Reconciling bottom-up and top-down estimates of GHG fluxes

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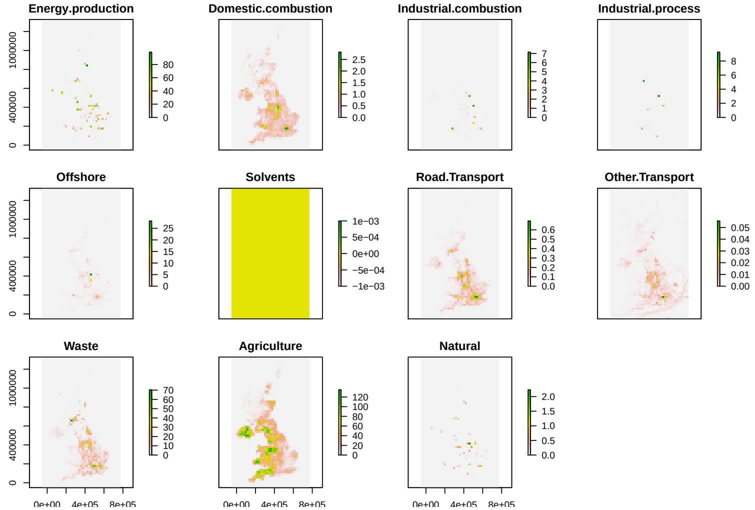
Reconciling bottom-up and top-down GHG flux estimates: Questions

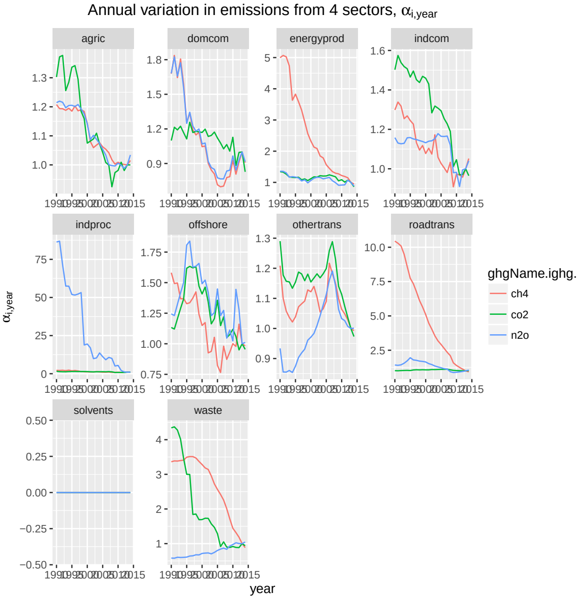
- Bottom-up GHG flux estimates
  - anthropogenic: from national GHG inventory process
    - approx. 600 models used in compiling
  - biogenic: from biogeochemical models run at national-scale
- Top-down GHG flux estimates
  - from inverse modelling of atmospheric GHG concentrations on tall-tower network

How to reconcile differences?
How to ascribe differences to emission sectors?
How to use both sources of information to best constrain the national GHG budget?

