The impacts of fossil fuel emission uncertainties and accounting for 3-D chemical CO$_2$ production on inverse natural carbon flux estimates from satellite and *in situ* data

To cite this article: James S Wang *et al.* 2020 *Environ. Res. Lett.* **15** 085002

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The impacts of fossil fuel emission uncertainties and accounting for 3-D chemical CO$_2$ production on inverse natural carbon flux estimates from satellite and in situ data

James S Wang, Tomohiro Oda, S Randolph Kawa, Sarah A Strode, David F Baker, Lesley E Ott, and Steven Pawson

1. Introduction

Top-down approaches for estimating greenhouse gas (GHG) fluxes, such as inverse modeling (Enting and Mansbridge 1989), rely on atmospheric GHG measurements and information on atmospheric transport to quantify anthropogenic and/or natural sources and sinks at scales ranging from point sources and
cities (e.g. Lauvaux et al 2016, Nassar et al 2017, Gourdji et al 2018) to sub-national and national entities (e.g. Manning et al 2011, Graven et al 2018, Liu et al 2018) to continents and the globe (e.g. Gurney et al 2002, Reuter et al 2014). There has been growing interest in employing flux inversions to support independent monitoring, reporting, and verification (MRV) of national and sub-national GHG emissions and sinks to complement the bottom-up inventories required under the UN Framework Convention on Climate Change (Leip et al 2018; https://ig3is.wmo.int/en, accessed 17 March 2019; IPCC 2019; https://carbon.nasa.gov/, accessed 17 March 2019). Inversions for estimating natural carbon fluxes help to provide insights into the capacity of the Earth system to remove anthropogenic additions of carbon to the atmosphere and its changes over time (Le Quéré et al 2015). Such analyses can also potentially be used to verify Agriculture, Forestry and Other Land Use (AFOLU) carbon dioxide (CO2) emissions and sinks estimated through stock change approaches, though it could be challenging in many cases to separate the AFOLU contributions to inferred fluxes from those of unmanaged lands and fossil fuel combustion (IPCC 2019).

Given that we are in an era of increasingly abundant satellite GHG data and flux inversions using them, along with continuous evolution towards higher-resolution models (e.g. Houweling et al 2015, Crowell et al 2019), it is necessary to re-examine the impacts of various methodological assumptions for flux inversions, which historically had been conducted using relatively sparse networks of mostly surface-air observations. For example, inversions using CO2 observations to estimate natural carbon fluxes typically do not allow for adjustment of fossil fuel CO2 emissions (FFCO2), simply prescribing them as if they are a known quantity based on the rationale that their uncertainties are smaller than those of natural fluxes at the coarse spatial scales of most global inversions (Gurney et al 2005, Peylin et al 2013). Given the significant spatial pattern differences among emission inventories (e.g. Oda et al 2018) and the often incorrect specification or even omission of international bunker fuel emissions (including shipping and aviation) in inversions (e.g. Peylin et al 2013), substantial errors could propagate to the inferred natural fluxes (Nassar et al 2010). But other than a study by Gurney et al (2005) that reported some sensitivity of inferred natural fluxes to the addition of seasonal and interannual variations to prescribed FFCO2 emissions, there has been a lack of inversion analyses isolating the impacts of differences in emission inventories and assumptions about bunkers, especially in the context of satellite column measurements.

Also, most current inversions assume that CO2 is released from fossil fuel combustion and biospheric sources entirely at the surface. In reality, ~1 Pg C yr⁻¹ of the emissions (cf a global net carbon flux, including fossil fuels, of ~5 Pg C yr⁻¹) occurs in the form of reduced carbon species, including carbon monoxide (CO) and volatile organic compounds (VOCs), which are eventually oxidized to CO2 in the atmosphere downwind of the emissions. As noted by a number of previous studies (Enting and Mansbridge 1991, Enting et al 1995, Baker 2001, Folberth et al 2005, Suntharalingam et al 2005, Jacobson et al 2007, Nassar et al 2010, Chevallier et al 2017), omission of this ‘chemical pump’ (Suntharalingam et al 2005) can result in significant systematic errors in the model distribution of atmospheric CO2. Furthermore, a subset of the studies (Enting and Mansbridge 1991, Enting et al 1995, Baker 2001, Suntharalingam et al 2005, Jacobson et al 2007, Chevallier et al 2017) found shifts in inferred total carbon fluxes among regions as a result, e.g. between the tropics and northern extratropics and between land and ocean. However, Suntharalingam et al (2005) noted that a dearth of surface measurement sites over tropical and Southern Hemisphere extratropical land areas may have limited the sensitivity of their inversion to the chemical pump in those regions. Chevallier et al (2017) explored the use of satellite column CO2 observations instead of surface measurements in their analysis.

