Estimating regional fluxes of CO\(_2\) and CH\(_4\) using space-borne observations of XCH\(_4\) : XCO\(_2\)

A. Fraser\(^1\), P. I. Palmer\(^1\), L. Feng\(^1\), H. Bösch\(^2\), R. Parker\(^2\), E. J. Dlugokencky\(^3\), P. B. Krummel\(^4\), and R. L. Langenfelds\(^4\)

\(^1\)School of GeoSciences, University of Edinburgh, UK
\(^2\)Department of Physics and Astronomy, University of Leicester, Leicester, UK
\(^3\)US National Oceanic and Atmospheric Administration, Global Monitoring Division, Earth System Research Laboratory, Boulder, Colorado, USA
\(^4\)Centre for Australian Weather and Climate Research, CSIRO Marine and Atmospheric Research, Aspendale, Victoria, Australia

Received: 23 May 2014 – Accepted: 6 June 2014 – Published: 17 June 2014

Correspondence to: P. I. Palmer (paul.palmer@ed.ac.uk)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

We use the GEOS-Chem global 3-D atmospheric chemistry transport model to interpret XCH\(_4\) : XCO\(_2\) column ratios retrieved using a proxy method from the Japanese Greenhouse gases Observing SATellite (GOSAT). The advantage of these data over CO\(_2\) and CH\(_4\) columns retrieved independently using a full physics optimal estimation algorithm is that they suffer less from scattering-related regional bias. We show the model is able to reproduce observed global and regional spatial (mean bias = 0.7 \%) and temporal variations (global \(r^2 = 0.92\)) of this ratio with model bias < 2.5 \%. We also show these variations are driven by emissions of CO\(_2\) and CH\(_4\) that are typically six months out of phase which may reduce the sensitivity of the ratio to changes in either gas. To simultaneously estimate fluxes of CO\(_2\) and CH\(_4\) we use a formal Bayesian inverse model infrastructure. We use two approaches to independently resolve flux estimates of these two gases using GOSAT observations of XCH\(_4\) : XCO\(_2\): (1) the a priori error covariance between CO\(_2\) and CH\(_4\) describing common source from biomass burning; and (2) also fitting independent surface atmospheric measurements of CH\(_4\) and CO\(_2\) mole fraction that provide additional constraints, improving the effectiveness of the observed GOSAT ratio to constrain fluxes. We demonstrate the impact of these two approaches using Observing System Simulation Experiments. A posteriori flux estimates inferred using only the GOSAT ratios and taking advantage of the error covariance due to biomass burning are not consistent with the true fluxes in our experiments, as the inversion system cannot judge which species’ fluxes to adjust. This can result in a posteriori fluxes that are further from the truth than the a priori fluxes. We find that adding the surface data to the inversion dramatically improves the ability of the GOSAT ratios to infer both CH\(_4\) and CO\(_2\) fluxes. We show that using real GOSAT XCH\(_4\) : XCO\(_2\) ratios together with the surface data during 2010 outcompetes inversions using the individual XCH\(_4\) or the full-physics XCO\(_2\) data products. Regional fluxes that show the greatest improvements have model minus observation differences with a large seasonal cycle such as Tropical South America for which we report a small but significant
annual source of CO$_2$ compared to a small annual sink inferred from the XCO$_2$ data. Based on our analysis we argue that using the ratios we may be reaching the limitations on the precision of these data.

1 Introduction

Space-borne atmospheric column measurements of CO$_2$ and CH$_4$ have the potential to improve our quantitative understanding of their surface fluxes and to underpin the development of testable climate policies. For these data to address these potential applications the column measurements have to meet strict precision requirements, reflecting small signals from surface fluxes (a few percent of the column amount) compared to the variations due to atmospheric transport. Any uncharacterized systematic error in these measurements compromises the ability of these data to infer surface fluxes. The CO$_2$ inverse problem is particularly sensitive to these systematic errors acting on length scales $10^3$–$10^4$ km, in between the spatial scales of numerical models and those observed by the sparse network of well characterized upward-looking Fourier transform spectrometers, regional aircraft, and the network of ground-based measurements. Here, we develop a method to infer simultaneous regional CO$_2$ and CH$_4$ flux estimates (Fig. 1) from XCH$_4$ : XCO$_2$ ratios, retrieved from the Japanese Greenhouse gases Observing SATellite (GOSAT) using the proxy approach (based on University of Leicester proxy XCH$_4$ v4.0), which are less prone to systematic error from aerosols (Schepers et al., 2012).

