR**: AIRS, TES, IASI, CrIS
- **Shortwave IR**: SCIAMACHY, GOSAT, TROPOMI

2002 2006 2009


1750 1775 1800 1825 (ppb)
Consider a system represented by,

\[ y = Kx + \epsilon \]

- \( y \) is a vector of measured concentrations
- \( x \) is a set of emissions
- \( K \) is the Jacobian matrix that maps from emissions to concentrations
- \( \epsilon \) is the error

Solving for \( y \) is known as a “forward problem”
- Well-posed with a unique solution

Solving for \( x \) is an “inverse problem”
- Ill-posed and may not have a unique solution
We can infer the most probable solution using Bayes Theorem:

$$P(x|y) \propto P(y|x)P(x)$$

By assuming that our distributions are normal we obtain:

$$P(x|y) \propto \exp \left\{ -\frac{1}{2}(y - Kx)^T S_o^{-1} (y - Kx) - \frac{1}{2}(x - x_a)^T S_a^{-1} (x - x_a) \right\}$$

Interested in \( \max\{P(x|y)\} \) which corresponds to \( \min\{\mathcal{J}(x)\} \):

$$\mathcal{J}(x) = \frac{1}{2}(y - Kx)^T S_o^{-1} (y - Kx) + \frac{1}{2}(x - x_a)^T S_a^{-1} (x - x_a)$$
Setting the gradient equal to zero and solving:

\[
\hat{x} = x_a + \left( K^T S_O^{-1} K + S_a^{-1} \right)^{-1} K^T S_O^{-1} (y - Kx_a)
\]

This work uses two methods:

- **Adjoint Method**
  - Don’t explicitly construct \( K \)
  - Iterative process

- **Analytical Method**
  - Construct \( K \)
  - Ensemble of \( N_x \) simulations

Solution assumes that the model is unbiased
Model compares well with observations

Turner et al. (2015)
Model compares well with observations

- Latitudinal gradient and seasonal cycle are represented
  - Compared to HIPPO, NOAA/ESRL, and TCCON

- Captures surface, free trop, and total column background

Turner et al. (2015)
Identifying a GOSAT/GEOS-Chem bias

Model/satellite comparison identifies a high-latitude bias
- Latitudinal bias not seen in surface, aircraft, or column comparison

Remove bias before estimating methane emissions
- Bias is either due to the model stratosphere or GOSAT retrievals

Observations are ready for inversion!

Turner et al. (2015)
General inversion framework: 2009–2011 GOSAT data

Global inversion provides dynamic BCs for North America

Turner et al. (2015)
Global inversion results

- **Overestimate of Chinese methane emissions**
  - Consistent with previous work (e.g., Bergamaschi et al. 2013, Bruhwiler et al. 2014, Schwietzke et al. 2014)

- **Underestimate in South-Central US emissions**
  - Will further investigate using Nested North American simulation
Adjoint is not ideal for long time horizons at hi-res!

Avoid the iterative process by constructing the Jacobian and solving analytically!

Simulation Walltime: 2.6 years
Estimating methane emissions at high resolution

Spatial error correlations are important at fine spatial scales!

Native resolution $\frac{1}{2}^\circ \times \frac{2}{3}^\circ$
state vector $\mathbf{x}$ ($n = 7366$)

Reduced-resolution state vector $\mathbf{x}_\omega$ (here $n = 8$)

Aggregation Matrix: $\mathbf{\Gamma}_\omega$

$\mathbf{x}_\omega = \mathbf{\Gamma}_\omega \mathbf{x}$

Posterior error depends on choice of state vector dimension

Choose $n = 369$ for negligible aggregation error; allows analytical inversion with full error characterization

Optimal size must balance **aggregation** and **smoothing** error

Turner & Jacob (2015)
Radial Basis Functions retain high resolution

- Decompose the state vector into Gaussians
  - Group based on correlated prior emission patterns

- Retain high resolution
  - Coarsen weak or uniform signals

Turner & Jacob (2015)
Prior methane emissions from EDGARv4.2 + LPJ

### Major Sources (Tg a\(^{-1}\))

<table>
<thead>
<tr>
<th>Source</th>
<th>Emissions (Tg a(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wetlands</td>
<td>20.4</td>
</tr>
<tr>
<td>Livestock</td>
<td>14.5</td>
</tr>
<tr>
<td>Oil/Gas</td>
<td>10.8</td>
</tr>
<tr>
<td>Landfills</td>
<td>9.7</td>
</tr>
<tr>
<td>Coal</td>
<td>4.3</td>
</tr>
</tbody>
</table>

**Total:** 63/537 Tg a\(^{-1}\)

**North America**

**Global**

Turner et al. (2015)
Methane emissions are a factor of 1.4 larger than the prior

Large underestimate in South-Central US emissions

Overestimate in Hudson Bay wetland emissions

Turner et al. (2015)
Does this posterior inventory improve things?

- **Consistent emission estimates with regional and local studies**
- Improves comparison with independent observations!

### State of California
- EDGARv4.2
- This work
- Santoni et al., (2014)
- Wecht et al., (2014b)
- Wennberg et al., (2012)

### SoCAB

![Graph showing methane emissions comparison](image)

**NOAA/ESRL Tall Tower Network**
- NOAA/ESRL Aircraft Program
- NOAA/ESRL Surface Flasks

**Prior**
- $y = 516 + 0.72x$ ($R^2 = 0.40$)
- $y = 468 + 0.75x$ ($R^2 = 0.54$)
- $y = 605 + 0.67x$ ($R^2 = 0.60$)

**Posterior**
- $y = -60 + 1.03x$ ($R^2 = 0.48$)
- $y = 125 + 0.94x$ ($R^2 = 0.61$)
- $y = -4 + 1.01x$ ($R^2 = 0.67$)

*Turner et al. (2015)*
US emissions are a factor of 1.5 larger than the US EPA

Livestock + Oil/Gas are the largest underestimated sources

Attribution is sensitive to assumption about the prior error

Turner et al. (2015)
Trend in US methane emissions?

Top-down studies point to an increase in US methane, not seen in bottom-up estimates.

Turner et al. (submitted)
What data do we have to corroborate this trend?

- Surface observations from the NOAA/ESRL flask network
- Nadir-mode observations from the GOSAT satellite
- Glint-mode observations from the GOSAT satellite

Turner et al. (submitted)
NOAA/ESRL surface flask observations

Billings, OK (SGP)
Bermuda (BMW)

Increasing difference between continental US and background

3.6% a^{-1}

Turner et al. (submitted)
What can we do with GOSAT?

- Can look at trends over locations where GOSAT samples
  - Many observations at coincident locations

- Do we find regional trends?

Turner et al. (submitted)
Increasing difference in GOSAT trends

GOSAT and NOAA background are consistent

Contiguous US enhanced from background

Turner et al. (submitted)
Where do we find regional trends?

Increases are coincident with agriculture and oil/gas

Turner et al. (submitted)
Space-borne observations can be used to estimate regional methane emissions

US methane emissions have increased more than 30% in the past decade
  - Likely due to anthropogenic (oil/gas or agriculture) sources

Could be a driver in the renewed methane growth