In this study, we assess the impacts of the aforementioned sources of error on posterior natural fluxes, with a novel aspect of conducting both satellite CO2 observation-based and surface in situ-based inversions. We employ a relatively high-resolution, global, Bayesian synthesis inversion system, which has been previously applied to observations from the Greenhouse gases Observing SATellite (GOSAT) as well as in situ measurements to examine the different constraints on the spatial and interannual variability of fluxes provided by the two observation types (Wang et al 2018). Our hypothesis in the present study is that there would be regional differences in the effects of fossil fuel uncertainties and the chemical pump (consisting of 3-D chemical CO2 production and a surface correction) on the GOSAT vs. in situ inversion due to differences in the horizontal and vertical sampling of the two observation types, with the satellite observations having greater sensitivity to processes occurring above the surface and greater overall sensitivity in the regions where they provide better coverage, such as tropical and southern land regions.

2. Methods

This study uses a number of modeling components and prior flux data sets developed at NASA Goddard Space Flight Center (GSFC) with support from the NASA Carbon Monitoring System (CMS) program, whose objective over the past decade has been to promote the development of frameworks for quantifying carbon stocks and fluxes built primarily upon NASA
observing systems and models that can potentially satisfy MRV requirements for policy and management purposes (https://carbon.nasa.gov/, accessed 17 March 2019). The CMS products used here include CASA-GFED terrestrial biospheric fluxes (described in section 2.1 of this paper), Open-source Data Inventory for Anthropogenic CO\textsubscript{2} (ODIAC) FFCO\textsubscript{2} emissions (section 2.2), a PCTM transport model-based, batch, Bayesian flux inversion system (section 2.1), and a new capability of including 3-D chemical CO\textsubscript{2} production and a surface correction in the inversion (section 2.3).

2.1. Flux inversion system

The inversion system used here has been described and evaluated in detail in the Wang et al (2018) paper. In brief, it involves a batch Bayesian synthesis inversion technique (which gives an exact solution to the flux optimization problem, subject to prior constraints) based on that used in the TransCom 3 (TC3) global CO\textsubscript{2} inversion intercomparisons (Gurney et al 2002, Baker et al 2006) and that of Butler et al (2010). Advances over the previous methods include higher spatial and temporal resolution for the flux optimization—108 land and ocean regions in total (figure S1a (available online at stacks.iop.org/ERL/15/085002/mmedia)) and 8-day intervals, and the use of individual flask-air observations and daily averages for continuous observations rather than monthly averages. The Parameterized Chemistry and Transport Model (PCTM) (Kawa et al 2004), with meteorology from the NASA Global Modeling and Assimilation Office (GMAO) MERRA reanalysis (Rienecker et al 2011), was run at a resolution of 2\degree latitude \times 2.5\degree longitude and 56 levels up to 0.4 hPa, and hourly temporal resolution. Prior constraints include gridded, 3-hourly net ecosystem production (NEP) and fire carbon fluxes estimated by the Carnegie-Ames-Stanford-Approach (CASA) biogeochemical model coupled to version 3 of the Global Fire Emissions Database (GFED3) (Randerson et al 1996, van der Werf et al 2006, 2010; with updates described in Ott et al 2015), and gridded, monthly, climatological, measurement-based air-sea CO\textsubscript{2} fluxes from Takahashi et al (2009). The prescribed FFCO\textsubscript{2} emissions in the Wang et al (2018) study were from the 1\degree \times 1\degree, monthly- and interannually-varying Carbon Dioxide Information Analysis Center (CDIAC) inventory (Andres et al 2012), but in the present study, we use emissions from ODIAC (described below in section 2.2) as the baseline and present results using CDIAC only in sensitivity analysis.