Two methods have been used to retrieve CO$_2$ and CH$_4$ columns from calibrated GOSAT L1B spectra: the “full physics” and the “proxy” methods (Cogan et al., 2012; Parker et al., 2011). The full physics method uses an optimal estimation approach and incorporates a rigorous treatment of the atmospheric radiative transfer including the effects of clouds and aerosols. This method uses optimized spectral windows to fit CO$_2$ and CH$_4$. The main advantage of this approach is the error characterization of the a posteriori state vector, and the main disadvantage is having to accurately characterize the atmospheric aerosol for the radiative transfer calculation. The proxy method, used to infer CH$_4$ columns, fits both gases in nearby spectral windows with the assumption that any fitting artefacts common to both gases (e.g. aerosol and clouds) will be removed by taking the ratio of the two gases. This method is simpler than the full physics approach and more robust against scattering and as a result many more retrievals are possible from the GOSAT spectra. We also believe that these measurements are less compromised by systematic errors on regional scales. Interpretation of this ratio has in the past relied on scaling it with a model CO$_2$ column so that any erroneous model information about CO$_2$ can influence the interpretation of the GOSAT CH$_4$ columns (e.g. Parker et al., 2011; Fraser et al., 2013). We propose a method to simultaneously optimize CH$_4$ and CO$_2$ fluxes using the retrieved XCH$_4$ : XCO$_2$ ratio. This eliminates the need for a CO$_2$ model, removing the impact of model uncertainty on the retrieved methane columns, and increases the number of observations available to constrain CO$_2$ fluxes (Fig. 2).

In the following section we describe the space-borne and ground-based data used in our experiments. In Sect. 3 we describe the GEOS-Chem chemical transport model, and the data assimilation scheme developed for this work. In Sect. 4 we report the GOSAT and model spatial and temporal distributions of XCH$_4$ : XCO$_2$ ratios (Sect. 4.1), we test the assimilation scheme using a series of Observing System Simulation Experiments (OSSEs, Sect. 4.2) and present inversion results (Sect. 4.3). We conclude the paper in Sect. 5.

2 Data

2.1 GOSAT CO$_2$ and CH$_4$ atmospheric column mole fraction measurements

GOSAT was launched in 2009 by the Japanese Space Agency in a sun-synchronous orbit with an equatorial local overpass time of 13:00 LT, providing global coverage every three days (Kuze et al., 2009). GOSAT includes two instruments: TANSO-FTS (Thermal
and Near Infrared Sensor for carbon Observations – Fourier Transform Spectrometer) and TANSO-CAI (TANSO – Cloud and Aerosol Imager). The TANSO-FTS instrument provides short-wave infrared (SWIR) radiances from which dry-air mole fraction observations of CO$_2$ and CH$_4$, XCO$_2$ and XCH$_4$, can be retrieved.

We provide a brief description of the proxy retrieval algorithm used for XCO$_2$ and XCH$_4$ and refer the reader to a detailed description (Parker et al., 2011). XCH$_4$ and XCO$_2$ are retrieved at 1.65 µm and 1.61 µm, respectively. Past work has used this approach to infer observations of XCH$_4$ by scaling it by XCO$_2$, using XCO$_2$ as a proxy for the light path through the atmosphere. The mole fraction of XCH$_4$ is then obtained using a model estimate for XCO$_2$: $XCH_4^{\text{PROXY}} = \left(\frac{XCH_4}{XCO_2}\right)^{\text{GOSAT}} \times XCO_2^{\text{MODEL}}$, but using an inaccurate model of atmospheric CO$_2$ will introduce erroneous variability and bias in resulting values for $XCH_4^{\text{PROXY}}$. In this work we use the ratio $\left(\frac{XCH_4}{XCO_2}\right)^{\text{GOSAT}}$ directly, removing the requirement of model CO$_2$. We filter ratio values using cloud-screening and quality-of-fit filters recommended by Parker et al. (2011), and we further filter data with a solar zenith angle > 70°, poleward of 60° latitude, or taken at medium gain (Fraser et al., 2013); the analysis of proxy XCH$_4$ reported by Fraser et al. (2013) used the previous version of the data. Figure 2 shows that the proxy method typically provides twice the number of observations available from the full physics approach.