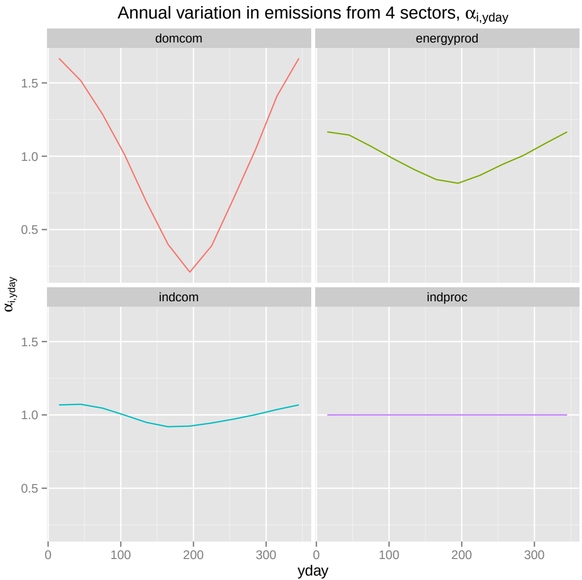
Spatial patterns by emission sector



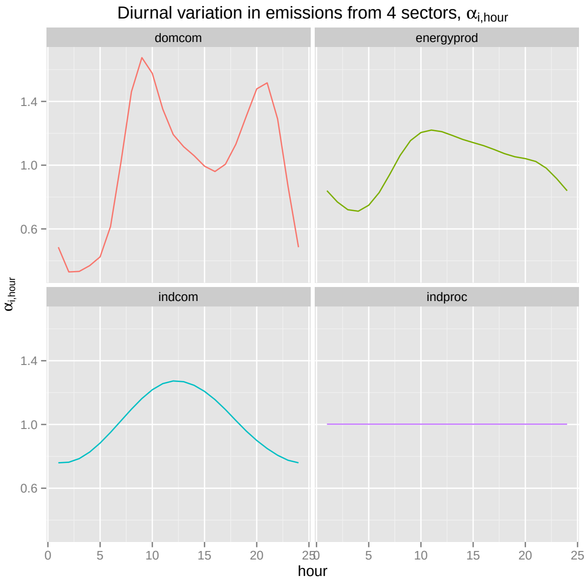
Temporal patterns by emission sector: annual



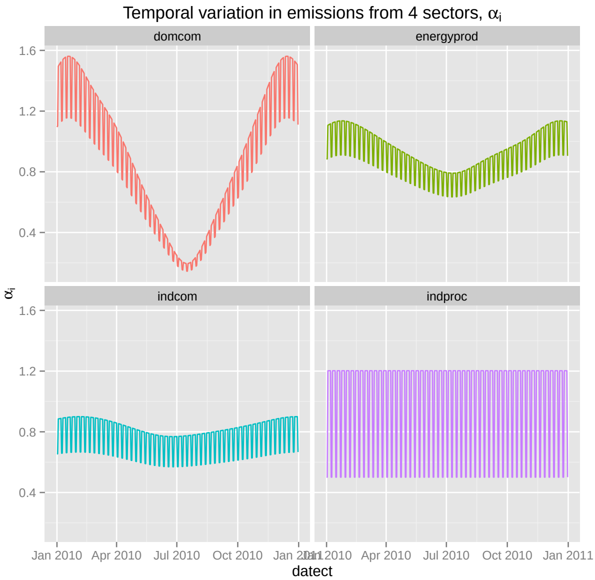
Temporal patterns by emission sector: seasonal



Temporal patterns by emission sector: diurnal



Temporal patterns by emission sector



Temporal patterns by emission sector

$$F_t = \sum_{i=1}^{n_{\mathrm{sector}}} F_{i,\mathrm{spatial}} \times \alpha_{it}$$

$$\begin{aligned}\alpha_{it} = & \alpha_{i,\mathrm{year}} \cdot \mathrm{f(year)} \times \alpha_{i,\mathrm{yday}} \cdot \mathrm{f(yday)} \times \\ & \alpha_{i,\mathrm{wday}} \cdot \mathrm{f(wday)} \times \alpha_{i,\mathrm{hour}} \cdot \mathrm{f(hour)}\end{aligned}$$

where
f(year), f(yday), f(wday) and f(hour) are cubic splines.
α is a vector of 40 coefficients: 10 sectors $\times$ 4 temporal scales.

Biogenic fluxes - CO_2 & CH_4

Different models for different GHGs:

- CO_2
  - Annual scale
    - Simplified LULUCF model
  - Seasonal & diurnal scale
    - $= f(LAI, T, Q)$ from eddy covariance data
- CH_4
  - Annual scale
    - $=$ f(vegetation composition)
    - Gray et al. (2013) Methane indicator values for peatlands: a comparison of species and functional groups. Global Change Biology. 19, 114150.
  - Seasonal & diurnal scale
    - $= f(T, \theta)$
    - Levy et al (2012) Methane emissions from soils: synthesis and analysis of a large UK data set. Global Change Biology. 18, 165769.