In both the previous and present study, we assimilated in situ atmospheric CO\textsubscript{2} observations from 87 flask and continuous measurement sites in the NOAA ESRL (Dlugokencky et al 2013, Andrews et al 2009) and Japan Meteorological Agency (JMA; Tsutsumi et al 2006) networks (figure S1a), and the ACOS B3.4 filtered and bias-corrected retrieval of column-average CO\textsubscript{2} dry air mole fractions (XCO\textsubscript{2}) from GOSAT-measured near infrared radiances (figure S1b; O’Dell et al 2012; Osterman et al 2013). And as in the previous study, our inversions span the period March 2009-September 2010 (with the focus starting from June 2009), which is sufficiently long for assessing the impacts of FFCO\textsubscript{2} uncertainties and the chemical pump on global inversions.

Inversion system components specific to the present study are described in the following subsections.

2.2. ODIAC fossil fuel emissions

ODIAC is a global, gridded FFCO\textsubscript{2} data product with 1 \times 1 km, monthly resolution over land and 1\degree \times 1\degree, annual resolution for international bunkers from year 2000 onward (Oda et al 2018); the data product is commonly used in flux inversions (e.g. Takagi et al 2011, Maksyutov et al 2013, Lauvaux et al 2016, Crowell et al 2019). It shares country-level estimates with CDIAC, another commonly used data set, but distributes emissions within countries differently and includes gridded international bunker emissions. Rather than distributing emissions based on population density as in CDIAC, ODIAC applies information such as power plant profiles (emissions intensity and geographical location) and satellite nighttime light observations to different fuel types. The resulting emission distribution is in better agreement with the US bottom-up inventory developed by Gurney et al (2009) than is CDIAC (Oda and Maksyutov 2011). Global total emissions in the ODIAC version used are 8.70 and 9.13 Pg C for 2009 and 2010.

Shipping and aviation total emissions are derived from CDIAC and distributed using ship and flight track data (Oda et al 2018). Global total emissions are 0.17 and 0.12 Pg C yr\textsuperscript{-1} for shipping and aviation in 2009 and 0.18 and 0.13 Pg C yr\textsuperscript{-1} in 2010. For the present study, a simple vertical distribution for the aviation emissions is implemented. The emissions are partitioned into three layers—surface-4 km (27\%), 4–10 km (34\%), and 10–13 km (39\%)—based on the altitude distribution from the AER02k 2002 aviation inventory (Eyers et al 2005).

In the present study, we use the 2017 version of ODIAC (ODIAC2017, 2000–2016, Oda and Maksyutov 2015), and degraded the resolution to 2\degree \times 2.5\degree for use in our version of PCTM. Figure 1 shows maps comparing ODIAC and CDIAC emissions. Sizable differences due to the spatial modeling approaches can be seen in many areas of high emissions, such as the eastern U.S. and East Asia (figure 1c)), although negative and positive differences tend to compensate each other within each of these regions, given the shared country-level data of ODIAC and CDIAC.
2.3. Atmospheric chemical CO$_2$ production and surface correction

We applied period-specific 3-D CO loss rates archived from a state-of-the-art NASA GEOS Chemistry and Climate Model (GEOSCCM; Oman et al 2013, Nielsen et al 2017) simulation in a forward PCTM run to simulate the distribution of CO$_2$ originating from oxidation of reduced carbon compounds. Since CO is an intermediate product in most oxidation pathways for carbon compounds and the only significant product of its oxidation is CO$_2$ (Folberth et al 2005), its rate of loss through reaction with

Figure 1. Fossil fuel CO$_2$ emissions on 2$^\circ$ × 2.5$^\circ$ PCTM model grid for January 2010 from (a) ODIAC (including international shipping and aviation), (b) CDIAC, and (c) the difference between the data sets (ODIAC–CDIAC). (Land-based emissions inadvertently regridded into ocean grid cells have been redistributed to the nearest onshore grid cells as in the TC3 protocol (Gurney et al 2000).) Note that in (a), the more heavily traveled flight and ship tracks cannot be distinguished from the less traveled areas given the particular color scale, and in (c), the contributions of international shipping and aviation are not visible at all, since they fall within the white part of the color scale.
Table 1. Chemical CO₂ production and surface correction budgets.

