On the Benefit of GOSAT Observations to the Estimation of Regional CO$_2$ Fluxes

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Abstract

We assessed the utility of global CO$_2$ distributions brought by the Greenhouse gases Observing SATellite (GOSAT) in the estimation of regional CO$_2$ fluxes. We did so by estimating monthly fluxes and their uncertainty over a one-year period between June 2009 and May 2010 from 1) observational data collected in existing networks of surface CO$_2$ measurement sites (GLOBALVIEW-CO$_2$ 2010; extrapolated to the year 2010) and 2) both the surface observations and column-averaged dry air mole fractions of CO$_2$ ($X_{\text{CO}_2}$) retrieved from GOSAT soundings. Monthly means of the surface observations and GOSAT $X_{\text{CO}_2}$ retrievals gridded to $5^\circ \times 5^\circ$ cells were used here. The estimation was performed for 64 subcontinental-scale regions. We compared these two sets of results in terms of change in uncertainty associated with the flux estimates. The rate of reduction in the flux uncertainty, which represents the degree to which the GOSAT $X_{\text{CO}_2}$ retrievals contribute to constraining the fluxes, was evaluated. We found that the GOSAT $X_{\text{CO}_2}$ retrievals could lower the flux uncertainty by as much as 48% (annual mean). Pronounced uncertainty reduction was found in the fluxes estimated for regions in Africa, South America, and Asia, where the sparsity of the surface monitoring sites is most evident.

1. Introduction

The rapid atmospheric buildup of carbon dioxide (CO$_2$) observed over the past several decades (e.g., Keeling et al. 1976) raised a broad array of concerns about future climatic changes because of the role CO$_2$ plays in determining the Earth’s heat budget (Ramanathan et al. 1987). For better understanding contemporary global carbon cycle dynamics and improving the accuracy of future climate forecasts, it is essential to quantify the surface CO$_2$ sources and sinks (or fluxes) and their inter-annual variability (Field and Raupach 2004). Past attempts successfully applied Bayesian inverse modeling schemes (e.g., Enting 2002) to inferring surface fluxes from data records obtained in the networks of surface monitoring sites (e.g., Rödenbeck et al. 2003; Gurney et al. 2004; Baker et al. 2006). The uncertainty of the estimates, however, was shown to be sizable due largely to the sparsity of the data-providing sites, particularly across tropical latitudes, Africa, and South America. Realizing the difficulty of placing new sites in those regions, Rayner and O’Brien (2001) showed that this problem could be relieved with the use of a spaceborne remote sensing platform. To this end, the Greenhouse gases Observing SATellite (GOSAT) was placed in orbit in early 2009. With an Earthward-looking Fourier transform spectrometer onboard, GOSAT takes global soundings of reflected sunlight from which column-averaged dry air mole fractions of CO$_2$ ($X_{\text{CO}_2}$) are retrieved. Prior to the launch of the spacecraft, theoretical studies by Maksyutov et al. (2008), Chevallier et al. (2009), and others showed that GOSAT $X_{\text{CO}_2}$ retrievals could improve the current knowledge on surface CO$_2$ fluxes if sufficient retrieval precision and accuracy were attained. Herein, we report the benefit of actual GOSAT observations to the estimation of CO$_2$ surface fluxes. We estimated monthly regional fluxes and their uncertainty from 1) data collected in the existing networks of surface in situ CO$_2$ measurement sites (GLOBALVIEW-CO$_2$, 2010; hereafter referred to as GV) and 2) both GV and GOSAT $X_{\text{CO}_2}$ retrievals, and compared these two sets of results in terms of change in flux uncertainty. This change, quantified as the rate of reduction in flux uncertainty, corresponds to the degree to which the GOSAT $X_{\text{CO}_2}$ retrievals contribute to constraining the surface fluxes. This analysis focused on a one-year period between June 2009 and May 2010, the first year of GOSAT sounding, and is based on the latest version of the GOSAT Level 2 $X_{\text{CO}_2}$ data product (Version 01.**).

