Estimating GHG fluxes from the UK

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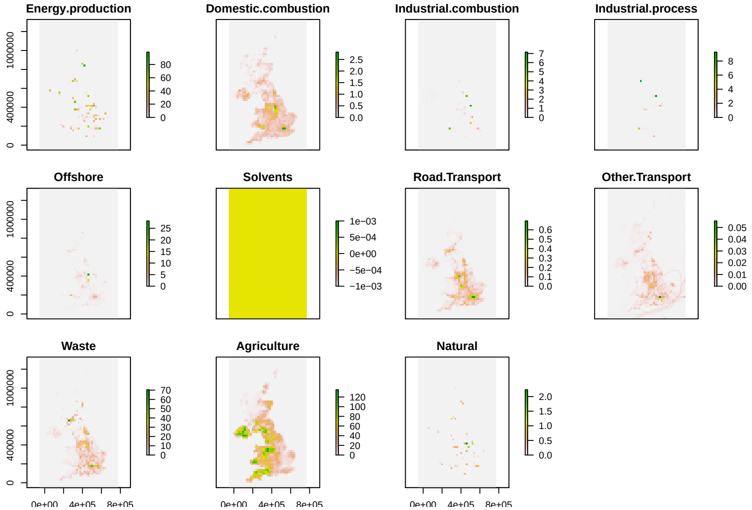
Bottom-up and atmospheric GHG flux estimates - Two Methods:

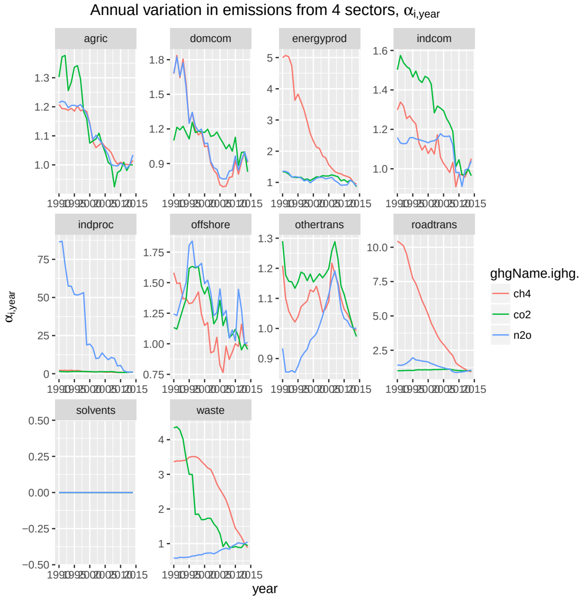
- Bottom-up GHG flux estimates
  - anthropogenic: from national GHG inventory process
  - biogenic: from biogeochemical models run at national-scale
- Atmospheric GHG flux estimates
  - from inverse modelling of atmospheric GHG concentrations on tall-tower network

How to reconcile differences?
How to use both methods to best constrain the national GHG budget?