| Component                                | Global, Annual Total (Pg C yr⁻¹) |
|------------------------------------------|----------------------------------|
| This work, mean (2009–2010)              | 1.15                             |
| Suntharalingam et al (2005), mean (1988–1997) | 1.10                             |
| Nassar et al (2010), mean (2006)         | 1.05                             |

| Component                                | Global, Annual Total (Pg C yr⁻¹) |
|------------------------------------------|----------------------------------|
| Total chemical production                | 1.26²                           |
| Total surface correction                 | 0.28                             |
| Fossil fuel combustion                   | 0.03                             |
| Biomass and biofuel burning              | 0.23                             |
| Biospheric CH₄                           | 0.16                             |
| Biospheric NMVOCs                        | 0.59                             |

²This surface correction exceeds the chemical production because we apply, for simplicity, the entire amount of reduced carbon emissions rather than just the portion that is oxidized to CO. To compensate for the imbalance, we apply simple, small adjustments to the inversion flux results. See Supplementary Material for details.

The atmospheric concentrations of CO₂ attributable to CO₂ chemical production and to the surface correction simulated by PCTM after a year of production/subtraction and transport are shown in figure 3 for illustrative purposes (similar to figures 3 and 4 of Suntharalingam et al 2005). Figures 3(a) and (b) show the impact for the model surface layer, and figures 3(d) and (e) are for the atmospheric column average. Figure 3(c)/(f) show the net effect of chemical production and surface correction in the surface layer/column. As expected, the surface correction has a stronger effect on surface concentrations than on the column average, and is less dominant over chemical production in the column average as compared to the surface concentrations.

3. Results

3.1. Impact of FFCO₂ spatial disaggregation differences on inversions

Inversions using either ODIAC FFCO₂ emissions, excluding the international bunkers, or CDIAC FFCO₂ emissions produce similar natural flux estimates in general, at least at the large spatial and temporal scales (e.g. sub-continental and seasonal) that are most relevant for the global carbon budget. Differences in estimated fluxes when GOSAT data are used in the inversions are within 0.25 Pg C yr⁻¹ (in absolute value) at the scale of large, aggregated...
regions (e.g. northern land, tropical oceans) and seasons; twelve-month means are shown in figure 4. Inversions using in situ data exhibit some noticeably larger differences, even at the scale of these large-aggregate regions and twelve-month means; for example, ODIAC results in a 0.30 Pg C yr\(^{-1}\) larger inferred source for southern land than does CDIAC, and a 0.28 Pg C yr\(^{-1}\) weaker sink for northern oceans (figure 4). For individual seasons, differences for the in situ inversions are as large as 1 Pg C yr\(^{-1}\) (not shown). However, the differences are probably mostly noise rather than real differences in inferred natural fluxes at these large scales; Wang et al. (2018) found the in situ inversion to be much noisier than the GOSAT inversion, with large temporal fluctuations, fewer degrees of freedom for signal, and more extensive flux error correlations, reflecting insufficient constraints on the flux estimation provided by the relatively sparse in situ observations. In the FFCO\(_2\) sensitivity results here, fluctuations in the differences between ODIAC- and CDIAC-based in situ inversions can be seen from season to season, as well as compensation between neighboring TC3 regions, e.g. ODIAC-CDIAC values of 0.52 and −0.33 Pg C yr\(^{-1}\) for Temperate Asia and Tropical Asia in DJF 2009–2010 and −2.37 and 1.47 Pg C yr\(^{-1}\) for Temperate Asia and Boreal Asia in JJA 2010, likely reflecting negative error correlations. The GOSAT inversions do not exhibit similar fluctuations and compensation. An explanation for the noisy impact of FFCO\(_2\) in particular is that the ODIAC and CDIAC emissions are distributed differently relative to the surface observation sites, some of which are located close to areas of high FFCO\(_2\).

