Bayesian Atmospheric Tomography for Detection and Estimation of Methane Emissions

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Motivation & Background

- Methane (CH_4) and carbon dioxide (CO_2) are the most prevalent anthropogenic greenhouse gases (GHGs) in the atmosphere.
- A major portion of the UNFCCC Paris Agreement is dedicated to the reduction of GHG emissions.
- While there have been substantial advances in the detection and measurement of GHG emissions, quantifying these emissions remains a predominantly open problem.

Motivation & Background

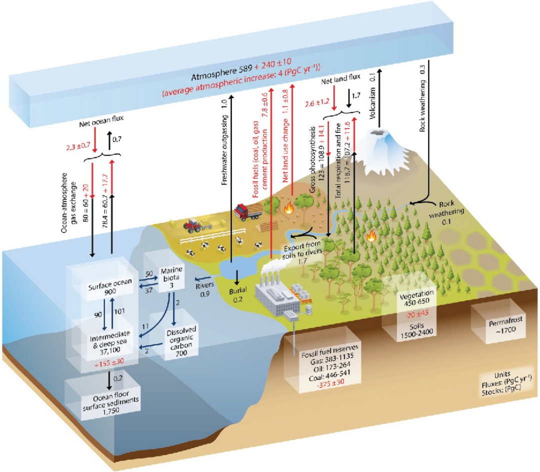


Figure 1: Simplified schematic of the global CO_2 cycle. Figure sourced from IPCC (2014).

Ginninderra Experiment

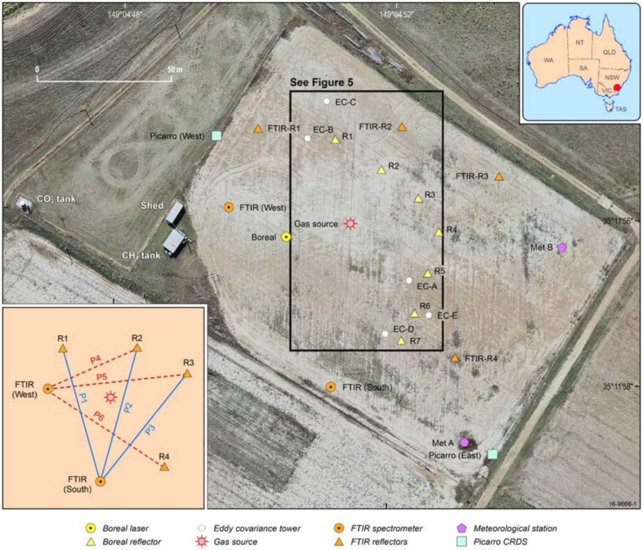
In 2015, a controlled-release experiment headed by Geoscience Australia was conducted at the Ginninderra Controlled Release Facility near Canberra.

Two methane release rate periods:

- 5.8 g min^{-1} between April 23 and June 7 (excluding May 26 and May 27);
- 5.0 g min^{-1} between June 8 and June 12.

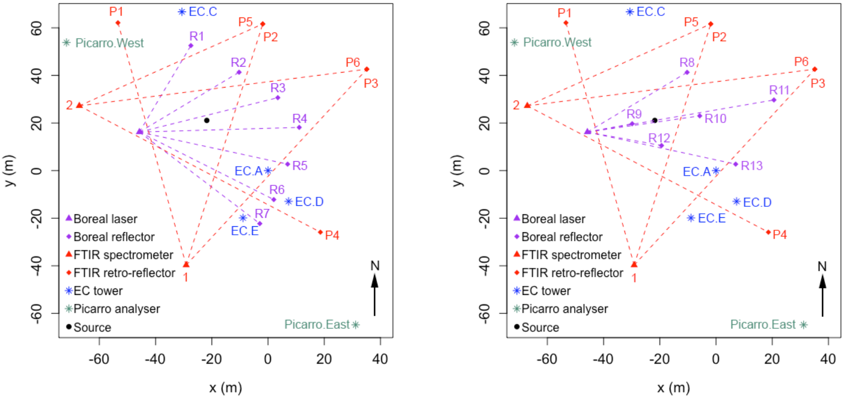
Aim: To develop methodology which can recover a range of plausible values for the emission rate irrespective of the specific type of instruments used.