### 2.2 In situ surface atmosphere mole fraction measurements

As described in Sect. 4.2, we use these data as independent constraints for CH$_4$ and CO$_2$ emission estimates, improving the ability of the GOSAT proxy ratio to act as a constraint on both CH$_4$ and CO$_2$ flux estimates. We assimilate data from 45 sites of the NOAA Earth System Research Laboratory (ESRL), Global Monitoring Division, version 28 August 2013 (Dlugokencky et al., 2013); nine sites from the CSIRO Global Atmospheric Sampling Laboratory (GASLAB), released August 2013 (Francey et al., 1996); and two sites from Environment Canada’s Greenhouse Gas Measurement Program (EC), released August 2013 (Worthy et al., 2003). Weekly air samples from all three networks are collected from sites distributed globally and data are reported on the NOAA 2004 (CH$_4$, all networks) and WMO X2007 (CO$_2$, ESRL, CSIRO) or WMO X83 (CO$_2$, EC) mole fraction scales. Figure 1 shows the location of the sites used in this work. Three sites are in both the ESRL and GASLAB networks: Mauna Loa, Hawaii; Cape Grim, Tasmania; and the South Pole. Alert, Nunavut is in all three networks. At these sites we average the data from the available networks, leaving 51 individual sites.

### 3 Models

#### 3.1 The GEOS-Chem transport model

We use version v9-01-03 of the GEOS-Chem global 3-D atmospheric chemistry transport model, driven by assimilated meteorological fields from the NASA Global Modeling and Assimilation Office (version 5), to interpret observed variations of GOSAT proxy ratio measurements. We use the GEOS-5 meteorology at a horizontal resolution of 4° (latitude) × 5° (longitude) with 47 vertical levels that span from the surface to the mesosphere, with typically 35 levels in the troposphere.

The CH$_4$ and CO$_2$ simulations are described and evaluated against correlative data in Fraser et al. (2011) and Feng et al. (2011), respectively. Table 1 and Fig. 3 show the global annual flux estimates and temporal distribution of CH$_4$ and CO$_2$ fluxes, respectively. The main atmospheric sink of CH$_4$ is the hydroxyl radical and is described in the troposphere by monthly mean 3-D fields generated by a full chemistry version of the model. Loss rates for methane in the stratosphere are adapted from a 2-D stratospheric model (Wang et al., 2004).

#### 3.2 The MAP inverse model

We use an inverse model that finds the maximum a posteriori (MAP) solution (Rodgers, 2000) to simultaneously optimize the magnitude of the CH$_4$ and CO$_2$ flux estimates by...
between CH$_4$ and CO$_2$ fluxes because they are not co-emitted, with the exception of biomass burning for which we include a region-specific correlation with a mean value of 0.8 following previous work (Palmer et al., 2006).

The measurement vector $y$ includes a spatial and temporal average of GOSAT XCH$_4$ : XCO$_2$ ratio measurements. We average the data into monthly means for the $4^\circ \times 5^\circ$ grid boxes of GEOS-Chem, which ensures a reasonable number of measurements for each month and increases the signal to noise of the observed ratio, as described below. Estimates inferred using finer temporal and spatial bins tend to be noisier, largely reflecting changes in the measurement coverage from clouds and aerosols, but still produce consistent results shown here when they are averaged monthly and on the model grid. For some experiments, $y$ also includes in situ surface measurements of CH$_4$ and/or CO$_2$.

We construct $S_y$ as a diagonal matrix with the diagonal elements being the square of the error in the a priori fluxes, which we assume to be 100% for the biospheric fluxes and 50% for the biomass burning and anthropogenic fluxes. We assume no temporal correlation between fluxes in the same region or sector. We generally assume no correlation between CH$_4$ and CO$_2$ fluxes because they are not co-emitted, with the exception of biomass burning for which we include a region-specific correlation with a mean value of 0.8 following previous work (Palmer et al., 2006).

The measurement vector $y$ includes a spatial and temporal average of GOSAT XCH$_4$ : XCO$_2$ ratio measurements. We average the data into monthly means for the $4^\circ \times 5^\circ$ grid boxes of GEOS-Chem, which ensures a reasonable number of measurements for each month and increases the signal to noise of the observed ratio, as described below. Estimates inferred using finer temporal and spatial bins tend to be noisier, largely reflecting changes in the measurement coverage from clouds and aerosols, but still produce consistent results shown here when they are averaged monthly and on the model grid. For some experiments, $y$ also includes in situ surface measurements of CH$_4$ and/or CO$_2$.