**Figure 2.** MERRA2-GMI distribution of CO oxidation (used as a proxy for CO\(_2\) chemical production in the present study) for March, 2010 (a) averaged over longitudes, and (b) at ~5 km altitude.
emissions. Given that the sensitivity to surface fluxes, or ‘footprint,’ of surface observations can be rather localized and can vary greatly with meteorological conditions, a shift in prescribed FFCO$_2$ emissions could strongly and variably affect the fluxes inferred by certain sites, and for a sparse observation network, the impact could be substantial even when aggregated to large spatial scales. The GOSAT column observations, in contrast, are influenced by broader areas of surface fluxes, and the GOSAT data set provides better coverage than the in situ data set over many regions. Thus, the GOSAT inversion is not as sensitive to detailed spatial patterns of FFCO$_2$ emissions.

3.2. Impact of international bunker emissions

We also examined the impacts on inversions of accounting for international bunker FFCO$_2$ emissions and vertically distributing international aviation emissions. Figure 4 shows in situ and GOSAT aggregated posterior fluxes when international bunkers are included, either placed entirely at the surface or distributed over flight altitudes, next to results based on only land-based ODIAC FFCO$_2$. The differences are small, especially between the inversions with 2-D vs. 3-D bunkers. The impact of bunkers is most noticeable in the north (as that is where there is the most maritime and air traffic), where inclusion of bunkers results in inferred fluxes that are more negative by up to 0.16 Pg C yr$^{-1}$ over land and 0.07 Pg C yr$^{-1}$ over ocean regions. (Global mass balance requires that larger FFCO$_2$ emissions be balanced by larger natural sinks.) The impact of vertically distributing aviation emissions is nearly imperceptible, with the largest impact being a decrease in the net source of 0.03 Pg C yr$^{-1}$ over tropical land in the in situ inversion.

We examine the posterior fit of the inversions to observations to assess whether that could provide an objective rationale for accounting for bunker emissions in CO$_2$ inversions. Results are presented and discussed in detail in the supplementary material. We find that the posterior fit differs little between the cases with and without bunkers for either the in situ or GOSAT inversions.

3.3. Impact of chemical pump

Results for inversions accounting for atmospheric chemical CO$_2$ production and the surface correction are shown alongside those for inversions without the chemical pump in figure 5. (All of the inversions are based on ODIAC land-based and vertically-distributed bunker emissions.) Notable features include larger net carbon sources over
tropical land and southern land when the chemical pump is included, larger net sinks or smaller net sources over ocean regions, and overall shifts in the global sink from the tropics to the north and, for the GOSAT inversions, from land to ocean. The effects can generally be explained by mass balance considerations—e.g. CO$_2$ production downwind of continental reduced carbon emissions necessitates more CO$_2$ uptake over ocean regions to fit observations, and surface corrections that are especially large over tropical and southern land necessitate more CO$_2$ emissions over those regions. The more negative oceanic flux is consistent with what was found in the previous inversion study by Suntharalingam et al (2005). However, the increased source over tropical land (and lack of flux adjustment over northern land) is different from the decreased tropical land source and decreased northern land sink of Suntharalingam et al (2005) and Jacobson et al (2007). Our analysis suggests this is due to differences in our
surface corrections, as discussed in detail later in this section.

The GOSAT inversion is more sensitive to the chemical pump than the in situ inversion in general, exhibiting relatively large twelve-month mean impacts of 0.28, 0.53, and $-0.47 \text{ Pg C yr}^{-1}$ over tropical land, global land, and global oceans; these are changes of 12%, 78%, and 15% relative to the posterior net sources/sinks. Note, however, that the impacts all lie within or close to the 1σ uncertainty ranges of the flux estimates. For comparison, the inversions of Suntharalingam et al (2005) (based on in situ observations) exhibited impacts of 0.10 and $-0.09 \text{ Pg C yr}^{-1}$ over global land and global oceans (averaged over multiple models). The differences between the in situ and GOSAT inversions are consistent with differences between the data sets in horizontal and vertical sampling. Some insight can be gained by examining the impact of the chemical pump on atmospheric CO$_2$ concentrations averaged over the locations and times of the in situ and GOSAT observations (table 2). The numbers, though of small magnitude, exhibit particular patterns. For example, the GOSAT sampling exhibits values that are more positive (or less negative) for ocean overall and in some of the zones, i.e. 0°–30°N and 30°–60°N, than the in situ sampling does. This reflects the greater sensitivity of the column observations to chemical CO$_2$ production, which occurs over a range of altitudes above the surface downwind of continents (figures 2(a) and (b)), and can explain the larger negative flux adjustments over oceans in the GOSAT inversion in response to the chemical pump. Also, the GOSAT combined land-ocean impacts are weighted towards the land values in all zones except for 60°–30°S, reflecting a much larger number of land nadir than ocean glint observations (figure 5ib), whereas the in situ combined impacts are weighted towards land only outside of the tropics, reflecting the dearth of land sites in the tropics (figure 5ia). This could explain the lack of flux adjustments over tropical and southern land in the in situ inversions in response to the land-based surface correction.