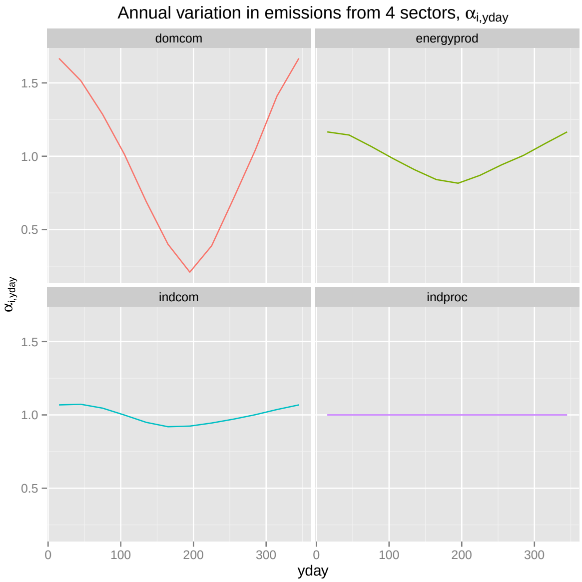
Spatial patterns by emission sector



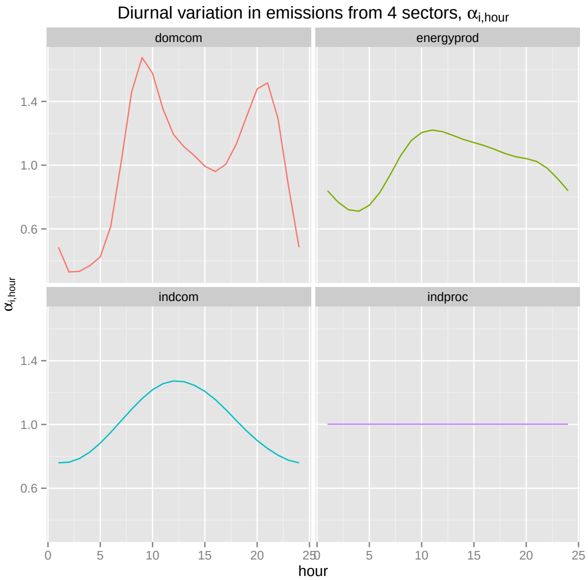
Temporal patterns by emission sector: annual



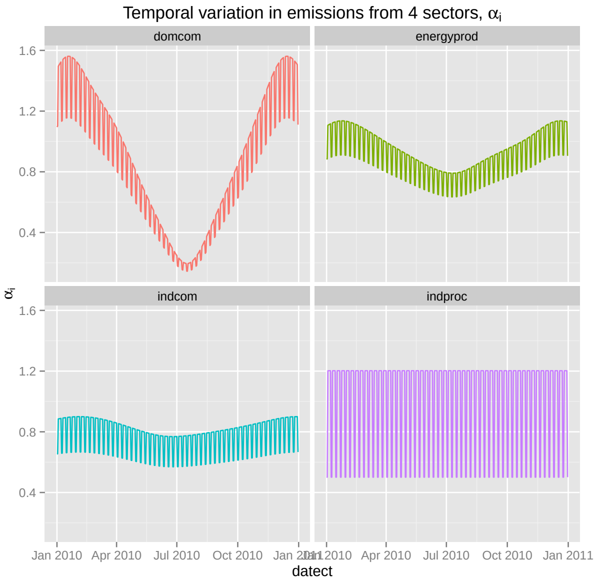
Temporal patterns by emission sector: seasonal



Temporal patterns by emission sector: diurnal



Temporal patterns by emission sector



Spatio-temporal model of emissions by sector

Each emissions sector has a characteristic spatio-temporal pattern.

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

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

where f(year), f(yday), f(wday) and f(hour) are cubic splines.
α is a vector of 44 coefficients: 11 sectors $\times$ 4 temporal scales.
We use this simple model to analyse discrepancies between atmospheric observations and bottom-up model predictions

Analyse discrepancies over time and space

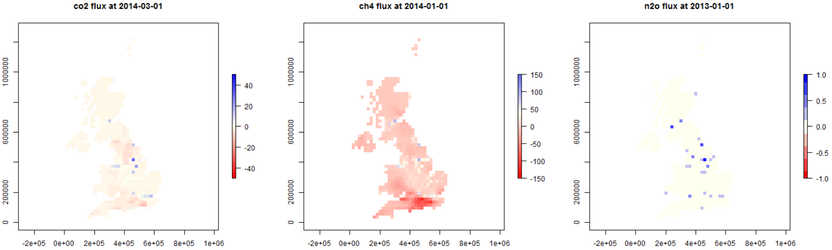
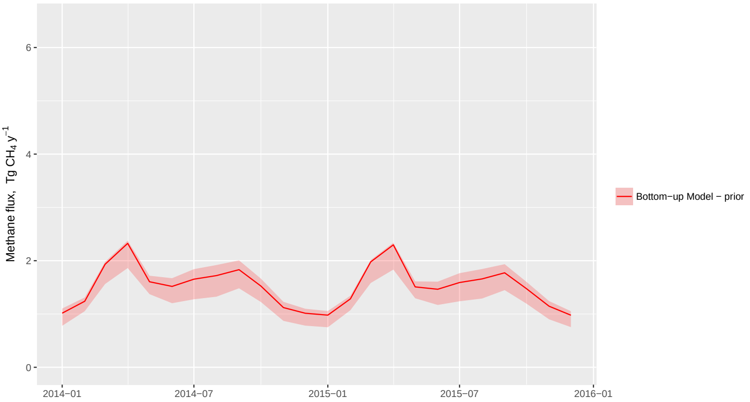


Figure: Difference between bottom-up and atmospheric flux estimates for CO_2, 2014 (left), CH_4, 2014-2015 (middle) and N_2O, 2013-2016 (right). Atmospheric estimates from NAME, University of Bristol and Met Office.