We construct $S_y$ as a diagonal matrix with the diagonal elements being the standard error of the mean measurement error. For GOSAT, we use the provided measurement error. For surface data the measurement error is the standard error of the monthly mean calculated from the observations made over that month (Fraser et al., 2013). When we average we sum these errors in quadrature. We also include a model transport error to each individual measurement error. For both the GOSAT ratio measurements and surface in situ data we describe this error as 0.25% for (X)CO$_2$ (Feng et al., 2011) and 0.5% for (X)CH$_4$ (Wang et al., 2004).

The Jacobian matrix, $K$, is constructed from forward runs of the model where the fluxes in each region and for each sector are perturbed by 1 Gt for CO$_2$ or 1 Tg for CH$_4$. The model is then sampled at the time and location of the observations, smoothed using GOSAT averaging kernels, and these sensitivities are averaged into monthly and regional means.
4 Results

4.1 Forward modelling of GOSAT XCH$_4$ : XCO$_2$ ratios

Figure 3 shows that for many geographical regions CH$_4$ and CO$_2$ flux estimates are six months out of phase, reflecting seasonal changes in wetland emissions of CH$_4$ and terrestrial CO$_2$ fluxes. This may reduce the sensitivity of the ratio to variations in either gas.

Figure 4 shows the observed annual variability of the XCH$_4$ : XCO$_2$ ratio is due mainly to XCH$_4$ variations. Common features include the gradient in the interhemispheric ratio and localized features due to orography, e.g., the Himalayan mountain range. The GEOS-Chem model reproduces the spatial pattern of the GOSAT ratio observations within $\approx 2.5\%$. The model has a negative bias over the tropics, which is largely due to model positive bias for XCO$_2$, as expected. This figure illustrates the demanding accuracy and precision requirements associated with this space-borne measurement if it is to become a useful constraint for carbon cycle science. The monthly variation of observed values, here shown as the 1-$\sigma$ value expressed as a percentage about the annual mean, is smallest for the XCH$_4$ : XCO$_2$ ratios for which scattering and other biases are removed.

Figure 5 shows that the model can typically capture 70% of the observed temporal variability of XCH$_4$ : XCO$_2$ over different geographical regions. Over most regions we find the model has a progressively larger negative bias, reflecting its overestimation of the CO$_2$ growth rate. The model generally agrees best with GOSAT in the Northern Hemisphere extra-tropics, and the worst over Tropical South America, where we know the model underestimates the CO$_2$ biological uptake. While XCH$_4$ variations determine the spatial distribution of the GOSAT XCH$_4$ : XCO$_2$ ratio, we find that XCO$_2$ determines its seasonal cycle. This is particularly noticeable over boreal regions and Europe, where the peak in the ratio in the second half of the year is a result of decreasing XCO$_2$ due to increased uptake from the biosphere.

Figure 5 also illustrates the importance of using the ratio instead of the contributory columns. Both XCH$_4$ and XCO$_2$ are too noisy (due to variations in the atmosphere and surface) by themselves but the observed variations cancel out in the ratio. It should be noted that the XCH$_4$ and XCO$_2$ plotted here are not the final data products from GOSAT, but the intermediary products from which the ratio is calculated. Comparing this figure to Fig. 5 in Cogan et al. (2012) and Fig. 5 in Parker et al. (2011) shows that the regional bias between GOSAT and the model is much smaller in the ratio than in the individual species. While GEOS-Chem tends to underestimate the GOSAT ratio, the bias is more or less consistent between regions, which is not the case for either XCO$_2$ or XCH$_4$.

4.2 Inverse modelling of GOSAT XCH$_4$ : XCO$_2$ ratios: OSSEs

We use OSSEs, realistic numerical experiments, to characterize the method we use to estimate simultaneously CO$_2$ and CH$_4$ regional fluxes from GOSAT XCH$_4$ : XCO$_2$ ratios. For all these experiments, we sample the model at the location of the clear-sky GOSAT observations, apply GOSAT averaging kernels, and add, as a minimum, random error based on actual GOSAT measurements. Similarly, we sample the model at the time and location of the surface observations and add characteristic random noise informed by the data.

We conducted four broad sets of OSSEs: (1) those that use only the GOSAT XCH$_4$ : XCO$_2$ ratios, (2) those that use the GOSAT data and in situ measurements of CH$_4$ and/or CO$_2$, (3) those that use the best setup from (2) and vary the a priori fluxes, and (4) as (3) but including regional bias.