Agricultural fluxes - N_2O

Two methods used:

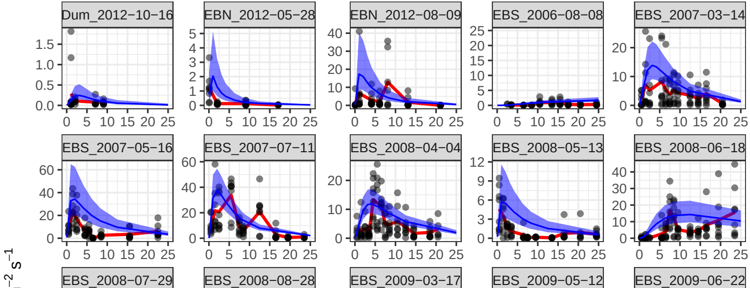
- Detailed disaggregation of agricutlural sector activity (see poster by Ed Carnell)
  - by practice e.g. housing periods, manure storage, fertiliser practice
  - by sub-sector e.g. Cattle, sheep, poultry
  - run in NAME in forwards mode (Alistair Manning, Met Office)
- Simple response surface model

Agricultural fluxes - N_2O

$$F_{N_2O} = \mathtt{dlnorm}(t, \Delta, k) N_{\mathrm{in}} \gamma \Omega^{\lambda}$$

To obtain the flux of N_2O at time t following fertilisation, we use the models of:

- Δ and k are time response parameters
- Ω is the emission factor
    - Levy et al. (in press) On the estimation of cumulative fluxes of N_2O: uncertainty in temporal upscaling and emission factors. *European Journal of Soil Science.*



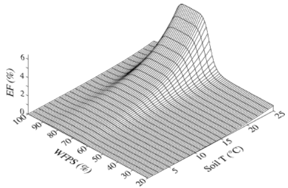
Agricultural fluxes - N_2O

$$F_{N_2O} = \texttt{dlnorm}(t, \Delta, k) N_{\text{in}} \gamma \Omega^{\lambda}$$

$$\lambda = f(\theta, T, P)$$

To obtain the flux of N_2O at time t following fertilisation, we use the models of:

- γ is the upscaling correction coefficient
  - van Oijen et al. (in review) Correcting errors from spatial upscaling of nonlinear greenhouse gas flux models. *Environmental Software and Modelling*.
- λ describes the response to soil moisture, temperature and precipitation
  - Flechard et al. (2007) Effects of climate and management intensity on nitrous oxide emissions in grassland systems across Europe. *Agriculture, Ecosystems and Environment* 121, 135-152.



Analyse discrepancies over time and space

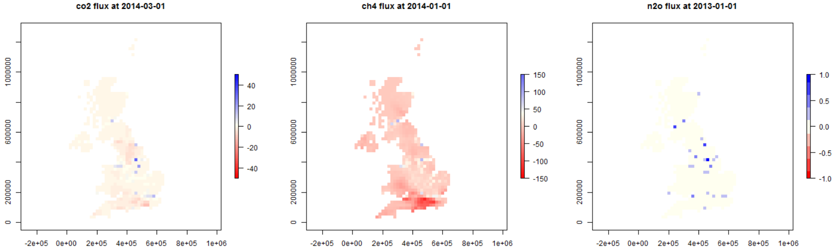


Figure: Difference between bottom-up and top-down flux estimates for CO_2, 2014 (left), CH_4, 2014-2015 (middle) and N_2O, 2013-2016 (right). Top-down estimates from NAME, University of Bristol and Met Office.