2. Data and method

As described by Kuze et al. (2009), GOSAT carries the TANSO Fourier Transform Spectrometer that measures surface-reflected sunlight and emitted thermal infrared radiation with wavelengths in between 0.76 µm and 14.3 µm. Soundings recorded under clear-sky conditions and associated with signal-to-noise ratios greater than 100 are used to retrieve $X_{\text{CO}_2}$. Over large masses of water, the instrument points toward bright glint spots to ensure high signal-to-noise ratios. The northern and southern most bounds of the GOSAT measurement, within which quality soundings are obtainable, are dependent on local solar zenith angles, which vary with season. Thus, the far northern parts of North America and Eurasia (> ~60°N) see very few GOSAT $X_{\text{CO}_2}$ retrievals during fall and winter months, and oceanic GOSAT $X_{\text{CO}_2}$ retrievals are only found below 41°N and 37°S. Despite these systematic limitations, the annual total number of $X_{\text{CO}_2}$ retrievals still surpasses that of single GV data records, which is around 15,000. Details on the GOSAT Level 2 operational retrieval algorithms, as well as data screening and quality control schemes, are found in a descriptive paper by Yoshida et al. (2011).

Morino et al. (2011) compared Version 01.** of the GOSAT Level 2 $X_{\text{CO}_2}$ data product against reference data obtained at nine ground-based observational sites of the Total Carbon Column Observing Network (Wunch et al. 2011) where sun-viewing, high-resolution Fourier transform spectrometers are installed. It was shown in their analysis that the GOSAT Level 2 $X_{\text{CO}_2}$ retrievals have a negative residual bias. We therefore corrected the bias by raising each $X_{\text{CO}_2}$ retrieval by 8.99 ppm, the reported accuracy of the data product. In estimating surface CO$_2$ fluxes with Bayesian inverse modeling schemes, observations are contrasted with corresponding predictions made by an atmospheric transport model in which the first guess (or a priori) estimates of the surface fluxes and a set of unit fluxes with pre-specified patterns are run forward to simulate CO$_2$ concentrations. The surface fluxes are estimated by making corrections to the a priori fluxes such that the mismatches between the model predictions and observations are minimized. For this study, we used version 08.1 of the National Institute for Environmental Studies atmospheric transport model (Belikov et al. 2011), which was driven by the Japan Meteorological Agency (JMA)’s
JCDAS (JMA Climate Data Assimilation System) wind analysis data (Onogi et al. 2007). The CO\textsubscript{2} forward simulations were performed on 2.5° × 2.5° horizontal grids at 32 vertical levels between the surface and the top of the atmosphere. This version of the transport model uses an isentropic vertical coordinate in the stratosphere for better X\textsubscript{CO2} simulation. The simulation performance of this model was validated against the observations of CO\textsubscript{2} (Niwa et al. 2011) and methane (Patra et al. 2011). The a priori flux dataset used here was comprised of the sum of four components: daily net ecosystem exchange (NEE) predicted by a terrestrial biosphere process model VISIT (Vegetation Integrative Simulator for Trace gases) (Ito et al. 2010; Saito M. et al. 2011); monthly ocean-atmosphere CO\textsubscript{2} fluxes generated with an ocean pCO\textsubscript{2} data assimilation system (VALSALA and Maksyutov 2010); monthly CO\textsubscript{2} emissions due to biomass burning stored in GFED (the Global Fire Emissions Database) version 3.1 (van der Werf et al. 2010); and monthly fossil fuel CO\textsubscript{2} emissions obtained via merging the ODIAC (Open source Data Inventory of Anthropogenic CO\textsubscript{2} emission) high-resolution dataset (ODA and Maksyutov 2011) and the Carbon Dioxide Information Analysis Center’s monthly 1° × 1° resolution dataset (Andres et al. 2011). Each of these component flux datasets, except for the biomass burning and fossil fuel burning emission data for the year 2010, was prepared specifically for this 2009–2010 analysis period.

Two parameters important in the flux estimation, the observation error and a priori flux uncertainty, were prescribed as follows. Following Law et al. (2003), the observation errors for the GV data records were estimated by weighting the GV residual standard deviations (stored in the GV dataset) such that a chi-square value for inverse modeling (see Gurney et al. 2003 for definition) becomes approximately unity. Similarly, those for the GOSAT X\textsubscript{CO2} retrievals were determined by weighing the standard deviations of GOSAT X\textsubscript{CO2} retrievals found in each of 5° × 5° grid cells in a month. Also, following the approach by Law et al. (2003), we took account of systematic errors associated with the GOSAT Level 2 operational retrieval by setting the minimum of the observation error for GOSAT X\textsubscript{CO2} retrievals to be 3 ppm (a conservative estimate). The evaluation of such systematic errors is yet to be completed. The uncertainty of the terrestrial a priori flux was set as twice the standard deviation of the VISIT model monthly NEE (1° × 1° resolution) about the past 30-year mean, and that of the oceanic a priori flux was prescribed as the standard deviation of the assimilated oceanic flux (1° × 1° resolution) about the 2001–2009 mean and climatological mean by Takahashi et al. (2009).