Figure 6a and b shows the results from experimental set (1). First, we assume that the a priori fluxes equal the true fluxes, allowing us to assess the level of numerical noise in the closed-loop system. We find that after setting the a priori to the true fluxes there is only a small difference between a posteriori and true fluxes that is within the uncertainty of the a posteriori fluxes. We then assume that the a priori fluxes are 20% higher than the truth, allowing us to assess the efficacy with which the synthetic obser-
vations can recover the true flux estimates. For this experiment the observing system reconciles the model minus observation difference by simultaneously changing the CH₄ and CO₂ fluxes that are not always within the a posteriori flux uncertainties, which we attribute to the fact that there is no additional information about allocating this difference to a particular gas.

Figure 6c–e shows results from experimental set (2). Adding either CH₄ or CO₂ surface observations to the measurement vector reduces the bias between the a posteriori and true fluxes, but also reduces the error reduction of the other species. We find that assimilating both CH₄ and CO₂ surface observations gives the smallest difference from the truth and the largest error reductions; we adopt this as our control experimental setup in the following sections. We accept the larger standard deviations as the fluxes are closer to the truth. For reference, using only the surface data returns error reductions of approximately 23 % for both species (not shown). Figure 7 shows the results from experimental set (3). This control observing system can return the true fluxes for a wide array of varying CH₄ and CO₂ fluxes for most geographical regions.

In experiment set (4) (not shown) we assess the impact of prescribed observation bias to the GOSAT data on the a posteriori flux estimates; assuming that the surface data is unbiased or at least can be identified readily via ongoing calibration/validation activities. We assume a latitudinally-varying bias, which was superimposed onto the “true” atmospheric measurements plus random error (0.005 ppb ppm⁻¹) for the monthly gridded measurement vector. To describe the latitudinal bias, we used a second-degree polynomial with a minimum at the South Pole and a maximum at the North Pole; our choice of this polynomial is based on the bias between the model and GOSAT data. This bias ranges from −0.08–0.06 ± 0.005 ppb ppm⁻¹. As part of the data pre-processing inverse model analysis, we either assume the data are unbiased or fit a latitudinally-varying bias. For our bias correction we fit a four-degree polynomial to the mean annual difference between the model and the data; we find that using higher degree polynomials did not significantly change our results. Not fitting for the bias results in CH₄ and CO₂ fluxes that are up to 10 Tg and 0.4 Gt different from the true fluxes, respectively. Removing the bias in pre-processing returns values that are close to the true fluxes.

4.3 Analysis of GOSAT XCH₄ : XCO₂ ratios

Figure 8 and Table 2 show flux estimates inferred from GOSAT XCH₄ : XCO₂ data and surface mole fraction observations of CH₄ and CO₂ (Sect. 2), and independent flux estimates of CH₄ and CO₂ inferred using an ensemble Kalman filter (EnKF) from GOSAT XCH₄ proxy data (Fraser et al., 2013) and XCO₂ full physics data (Feng et al., 2011).

For CH₄, the general tendency of a posteriori fluxes, relative to a priori values, are consistent between the XCH₄ : XCO₂ ratio and the proxy XCH₄ data, but based on a posteriori uncertainties the magnitude of these fluxes can be statistically different. The ratio infers larger emissions from Tropical South America, Northern Africa, and Temperate Eurasia. Error reductions resulting from assimilating XCH₄ : XCO₂ ratio data are typically 30 % but can be up to 60 % (Temperate Eurasia). For some regions, the error reduction from using the ratio is larger from using the individual gas but for others the reduction is smaller. Geographical regions with notable improvements in our understanding from assimilating the ratio data include Tropical and Temperate South America, Northern Africa, and Temperate Eurasia. Strictly speaking we cannot compare directly the CH₄ flux estimated reported by Fraser et al. (2013) and those inferred from the XCH₄ : XCO₂ ratio data. As noted above we are using a newer version of the proxy retrieval that includes updated a priori information particularly for stratospheric CH₄ concentrations and updates to the retrieval grid and spectroscopic input, resulting in 5–10 % more clear-sky measurements; we are using a newer version of the GEOS-Chem transport model; and most importantly we treat the measurements differently, reflecting the difficulty in the small observed changes in the XCH₄ : XCO₂ ratio.