Analyse discrepancies over time and space

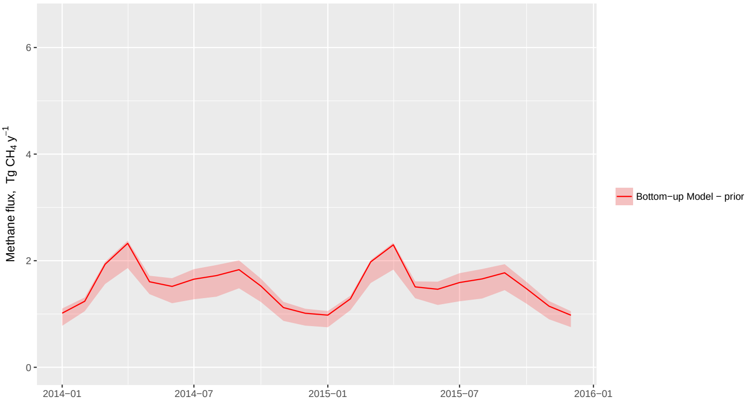
$$F_t = \sum_{i=1}^{n_{\mathrm{sector}}} F_{i,\mathrm{spatial}} \times \alpha_{it}$$

$$\begin{aligned}\alpha_{it} = & \alpha_{i,\mathrm{year}} \cdot \mathrm{f(year)} \times \alpha_{i,\mathrm{yday}} \cdot \mathrm{f(yday)} \times \\ & \alpha_{i,\mathrm{wday}} \cdot \mathrm{f(wday)} \times \alpha_{i,\mathrm{hour}} \cdot \mathrm{f(hour)}\end{aligned}$$

We fit the 44 α parameters in the bottom-up model by Bayesian methods:

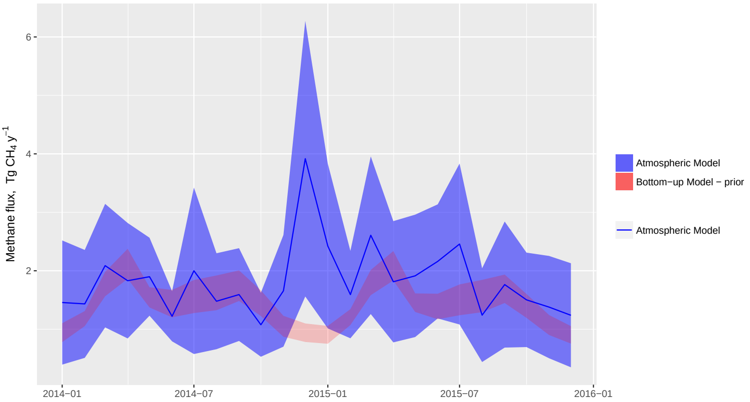
- prior estimates of the parameters from national inventory and air quality work
- uncertainty in top-down estimates from posterior distrbution
- likelihood calculated for each point in time and space
- run the bottom-up model for corresponding time-steps of the top-down model
- calculate posterior distribution of parameters and flux estimates via MCMC (DEsz algorithm)

Results - CH_4



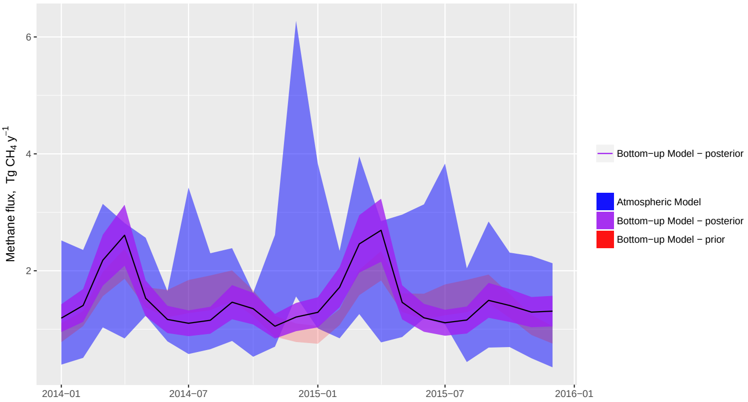
Methane flux, Tg CH4 y−1
0
2
4
6
2014−01
2014−07
2015−01
2015−07
2016−01
Bottom−up Model − prior