Ginninderra Experiment



Source: Feitz et al. (2018)

Ginninderra Experiment



Atmospheric Transport Model

We model the dispersion of methane from the source via a Gaussian plume dispersion model:

$$C(x_i, y_i, z_i, Q, U_i, H) = \frac{Q}{2\pi U_i \sigma_{y_i,k_i} \sigma_{z_i,k_i}} \exp\left(-\frac{y_i^2}{2\sigma^2_{y_i,k_i}}\right) \times \left[\exp\left(-\frac{(z_i - H)^2}{2\sigma^2_{z_i,k_i}}\right) + \exp\left(-\frac{(z_i + H)^2}{2\sigma^2_{z_i,k_i}}\right)\right],$$

where

- $C(x_i, y_i, z_i, Q, U_i, H)$ is the concentration of methane at a point (x_i, y_i, z_i);
- Q is the methane release rate;
- U_i is the ith wind speed;
- H is the height of the gas source;
- k_i refers to one of six Pasquill stability classes;
- σ_{z_i,k_i} and σ_{y_i,k_i} are the standard deviations of the time averaged plume concentrations in the ith z and y directions respectively.

(see Turner, 1994; Wark et al., 1998, for more details)

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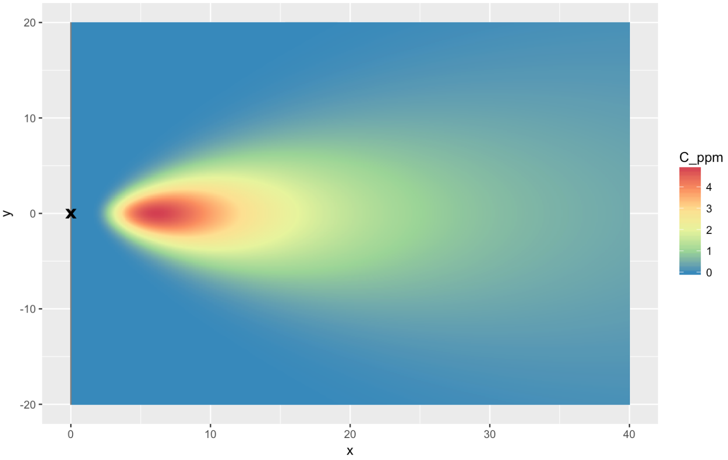
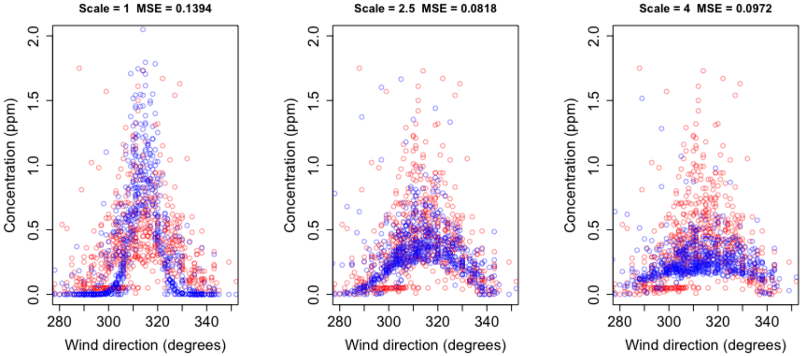
Atmospheric Transport Model

The Gaussian plume at height $z_i = 1.5$ m, and $k_i =$ extremely unstable.



Atmospheric Transport Model

It is noted that the coefficients of σ_{y_i,k_i} and σ_{z_i,k_i} could be off by a factor of two or more (Wark et al., 1998). This also appears to be the case with our categorisation scheme.



Atmospheric Transport Model

To alleviate the need for the analyst to choose scaling factors for σ_{y_i,k_i} and σ_{z_i,k_i}, we replace them in the plume model with $\tilde{\sigma}_{y_i,k_i}$ and $\tilde{\sigma}_{z_i,k_i}$, such that

$$\tilde{\sigma}_{y_i,k_i} \equiv \omega_y \sigma_{y_i,k_i}, \qquad \text{and} \qquad \tilde{\sigma}_{z_i,k_i} \equiv \omega_z \sigma_{z_i,k_i},$$

where ω_y and ω_z are unknown, positive scaling parameters.