For CO₂, a posteriori fluxes inferred from the GOSAT ratio can be statistically different to those inferred from the EnKF inversion, including Tropical South America, Southern Africa, Boreal Eurasia, Tropical Asia, and Australasia. These differences between the
inversion largely reflect the larger volume of $XCH_4: XCO_2$ ratio data resulting in better spatial and temporal coverage (Fig. 2). We may also expect the largest differences where we believe there are the greatest biases in the other single gas retrievals. We find that the associated error reductions for the $CO_2$ fluxes inferred from the $XCH_4: XCO_2$ ratio data are typically larger than those for $CH_4$, and are different from those inferred from the EnKF inversion.

5 Concluding remarks

We have interpreted measurements of $XCH_4: XCO_2$ from GOSAT in which $XCH_4$ and $XCO_2$ are retrieved in nearby spectral windows under the assumption that their ratio will largely remove common sources of biases. By interpreting the ratio directly we minimize any bias introduced by model $XCO_2$; although we acknowledge other sources of model bias remain. A major advantage of the ratio is this data product does not suffer from the measurement bias that befalls the full physics $XCO_2$ data. Another advantage is that the volume of these data is greater than their full physics counterpart.

While the ratio benefits from these three advantages the difference between model and observed quantities are much smaller (typically $< \pm 2\%$) than either $XCO_2$ or $XCH_4$ becoming comparable in magnitude to other sources of error, e.g. model transport error, that cannot easily be characterized and removed. By using the ratio we may be reaching the limitations on the precision of these data and our ability to interpret them using current-day transport models. However, over particular geographical regions we find there are seasonally varying GOSAT minus model ratio differences that are large enough to be exploited, e.g., Tropical South America and Tropical Asia.

Using a series of numerical experiments we showed that the simultaneous estimation of $CO_2$ and $CH_4$ fluxes using the GOSAT ratio is possible with the information split as a function of the a priori uncertainties, however the inversion system returns unphysical fluxes in some regions. We showed that including surface mole fraction measurements of $CO_2$ and $CH_4$ in the measurement vector provides an “anchor” for the inversion, and we showed that the combined GOSAT and surface data can distinguish between $CO_2$ and $CH_4$ fluxes.

Using real data for 2010 we showed that the combination of the GOSAT $XCH_4: XCO_2$ ratio and the surface mole fraction data outcompeted inversions using the individual $XCH_4$ and $XCO_2$ GOSAT data and corresponding surface data. We found the greatest differences between the two approaches over the regions where we found that the GOSAT minus model difference had a seasonal variation that was larger than a few percent. For instance, we found that Tropical South America was a small but significant source of $CO_2$ while analysis of full physics $XCO_2$ showed a small sink term. Analysis of the ratio led to slightly larger reductions globally, and in some regions, primarily in the tropics, much larger reductions in uncertainty of $CO_2$ and $CH_4$.

The main reason for using the $XCH_4: XCO_2$ ratio is that it minimizes scattering and potentially other biases and significantly increases geographical coverage. Although $CO_2$ and $CH_4$ do not share many common sources that result in significant atmospheric covariance we have shown that: (1) the combined information from these two gases can be disentangled using other data, and (2) the result is an improvement over what can be achieved using observations of either full-physics $XCO_2$ or $XCH_4$. Consequently, the use of space-borne observations of the $XCH_4: XCO_2$ ratio will be of particular interest for estimating $CO_2$ surface fluxes over regions that are characterized by frequent cloud cover and high aerosol loading such as the tropics where the quality and coverage of full-physics $XCO_2$ retrieval approaches will be limited even for missions with spatial footprints smaller than GOSAT. This ratio approach could also be used in combination with other atmospheric tracers that help improve the source attribution of $CO_2$, e.g. carbon monoxide, where the ensuing correlation is driven by incomplete combustion (Palmer et al., 2006). Space-borne mission concept development related to the carbon cycle should not only focus on the primary compound but also on any secondary compound that will help interpret the observed variability of that primary gas.
Acknowledgements. We thank Doug Worthy for the Environment Canada data. NOAA ESRL is supported by NOAA’s Climate Program Office; and CSIRO research at Cape Grim is supported by the Australian Bureau of Meteorology. AF and RP were supported by the Natural Environment Research Council National Centre for Earth Observation (NCEO). LF was partly funded by the “Data Assimilation Project-Interfacing EO data with atmospheric and land surface models” ESA contract 4000104980/1-LG. HB, RP and LF also acknowledge funding by the ESA Climate Change Initiative (GHG-CCI). PIP gratefully acknowledges his Royal Society Wolfson Research Merit Award.