We used the fixed-lag Kalman Smoother (Bruhwiler et al. 2005), a computationally-efficient sequential inverse modeling scheme, to infer monthly fluxes for 42 sub-continental terrestrial regions and 22 oceanic basins as defined by Patra et al. (2005). This 64-regional boundary definition was created by subdividing an original 22-regional boundary definition (11 + 11 terrestrial and oceanic regions) used extensively in the TransCom atmospheric transport model inter-comparison campaign (Gurney et al. 2003). Also estimated in the inverse modeling was a global CO\textsubscript{2} offset, which represents the global mean atmospheric CO\textsubscript{2} concentration in the absence of any surface fluxes (see Bousquet et al. (1999) for further explanation). We calculated the offset value for the GV data records and GOSAT X\textsubscript{CO2} retrievals separately. The estimation of fluxes for Greenland, Antarctica, and the Mediterranean Sea is not performed in the current setup. The input to this modeling setup were monthly-mean GV observations and bias-corrected GOSAT X\textsubscript{CO2} retrievals gridded to 5° × 5° cells and averaged on a monthly basis. Large X\textsubscript{CO2} outliers were precluded based on ensemble climatological X\textsubscript{CO2} means derived from forward simulation results by six different transport models (Saito R. et al. 2011). The GV site selection criteria adopted here is based on the approach by Law et al. (2003). We additionally included in our list all airborne measurement sites available in the current GV dataset (139 sites altogether). The GV dataset available at the time of this study contained data until December 2009, therefore we extrapolated them to the year 2010 using a least squares fit. Shown in Fig. 1 is the number of GOSAT X\textsubscript{CO2} retrievals per each of 5° × 5° grid cells over the one-year analysis period. Overlaid onto this figure are the locations of the selected GV measurement sites (red circles). The boundaries of the 64 source regions are also drawn in the figure. Successful GOSAT X\textsubscript{CO2} retrievals are particularly numerous over Africa, South America, and Australia, owing to the frequent occurrence of clear-sky days.

3. Results

Presented in Fig. 2 are the rates of reduction in the uncertainty of monthly fluxes estimated for the 64 source regions (in percent). The results shown are the annual means of monthly values over the June 2009–May 2010 analysis period. The rate of uncertainty reduction (UR) in percent is defined as

\[
UR = \left( 1 - \frac{\sigma_{GV, GV}^{\text{GOSAT}}}{\sigma_{GV}} \right) \times 100,
\]

where \(\sigma_{GV}\) and \(\sigma_{GV, GV}^{\text{GOSAT}}\) denote the uncertainty of a monthly flux estimated from the GV dataset and both the GV dataset and GOSAT X\textsubscript{CO2} retrievals, respectively. Pronounced reductions are found in the uncertainty of fluxes estimated for south-western
Temperate Asia (#29 on Fig. 2; 45%), south-western Tropical Africa (#17; 33%), and south-eastern South Africa (#22; 27%) where the sparsity of the GV sampling network, as indicated in Fig. 1, is evident. High-latitude regions of the Northern Hemisphere, such as Boreal North America (#1 through 4) and Boreal Eurasia (#25 through 28), received lower numbers of GOSAT retrievals mainly due to the seasonal shift in the north-south latitudinal upper bounds of the GOSAT X CO2 retrieval. This is reflected in the lower percentages of the flux uncertainty reduction (1 to 7% for Boreal North America; 3 to 7% for Boreal Eurasia). The lowest uncertainty reduction is found in north-eastern Tropical Africa (#20); this is attributable to a very small a priori flux uncertainty assigned to this desert region.

Figure 3 shows the monthly time series of a priori flux (blue line), a posteriori flux estimated from GV (red line), a posteriori flux estimated from both GV and GOSAT X CO2 retrievals (green line), and the uncertainty reduction rate (gray vertical bar) for north-western Temperate North America (#7; top panel) and south-western Tropical Africa (#17; bottom panel). Note here that the uncertainty reduction rate is variable in a year since the number of GOSAT X CO2 retrievals, which is subject to the occurrence of clear-sky days and the local solar zenith angle, changes with season. Both regions received a relatively larger number of GOSAT X CO2 retrievals over the one-year period (Fig. 1), but these two regions are quite contrasting in the density of GV stations therein and nearby. This is clearly reflected in the difference in the flux uncertainty reduction. The flux inferred for north-western Temperate North America finds much less uncertainty reduction by GOSAT X CO2 retrievals than that for south-western Tropical Africa does. The trends of a posteriori fluxes estimated from GV only and GV and GOSAT X CO2 retrievals are nearly identical over the analysis period. This is attributed to the fact that the weighted observation errors prescribed to GV data records are nearly one order of magnitude smaller than those of GOSAT X CO2 retrievals, allowing the GV data records to constrain the flux more strictly than the GOSAT X CO2 retrievals do. New information brought by GOSAT is therefore found in the Tropical Africa a posteriori flux estimated from both GV and GOSAT X CO2 retrievals. Eastern Pacific (#47, not shown in Fig. 3) is one of the oceanic basins that received larger numbers of GOSAT X CO2 retrievals. The uncertainty reduction on the order of a few percent (Fig. 2) indicates the challenging nature of estimating oceanic fluxes, which are approximately one order of magnitude smaller than the terrestrial counterparts, via the “top-down” Bayesian surface CO2 flux inference.