Bayesian Data assimilation approach

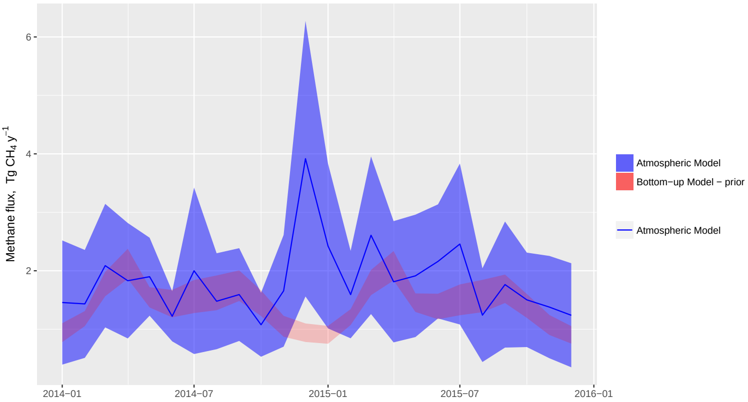
- Combine atmospheric model output with bottom-up model predictions
  - vary the bottom-up model α parameters
  - calculate likelihood (goodness-of-fit)
- produces uncertainty distribution for parameters and estimates of GHG flux

Results - CH_4



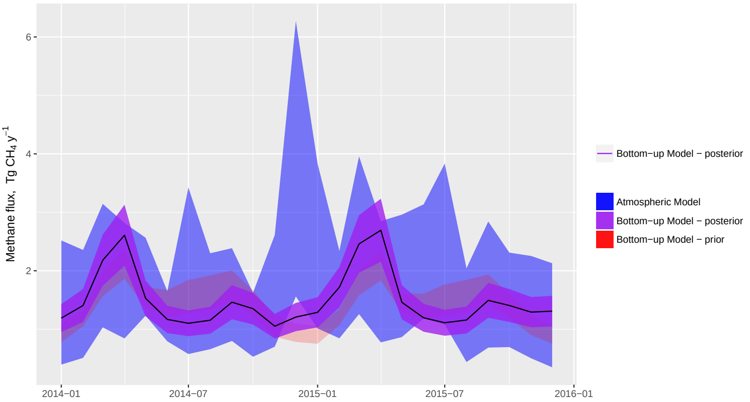
Methane flux, Tg CH_4 y^{-1}
6
4
2
0
2014−01
2014−07
2015−01
2015−07
2016−01
Bottom−up Model − prior

Results - CH_4



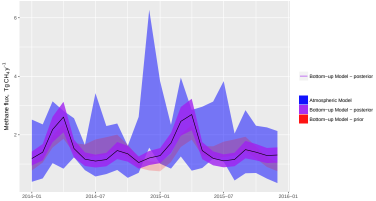
Methane flux, Tg CH4 y−1
6
4
2
2014−01
2014−07
2015−01
2015−07
2016−01
Atmospheric Model
Bottom−up Model − prior
Atmospheric Model

Results - CH_4

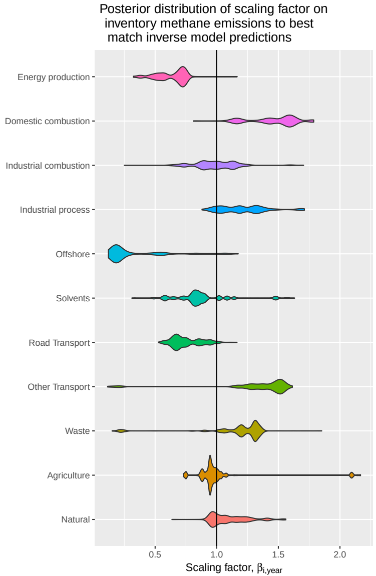


Methane flux, Tg CH_4 y^{-1}
6
4
2
2014−01
2014−07
2015−01
2015−07
2016−01
Bottom−up Model − posterior
Atmospheric Model
Bottom−up Model − posterior
Bottom−up Model − prior