References


### Table 1. A priori sources of carbon dioxide and methane used in the GEOS-Chem model for 2010.

<table>
<thead>
<tr>
<th>Source</th>
<th>CO$_2$ A priori magnitude (Gt year$^{-1}$)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fossil fuel</td>
<td>14.8</td>
<td>ODIAC (Oda and Maksyutov, 2011)</td>
</tr>
<tr>
<td>Oceans</td>
<td>-5.2</td>
<td>Takahashi et al. (2009)</td>
</tr>
<tr>
<td>Biosphere</td>
<td>3.4</td>
<td>CASA (Randerson et al., 1997)</td>
</tr>
<tr>
<td>Biomass burning</td>
<td>8.6</td>
<td>GFEDv3 (van der Werf et al., 2010)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source</th>
<th>CH$_4$ A priori magnitude (Tg year$^{-1}$)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ruminant animals</td>
<td>92.8</td>
<td>EDGAR 3.2 FT (Olivier et al., 2005)</td>
</tr>
<tr>
<td>Coal mining</td>
<td>47.1</td>
<td>EDGAR 3.2 FT (Olivier et al., 2005)</td>
</tr>
<tr>
<td>Oil and natural gas production</td>
<td>42.8</td>
<td>EDGAR 3.2 FT (Olivier et al., 2005)</td>
</tr>
<tr>
<td>Landfills</td>
<td>44.7</td>
<td>EDGAR 3.2 FT (Olivier et al., 2005)</td>
</tr>
<tr>
<td>Rice</td>
<td>68.0</td>
<td>Bloom et al. (2012)</td>
</tr>
<tr>
<td>Wetlands</td>
<td>192.0</td>
<td>Bloom et al. (2012)</td>
</tr>
<tr>
<td>Biomass burning</td>
<td>19.4</td>
<td>GFEDv3 (van der Werf et al., 2010)</td>
</tr>
<tr>
<td>Oceans</td>
<td>15.1</td>
<td>Houweling et al. (1999)</td>
</tr>
<tr>
<td>Termites</td>
<td>20.1</td>
<td>Fung et al. (1991)</td>
</tr>
<tr>
<td>Hydrates</td>
<td>5.0</td>
<td>Fung et al. (1991)</td>
</tr>
<tr>
<td>Soil Sink</td>
<td>-25.2</td>
<td>Fung et al. (1991)</td>
</tr>
</tbody>
</table>

### Table 2. A priori and a posteriori CH$_4$ and CO$_2$ regional land fluxes and 1-$\sigma$ uncertainties inferred from GOSAT XCH$_4$ : XCO$_2$ and in situ mole fraction measurements. Fluxes inferred from previous work (Fraser et al., 2013; Feng et al., 2011) using and ensemble Kalman Filter are denoted EnKF. CH$_4$ and CO$_2$ fluxes are reported as Tg CH$_4$ year$^{-1}$ and Gt C year$^{-1}$, respectively.

<table>
<thead>
<tr>
<th>Region</th>
<th>CH$_4$ Flux</th>
<th>CH$_4$ 1-$\sigma$</th>
<th>CO$_2$ Flux</th>
<th>CO$_2$ 1-$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boreal North America</td>
<td>4.1</td>
<td>1.0</td>
<td>-0.4</td>
<td>0.5</td>
</tr>
<tr>
<td>Boreal Eurasia</td>
<td>15.2</td>
<td>2.5</td>
<td>-0.7</td>
<td>1.0</td>
</tr>
<tr>
<td>Temperate North America</td>
<td>58.5</td>
<td>4.1</td>
<td>-0.2</td>
<td>0.5</td>
</tr>
<tr>
<td>Northern Africa</td>
<td>49.6</td>
<td>4.3</td>
<td>0.3</td>
<td>0.6</td>
</tr>
<tr>
<td>Temperate Eurasia</td>
<td>127.9</td>
<td>11.8</td>
<td>2.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Tropical South America</td>
<td>45.1</td>
<td>5.6</td>
<td>-0.2</td>
<td>0.5</td>
</tr>
<tr>
<td>Southern Africa</td>
<td>46.0</td>
<td>5.1</td>
<td>-0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Australasia</td>
<td>16.7</td>
<td>1.4</td>
<td>-0.4</td>
<td>0.2</td>
</tr>
</tbody>
</table>
Figure 1. Distribution of the 13 geographical regions for which we estimate CO₂ and CH₄ fluxes, and the location of 57 co-operative flask sampling sites with data covering the study period, January–December 2010. The land regions, informed by previous work (Gurney et al., 2002) include: Boreal North America (BNA), Temperate North America (TNA), Tropical South America (TrSA), Temperate South America (TSA), Northern Africa (NAf), Southern Africa (SAf), Boreal Eurasia (BEr), Temperate Eurasia (TEr), Tropical Asia (TrAs), Australasia (Aus), and Europe (Eur). The ground-based measurement sites run by NOAA ESRL, CSIRO GASLAB, and EC are denoted by white circles, white diamonds, and white squares, respectively.