Results - CH_4



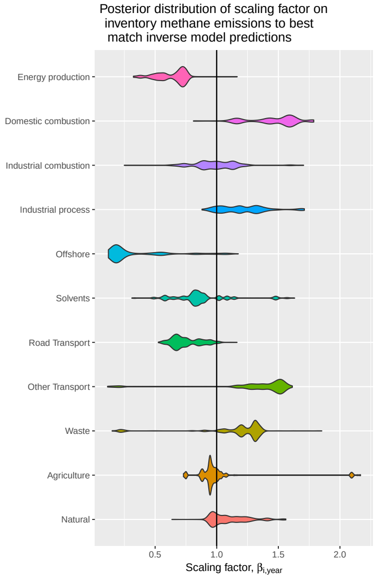
Methane flux, Tg CH4 y−1
6
4
2
2014−01
2014−07
2015−01
2015−07
2016−01
Atmospheric Model
Bottom−up Model − prior
Atmospheric Model

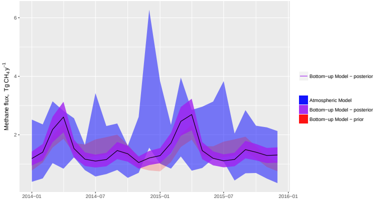
Results - CH_4



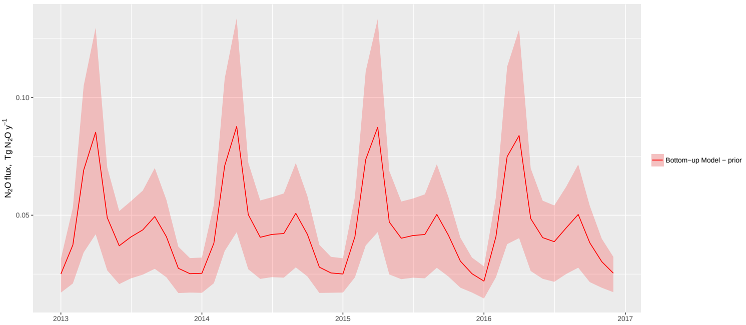
Methane flux, Tg CH4 y−1
6
4
2
2014−01
2014−07
2015−01
2015−07
2016−01
Bottom−up Model − posterior
Atmospheric Model
Bottom−up Model − posterior
Bottom−up Model − prior

Results - CH_4


Posterior distribution of scaling factor on inventory methane emissions to best match inverse model predictions
Energy production
Domestic combustion
Industrial combustion
Industrial process
Offshore
Solvents
Road Transport
Other Transport
Waste
Agriculture
Natural
0.5
1.0
1.5
2.0
Scaling factor, $\beta_{i,year}$

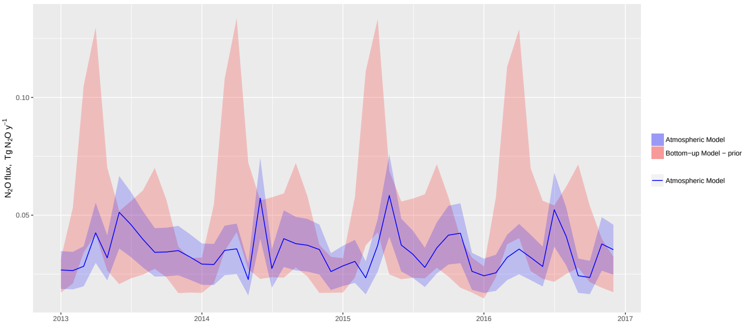

Methane flux, Tg CH_4 y^{-1}
6
4
2
2014−01
2014−07
2015−01
2015−07
2016−01
Bottom−up Model − posterior
Atmospheric Model
Bottom−up Model − posterior
Bottom−up Model − prior