Atmospheric Transport Model

The Gaussian plume dispersion model is also known to be less accurate for low wind speeds (e.g., Turner, 1994), likely because the wind-speed U_i is in the denominator of the scaling coefficient.

We could simply remove data at low wind speeds (e.g., Feitz et al., 2018)??

However:

By the Central Limit Theorem and the Delta Method, we determine that, approximately,

$$\mathrm{Var}\left(\frac{1}{U_i}\right) \propto \frac{1}{\mu_{U_i}^4},$$

where μ_{U_i} is the mean wind speed over the ith time interval.

Data model

Each measured methane concentration can be written as

$$\tilde{Y}_i = C_i + X_i + \varepsilon_i,$$

where

- C_i is the ith plume-predicted concentration;
- X_i is the sum of the ith CH_4 background concentration and instrument-specific bias; and
- ε_i captures both the ith atmospheric transport model error and the ith measurement error (assumed to be Gaussian but not independent).

As in Zammit-Mangion et al. (2015) we estimate X_i as the 5th percentile of all the measurements from the instrument associated with the ith measurement.

Data model

Each concentration corrected for background and instrument-specific bias, termed an *enhancement* and denoted by Y_i, can be written as

$$Y_i = \tilde{Y}_i - X_i = C_i + \varepsilon_i.$$

To account for the transport model error portion of variability in the ε_i terms, we take the following steps:

1. Introduce an auxiliary variable, m_i ($m_i = 1, 2, \ldots, M$), where M is the total number of unique combinations of stability class and instrument type.

We consider M different precision parameters τ_{m_i}, one for each combination.

Data Model

2. We take the influence of low wind speeds into account by taking the precision of ε_i to be the appropriate τ_{m_i} multiplied by $\hat{U}_i$, where

$$\hat{U}_i = \begin{cases} U_i^4, & 0 < U_i < 1, \\ 1, & U_i \geq 1. \end{cases}$$

We assume the ε_i terms follow a Gaussian distribution, such that

$$(\varepsilon_i \mid m_i) \sim \mathrm{Gau}(0, 1/(\tau_{m_i} \hat{U}_i)).$$

Bayesian inversion

Let

- $\mathbf{Y} = (Y_1, Y_2, \ldots, Y_N)'$ be the N enhancements;
- $\boldsymbol{\tau} = (\tau_{m_1}, \tau_{m_2}, \ldots, \tau_{m_M})'$ be the M precision parameters; and
- $\mathbf{U} = (U_1, U_2, \ldots, U_N)'$ be the N wind speeds;

and recall

- H is the height of the source;
- Q is the true methane release rate in g sec^{-1};
- ω_y and ω_z are the standard deviation scaling parameters.

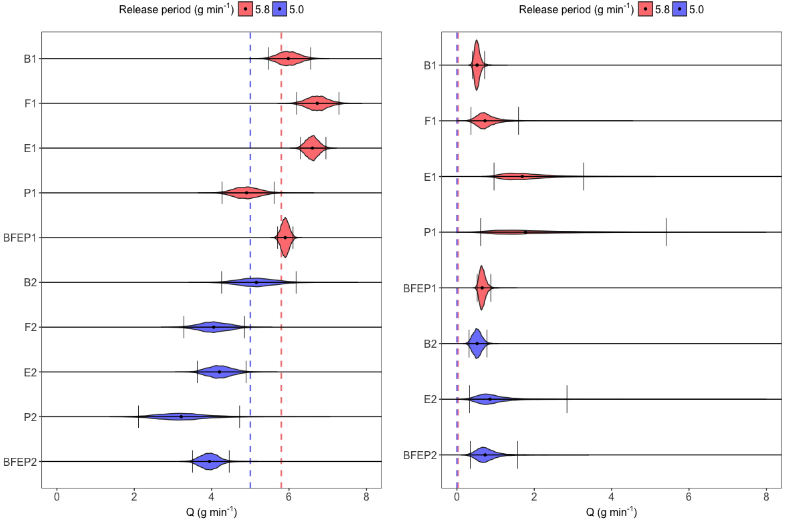
By Bayes' Rule:

$$p(Q \mid \mathbf{Y}, \mathbf{U}, H) \propto p(Q) \int_0^\infty \int_0^\infty \int_{\mathbb{R}^{M+}} p(\mathbf{Y} \mid Q, \boldsymbol{\tau}, \omega_y, \omega_z, \mathbf{U}, H) \times p(\boldsymbol{\tau}) p(\omega_y) p(\omega_z) \, \mathrm{d}\boldsymbol{\tau} \, \mathrm{d}\omega_y \, \mathrm{d}\omega_z,$$