Results - CH_4

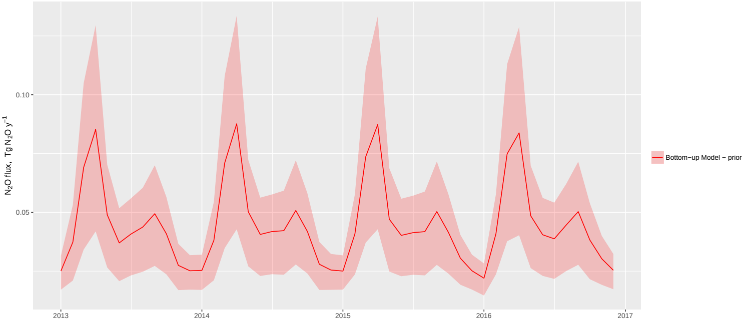


Methane flux, Tg CH4 y−1
6
4
2
2014−01
2014−07
2015−01
2015−07
2016−01
Bottom−up Model − posterior
Atmospheric Model
Bottom−up Model − posterior
Bottom−up Model − prior



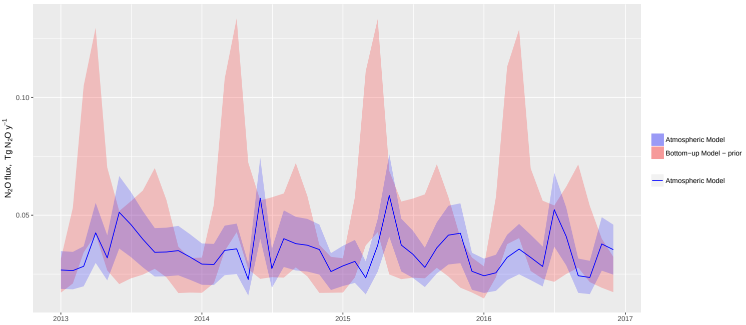
Posterior distribution of scaling factor on
inventory methane emissions to best
match inverse model predictions
Energy production
Domestic combustion
Industrial combustion
Industrial process
Offshore
Solvents
Road Transport
Other Transport
Waste
Agriculture
Natural
0.5
1.0
1.5
2.0
Scaling factor, βi,year

Results - N_2O



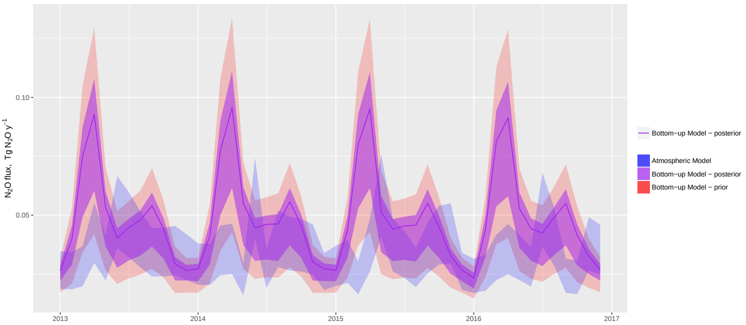
N_2O flux, Tg N_2O y^{-1}
0.10
0.05
2013
2014
2015
2016
2017
Bottom−up Model − prior

Results - N_2O



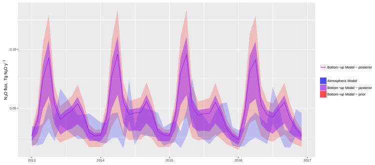
N2O flux, Tg N2O y^-1
0.10
0.05
2013
2014
2015
2016
2017
Atmospheric Model
Bottom−up Model − prior
Atmospheric Model

Results - N_2O

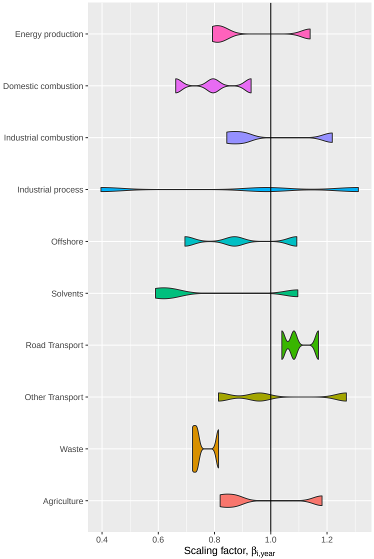


N2O flux, Tg N2O y−1
0.10
0.05
2013
2014
2015
2016
2017
Bottom−up Model − posterior
Atmospheric Model
Bottom−up Model − posterior
Bottom−up Model − prior