Figure 2. The number of GOSAT observations available per month during 2010 over specific geographical regions (Fig. 1) from the full-physics and proxy retrieval algorithms.
Figure 3. Monthly a priori emissions for CH₄ (Tg CH₄ year⁻¹) and CO₂ (Gt C year⁻¹) for the land regions shown in Fig. 1. Note the different y-scales.

Figure 4. Annual mean GOSAT (top row) and GEOS-Chem model (second row) XCH₄, XCO₂, and XCH₄ : XCO₂ ratio measurements from GOSAT during 2010 averaged on the model 4° × 5° grid. The third row shows the percentage difference between them (GOSAT minus GEOS-Chem). For XCH₄ and XCO₂, we truncate at the mean ± 2-σ. The bottom row shows the 1-σ value in the difference as a percentage about the mean GOSAT XCH₄, XCO₂, and XCH₄ : XCO₂ data. The model has been sampled at the time and location of the GOSAT observations, and convolved with scene-dependent averaging kernels.
Figure 5. GOSAT and GEOS-Chem daily mean $XCH_4 : XCO_2$ ratios (top panels) for 2010–2011, averaged over each land region shown in Fig. 1. Squared Pearson correlation coefficients between GOSAT and GEOS-Chem are shown inset for the ratio (black), $XCH_4$ (purple), and $XCO_2$ (green). Bottom panels show the corresponding GOSAT and GEOS-Chem daily mean $XCH_4$ and $XCO_2$. The model has been sampled at the time and location of the GOSAT observations, and convolved with scene-dependent averaging kernels.

Figure 6. Regional flux estimates of $CH_4$ (left) and $CO_2$ (right) inferred from various observing system simulation experiments, where values are described as the departure from the corresponding true flux. The first six regions are aggregates: global represents all regional fluxes; land omits the oceans and vice versa; NH land sums fluxes from Boreal and Temperate North America, Europe, and Boreal and Temperate Eurasia; Trop land sums fluxes from Tropical South America, Northern Africa, and Tropical Asia; and SH land sums fluxes from Temperate South America, Southern Africa, and Australasia. The remaining regions are defined in Fig. 1. Experiment (a) for which the a priori and the truth are the same and only GOSAT data are used; experiment (b) is as (a) but the a priori fluxes are 20% higher than the truth; experiment (c) is as (b) but $CH_4$ surface flask data are also used; experiment (d) is as (b) but $CO_2$ surface flask data are also used; experiment (e) is as (b) but $CH_4$ and $CO_2$ surface flask data are also used. Note the different y-scale for $CO_2$ in (b). The error reduction in the global fluxes ($\gamma$), the mean ($\bar{x}$) and standard deviation ($\sigma$) of the difference in the individual regions are shown inset of each panel.
Figure 7. As Fig. 6 but all experiments use CH$_4$ and CO$_2$ surface flask data and GOSAT data. Experiment (a) for which a priori fluxes are equal to the true fluxes; experiment (b) for which CH$_4$ a priori fluxes are 20 % larger than the true fluxes; experiment (c) for which CO$_2$ a priori fluxes are 20 % larger than the true fluxes; experiment (d) for which CH$_4$ and CO$_2$ a priori fluxes are 20 % larger than their true fluxes; experiment (e) for which CH$_4$ a priori fluxes are 20 % smaller than their true fluxes; and experiment (f) for which all a priori fluxes are perturbed stochastically, ranging from -20 % to 20 %, from the true fluxes.

Figure 8. A priori and a posteriori CO$_2$ and CH$_4$ regional land fluxes inferred from GOSAT XCH$_4$ - XCO$_2$ and surface measurements of CO$_2$, and CH$_4$ and from XCO$_2$ or XCH$_4$ using an ensemble Kalman filter (top) (Feng et al., 2011; Fraser et al., 2013), and the corresponding reduction in uncertainty (bottom), during 2010. Error bars atop of emission estimates represents the 1-$\sigma$ uncertainty.