Estimating North American methane emissions using GOSAT

Alexander J. Turner
Daniel J. Jacob, Kevin J. Wecht, Vivienne Payne, and Kevin Bowman

Thanks to Steven C. Wofsy, Robert Parker, Hartmut Boesch, Colm Sweeney, Anna Karion, Sebastien C. Biraud, Edward J. Dlugockencky, and Debra Wunch
Why is methane important?

“Curbing emissions of methane is critical to our overall effort to address global climate change.”

–The President’s Climate Action Plan
June 2013

Methane is a substantial contributor to both climate change and air pollution

- Methane is the 2nd largest anthropogenic radiative forcer.
- Comparable to CO$_2$ over 20-year horizon.
  - Can affect climate change over decadal timescales.
- Methane controls have also been shown to be a viable ozone management option [West and Fiore 2005]

IPCC (2013)
Methane sources are diverse and uncertain
Methods of estimating methane emissions

Bottom-up

- Cattle Density
- Global map of cattle emissions (FAO 2007)

Top-down

- Inverse Model
- Forward Model

Satellites provide better spatial coverage but have larger uncertainties
Disagreement on US methane emissions

- Allen et al., (2013) find a natural gas leakage rate of 0.42%
  - \( \sim 20\% \) less than the total EPA inventory

- Karion et al., (2013) find a natural gas leakage rate of 6.2% – 11.7%
  - Leakage rate is \( 10\times \) greater than EPA

- Miller et al., (2013) find fossil fuel to be underestimated by \( 4.9\times \)
  - Total inventory is \( 1.5\times \) greater than EPA
Satellites Observing Methane:

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

- **Shortwave IR**
  - SCIAMACHY (6-day)
  - GOSAT (3-day, sparse)
  - TROPOMI (1-day)

Observing System:

- **2002**
- **2006**
- **2009**
- **2015**

Map of North America with color coding:

- \[ N_{\text{Obs.}} = 74,687 \]
North American methane observing system

- GOSAT XCH4 Observations Available
- TCCON Observations Available
- NOAA/DOE CCGG Flights
- NOAA GMD Observations Available

 observable from
- H-I
- H-II
- H-III
- H-IV
- H-V

× TCCON
• NOAA Ground Station
• NOAA Flight Data

Observing System
4°×5° GEOS-Chem compares well to observations
Latitudinal bias in the GOSAT data?

GEOS-Chem compared well to in situ data...

→ There shouldn’t be a large latitudinal bias

In situ data | GEOS-Chem | GOSAT
No Latitudinal Bias | Latitudinal Bias

GC – GOSAT [ppbv]
Impact of the bias correction

GOSAT data is now ready for assimilation!
Define a Bayesian cost function:

\[
J(x) = \frac{1}{2} (y - F(x))^T S_O^{-1} (y - F(x)) + \frac{1}{2} (x - x_a)^T S_a^{-1} (x - x_a)
\]

Can find most probable solution by minimizing \(J\)

\[
\nabla_x J = S_a^{-1} (x_a - x) + K^T S_O^{-1} (F(x) - y)
\]

I’ll be using two approaches:

<table>
<thead>
<tr>
<th><strong>Adjoint Approach</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Don’t explicitly construct (K)</td>
</tr>
<tr>
<td>Iterative process</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Analytical Approach</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Construct (K)</td>
</tr>
<tr>
<td>Ensemble of (N_x) simulations</td>
</tr>
</tbody>
</table>
- **Large overestimate in Chinese coal emissions?**
  - Consistent with Bergamaschi et al., (2013)
  - Co-located with Rice, Livestock, and Waste

- **Underestimating Rice emissions in Southeast Asia?**

- **Obtain time-dependent boundary conditions for NA**
Adjoints are not ideal for long time horizons at hi-res.

Iteration:
- Forward
- Backward

Approximately 10 hours per month

= 12.5 days

Simulation Walltime: 2.6 years

Avoid the iterative process by constructing the Jacobian and solving analytically!
Intelligently aggregating the state vector

- **Native:**
  - Perform the inversion on the native resolution
  - Would require running 7,366 simulations
Intelligently aggregating the state vector

- **Simple:** “Big regions”
  - Aggregate pixels into “big regions”
  - Will induce large aggregation error
Intelligently aggregating the state vector

- **Good:** Clustering
  - Group state vector elements based on “features”
  - Should allow keep hi-res features (e.g., Mexico City & Central Valley)

Each color is a different cluster
- Cannot have multiple memberships
Intelligently aggregating the state vector

- **Even Better:** Radial Basis Functions
  - Each pixel is weighted by each state vector element
  - Weights come from a Gaussian Mixture Model

- Partial weight on the edges
  - Gaussian kernel

---

Radial Basis Functions
Aggregation error decreases quickly!

Aggregation error is due to grouping many state vector elements
What is the optimal state vector size?

Optimal size must balance aggregation and smoothing error.

- $\varepsilon_I$: 12.5 ppbv
- $\varepsilon_{1480}$: 13.2 ppbv
- $\varepsilon_{369}$: 14.0 ppbv

![Graph showing the relationship between the number of state vector elements and error](chart.png)
What is the optimal basis set?

Provides an objective comparison of different basis sets
Prior methane emissions in North America

**Major Sources** [Tg yr\(^{-1}\)]

<table>
<thead>
<tr>
<th>Source</th>
<th>Tg yr(^{-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></td>
</tr>
<tr>
<td>Coal</td>
<td>4.3</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>63.3</td>
</tr>
</tbody>
</table>

**North America**

<table>
<thead>
<tr>
<th>Source</th>
<th>Tg yr(^{-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></td>
</tr>
<tr>
<td>Coal</td>
<td>4.3</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>63.3</td>
</tr>
</tbody>
</table>

**Global**

<table>
<thead>
<tr>
<th>Source</th>
<th>Tg yr(^{-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></td>
</tr>
<tr>
<td>Coal</td>
<td>4.3</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>63.3</td>
</tr>
</tbody>
</table>
Constraining North American methane sources

(a) Prior Emissions (2010 - 2011 average)

Total: 63.3 Tg CH₄ yr⁻¹

(b) Posterior Methane Emissions

Total: 91.3 ± 2.2 Tg CH₄ yr⁻¹

(c) Change in Emissions (Posterior - Prior)

ΔCH₄: 27.9 ± 2.2 Tg CH₄ yr⁻¹

(d) Diagonal of the Averaging Kernel, Aᵢᵢ
Does this inventory improve things?

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

- Start estimating methane emissions for individual basins

---

![Graph showing methane emissions](image)

**Prior**

\[ y = 295 + 0.85x \quad (R^2 = 0.48) \]

\[ y = 259 + 0.86x \quad (R^2 = 0.60) \]

**Posterior**

\[ y = 651 + 0.65x \]

\[ y = 535 + 0.71x \]

**Source:**
- EDGARv4.2 + Kaplan
- Santoni et al., (2014)
- Wecht et al., (2014)
- Wennberg et al., (2012)
Comparing US emissions to recent work

- Similar spatial pattern, disagreement on some point sources
  - Four Corners region
  - Canadian oil sands
Constraining the Canadian wetlands

Anthropogenic
(Canadian oil sands)

Miller et al. (2014)

Posterior estimate

This study minus prior

This study (2010–2011 average)
US emissions not statistically different from Miller et al., (2013) at 95% CI

Oil/Gas seem to be the largest underestimated source
Next steps...

Investigate emissions from predominantly Natural Basins and Anthropogenic Basins that GOSAT sees.