Results - N_2O

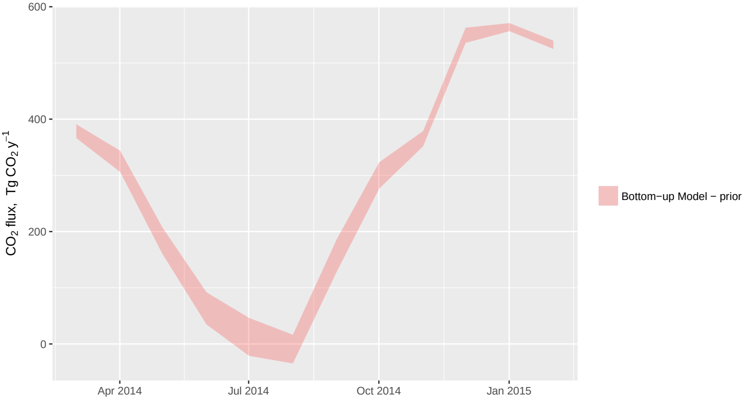


N2O flux, Tg N2O y-1
0.10
0.05
2013
2014
2015
2016
2017
Bottom−up Model − posterior
Atmospheric Model
Bottom−up Model − posterior
Bottom−up Model − prior



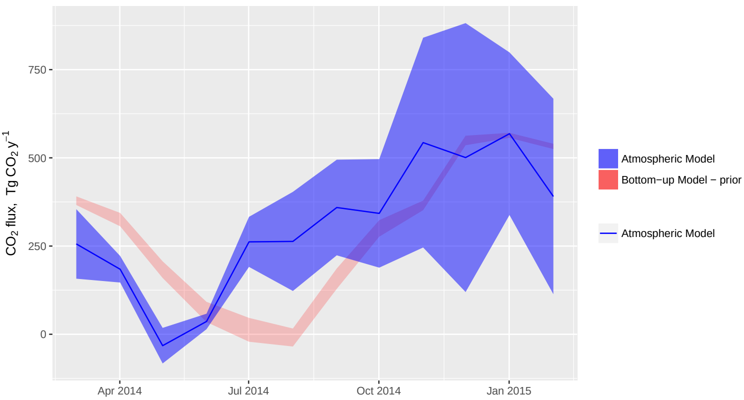
Energy production
Domestic combustion
Industrial combustion
Industrial process
Offshore
Solvents
Road Transport
Other Transport
Waste
Agriculture
0.4
0.6
0.8
1.0
1.2
Scaling factor, βi,year

Results - CO_2



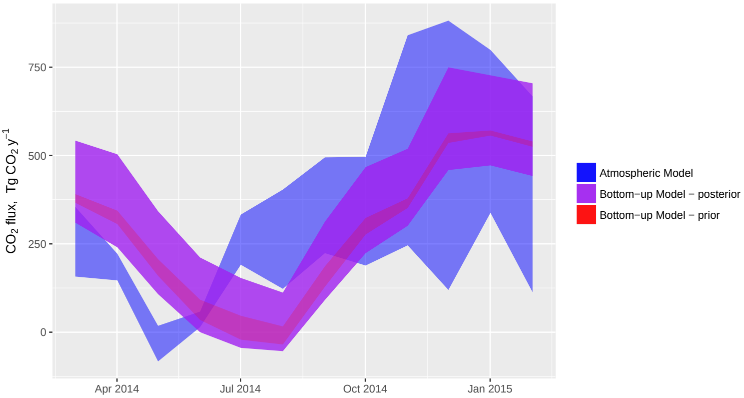
600
400
200
0
CO_2 flux, Tg CO_2 y^{-1}
Apr 2014
Jul 2014
Oct 2014
Jan 2015
Bottom−up Model − prior

Results - CO_2



CO_2 flux, Tg CO_2 y^{-1}
750
500
250
0
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 atmospheric models
  - Bayesian data assimilation methodology allows uncertainties to be combined in a consistent way
- Total emissions
  - increased for N_2O, uncertainty decreased
  - unchanged for CH_4, uncertainty increased
  - increased for CO_2, uncertainty increased
- Analysis allows us to attribute discrepancies
  - at sector level
    - e.g. spring peak in agricultural methane
  - at process level
    - e.g. emission factor from N fertilisation