The global mean offset value estimated for the GOSAT X CO2 retrievals turned out to be 8.34 ppm, which varied within +/-0.26 ppm over the analysis period. The offset value of 8.34 ppm indicates deviation from the reported accuracy of the GOSAT X CO2 retrievals (8.99 ppm), possibly owing to unresolved errors associated with the forward X CO2 simulation or the spatiotemporal dependence of the residual bias. This discrepancy was handled in the inverse modeling via offsetting the GOSAT X CO2 retrievals by the difference between the reported accuracy (8.99 ppm) and the global mean offset (8.34 ppm).

Through correcting the residual bias of the GOSAT X CO2 retrievals with the data validation information and further adjusting them based on the global mean offset, the “global constant” part of the residual bias was removed. Possible remaining part, which may come from spatiotemporal variation of the residual bias if it existed, was taken into account in the minimum value of the observation error for GOSAT X CO2 retrievals (set to 3 ppm in this analysis). Table 1 shows the sensitivity of the annual-mean flux uncertainty reduction rate to the choice of this minimum value (evaluated for the TransCom 11 terrestrial regions). Four cases were considered here (3.0, 2.0, 1.0, and 0.5 ppm). The uncertainty reduction rate becomes larger with decreasing minimum observation error. This result indicates that if such remaining systematic errors were quantified and reduced, larger uncertainty reduction could be achieved.

4. Concluding remarks

The results presented above were obtained by using the monthly means of the GV data records and GOSAT X CO2 retrievals gridded to 5° x 5° cells. One important aspect to note here is that the reduction of a posteriori flux uncertainty is dependent on the number of the observations used for constraining surface fluxes and how well an atmospheric transport model used in the inverse modeling can simulate each observational data record. The number of observations available for constraining surface fluxes is significantly reduced via averaging (e.g., a few tens of observations in a grid cell down to a single monthly mean). Thus, the result presented herein shows only a portion of the full benefit that GOSAT soundings can bring to the surface CO2 flux estimation.

Proper handling of the residual bias present in the current GOSAT Level 2 X CO2 data product is essential in obtaining sound estimates of surface CO2 fluxes. We herein applied the latest data

<table>
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<th>Region</th>
<th>Min. error (ppm)</th>
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<th>2.0</th>
<th>1.0</th>
<th>0.5</th>
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<td>12.7</td>
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<tr>
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<td>22.0</td>
<td>28.4</td>
<td>35.8</td>
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<td>43.4</td>
<td>48.1</td>
<td>49.1</td>
<td></td>
</tr>
<tr>
<td>South Africa</td>
<td>32.6</td>
<td>39.3</td>
<td>46.6</td>
<td>48.9</td>
<td></td>
</tr>
<tr>
<td>Boreal Eurasia</td>
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<td>13.4</td>
<td>17.2</td>
<td>19.1</td>
<td></td>
</tr>
<tr>
<td>Temperate Asia</td>
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<td>29.8</td>
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<tr>
<td>Tropical Asia</td>
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<td>Australia</td>
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<td>Europe</td>
<td>17.5</td>
<td>21.8</td>
<td>25.7</td>
<td>27.0</td>
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<tr>
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<td>23.2</td>
<td>28.7</td>
<td>30.8</td>
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</table>

Table 1. The sensitivity of annual-mean flux uncertainty reduction rate (in percent) to the choice of minimum observation error (in ppm).
validation knowledge provided by Morino et al. (2011) to correcting the residual bias. More rigorous investigation, however, is needed as to its spatiotemporal persistence. Identifying the sources of the bias is the utmost priority of ongoing investigations. Studies in XCO₂ retrieval techniques are also underway to minimize retrieval errors and improve the precision of the data product. These ongoing studies will lay a solid foundation for obtaining reliable surface flux estimates from GOSAT XCO₂ retrievals.

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