Results - N_2O



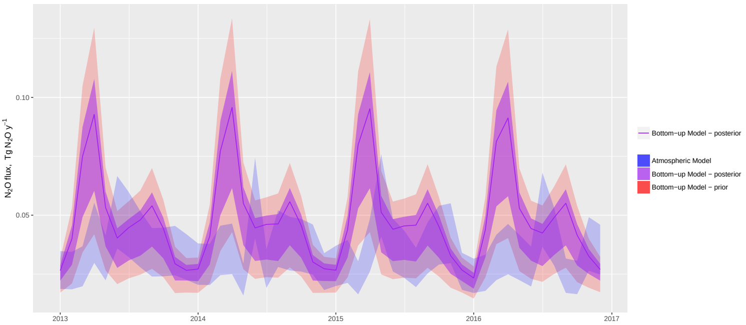
0.10
0.05
N_2O flux, Tg N_2O y^{-1}
2013
2014
2015
2016
2017
Bottom−up Model − prior

Results - N_2O



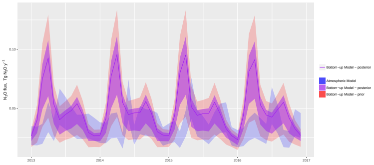
0.10
0.05
N2O flux, Tg N2O y−1
2013
2014
2015
2016
2017
Atmospheric Model
Bottom−up Model − prior
Atmospheric Model

Results - N_2O

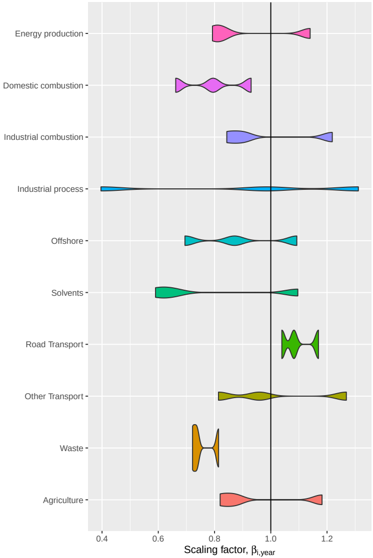


N2O flux, Tg N2O y^-1
0.10
0.05
2013
2014
2015
2016
2017
Bottom−up Model − posterior
Atmospheric Model
Bottom−up Model − posterior
Bottom−up Model − prior

Results - N_2O



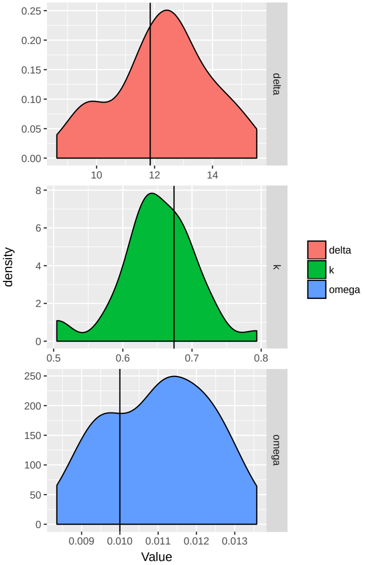
N2O flux, Tg N2O y-1
0.10
0.05
2013
2014
2015
2016
2017
Bottom−up Model − posterior
Atmospheric Model
Bottom−up Model − posterior
Bottom−up Model − prior