Bayesian inversion

- The posterior distribution is not of a known form, and so we cannot directly compute a posteriori estimates for $Q, \boldsymbol{\tau}$, ω_y, and ω_z.
- Instead we use a Metropolis-within-Gibbs Markov Chain Monte Carlo (MCMC) scheme.
- We take 60000 samples of each unknown parameter, discard the first 20000 samples as burn-in, and set a thinning factor of 10.
- We use R to perform the inversions.

Results



Release period (g min^{-1}) 5.8 5.0
B1
F1
E1
P1
BFEP1
B2
F2
E2
P2
BFEP2
0 2 4 6 8
Q (g min^{-1})
Release period (g min^{-1}) 5.8 5.0
B1
F1
E1
P1
BFEP1
B2
E2
BFEP2
0 2 4 6 8
Q (g min^{-1})

Conclusion

- We have proposed efficient and simple methodology for recovering a range of flux estimates which is able to accept different types of instruments.
- The simplicity of the Gaussian plume model used allows for predicted concentrations to be calculated in less than a second.
  - Contributes greatly to the efficiency of the inversion;
  - Flexibility to introduce uncertainty on parameters within the model itself at little to no computational cost.
- We recover all median emission-rate estimates within 36% of the true value, while all posterior 95% credible interval have a limit within 11% of the true value.

Acknowledgements

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Assets

- The discussion paper for this research is available at `https://www.atmos-meas-tech-discuss.net/amt-2019-124/`.
- The curated dataset used in this research is available at `https://doi.org/10.26186/5cb7f14abd710`.
- Code to reproduce all results in the discussion paper is available at `https://github.com/LCartwright94/BayesianAT`.

References I

Cartwright, L., Zammit-Mangion, A., Bhatia, S., Schroder, I., Phillips, F., Coates, T., Neghandhi, K., Naylor, T., Kennedy, M., Zegelin, S., Wokker, N., Deutscher, N. M., and Feitz, A. (2019). Bayesian atmospheric tomography for detection and quantification of methane emissions: Application to data from the 2015 Ginninderra release experiment. *Atmospheric Measurement Techniques Discussions*, pages 1–22.

Feitz, A., Schroder, I., Phillips, F., Coates, T., Neghandhi, K., Day, S., Luhar, A., Bhatia, S., Edwards, G., Hrabar, S., Hernandez, E., Wood, B., Naylor, T., Kennedy, M., Hamilton, M., Hatch, M., Malos, J., Kochanek, M., Reid, P., Wilson, J., Deutscher, N., Zegelin, S., Vincent, R., White, S., Ong, C., George, S., Maas, P., Towner, S., and Griffith, D. (2018). The Ginninderra CH_4 and CO_2 release experiment: an evaluation of gas detection and quantification techniques. *International Journal of Greenhouse Gas Control*, 70:202–224.

References II

Humphries, R., Jenkins, C., Leuning, R., Zegelin, S., Griffith, D., Caldow, C., Berko, H., and Feitz, A. (2012). Atmospheric tomography: a Bayesian inversion technique for determining the rate and location of fugitive emissions. *Environmental Science and Technology*, 46:1739–1746.

IPCC (2014). *Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. [Core Writing Team, R. K. Pachauri and L. A. Meyer (eds.)]. Geneva, Switzerland: IPCC.

Turner, B. (1994). *Workbook of Atmospheric Dispersion Estimates*. Lewis Publishers, Boca Raton, FL, 2nd edition.

Wark, K., Warner, C. F., and Davis, W. T. (1998). *Air Pollution: Its Origin and Control*. Addison Wesley Longman, Menlo Park, CA.

Zammit-Mangion, A., Cressie, N., Ganesan, A. L., O'Doherty, S., and Manning, A. J. (2015). Spatio-temporal bivariate statistical models for atmospheric trace-gas inversion. *Chemometrics and Intelligent Laboratory Systems*, 15:227–241.