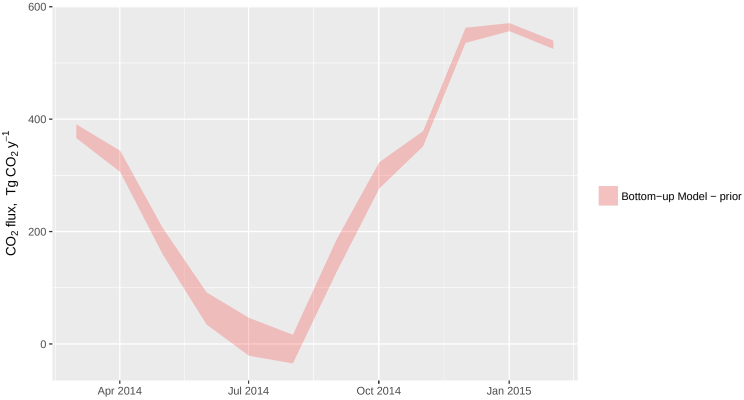
Energy production
Domestic combustion
Industrial combustion
Industrial process
Offshore
Solvents
Road Transport
Other Transport
Waste
Agriculture
0.4
0.6
0.8
1.0
1.2
Scaling factor, βi,year

Results - N_2O

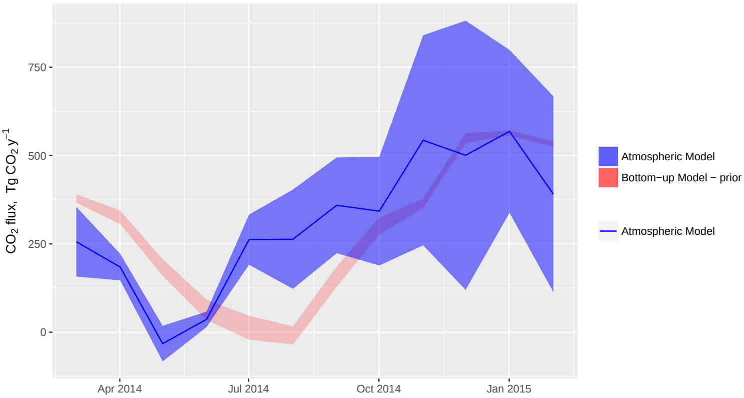
- Δ is a time response parameter (delay)
- k is a time response parameter (decay)
- Ω is the emission factor
  - Tier 1 default $= 0.01$



Results - CO_2

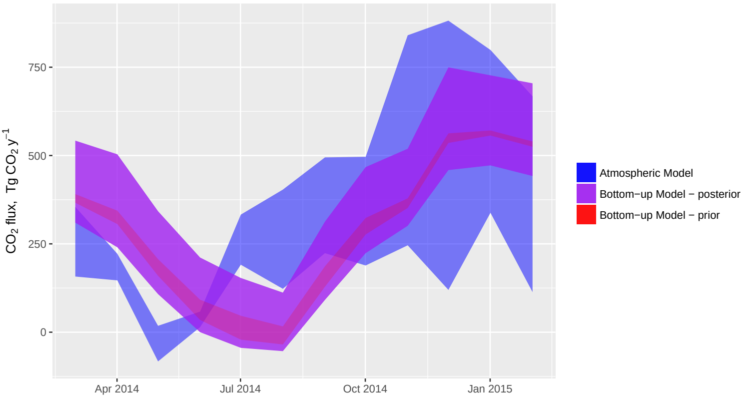

600
400
200
0
CO_2 flux, Tg CO_2 y^{-1}
Apr 2014
Jul 2014
Oct 2014
Jan 2015
Bottom−up Model − prior

Results - CO_2



750
500
250
0
CO2 flux, Tg CO2 y−1
Apr 2014
Jul 2014
Oct 2014
Jan 2015
Atmospheric Model
Bottom−up Model − prior
Atmospheric Model

Results - CO_2



750
500
250
0
Apr 2014
Jul 2014
Oct 2014
Jan 2015
CO2 flux, Tg CO2 y−1
Atmospheric Model
Bottom−up Model − posterior
Bottom−up Model − prior

Summary

- We have a method for comparing bottom-up and top-down models
- Bayesian methodology allows uncertainties to be combined in a consistent way
- Analysis allows us to (provisionally) attribute discrepancies
  - at sector level
    - e.g. spring peak in agricultural methane
  - at process level
    - e.g. emission factor from N fertilisation
- More work needed
  - computation time / efficiency
  - refining priors
  - use fine temporal resolution