We examine the posterior fit of the inversions to observations for the cases with and without the chemical pump also. (See the Supplementary Material for details.) We find that the posterior fit generally differs little between the cases.

Since our surface corrections differ in important ways from those assumed in previous studies, we also examine results of an alternative set of inversions using surface corrections that are more similar to those of previous studies. Specifically, the global, annual magnitude of the correction for biospheric NMVOCs is the same as that of Suntharalingam et al (2005) and Nassar et al (2010), rather than much larger as with our baseline correction (table 1). In addition, the fossil fuel correction is based on the uniform 4.89% scaling of Nassar et al (2010), which makes it much larger over developed countries (located mostly in the north) and smaller over developing countries and possibly more similar to that of Suntharalingam et al (2005), whose earlier study period may have occurred before emissions controls greatly reduced the proportion of incomplete combustion products in developed countries. These alternative surface corrections result in a chemical pump impact on atmospheric CO$_2$ with a north-south interhemispheric difference of $-0.23 \text{ ppm sampled at in situ sites}$, which is quite different from the $-0.07 \text{ ppm of our baseline experiment}$ and more similar to the $-0.20 \text{ ppm of Suntharalingam et al (2005)}$ (though the networks of in situ sites are not exactly the same). Accounting for this version of the chemical pump shifts a portion of the global CO$_2$ sink from the north to the tropics and south, as in previous studies (figure S3). Unchanged from our baseline inversions is the overall shift in the sink from land to oceans in the GOSAT inversion. Thus, regional flux shifts are sensitive to the surface correction, and differences in the correction appear to explain the contrasting latitudinal shifts in our analysis and previous studies.

4. Discussion and conclusions

Here, we present an assessment of the impact of several types of prior emissions errors on land and ocean carbon fluxes estimated through atmospheric inversions. Unlike previous studies, we consider both surface and satellite data inversions. As the international community seeks to use inverse methods and an international constellation of carbon observing satellites in support of emissions MRV, evaluating the potential of such uncertainties to influence inferred fluxes is critically important.

Our results show that large-scale natural fluxes in a global inversion are not substantially affected by differences between two commonly used sets of prescribed FFCCO$_2$ emissions, ODIAC and CDIAC, though we do see noise in the in situ inversion results that is probably an artifact of the sparseness of the observation network combined with the location of some of the sites close to large FFCCO$_2$ emissions. Inferred fluxes can exhibit larger impacts in relative terms at smaller spatiotemporal scales, this being especially relevant for higher-resolution regional-scale inversions. We should also point out that the differences between ODIAC and CDIAC may not be as large as those between other data sets, such as EDGAR vs. CDIAC (Oda et al 2018), given that the two share country-level estimates. Note that evaluating whether one of the FFCCO$_2$ data sets is more accurate than the other was not one of the objectives of this study.

The small impacts on inversions of including international bunker emissions and vertically distributing the aviation portion are not all that surprising, given the relatively small amounts of the
emissions, making up around 3% of global FFCO$_2$. This finding should provide reassurance that imprecise treatment of bunker emissions by past and ongoing inversion studies has not been significantly biasing results.

Accounting for 3-D chemical CO$_2$ production and surface corrections results in sizable shifts in sources and sinks between some regions, especially in the inversions using GOSAT column-average data, with, most notably, increased sources of 0.28 and 0.53 Pg C yr$^{-1}$ over tropical and global land and an increased ocean sink of 0.47 Pg C yr$^{-1}$. An important difference between our results and those of the most similar, previous inversion studies is the direction of the latitudinal shift in global sink, with our baseline analysis indicating a shift from the tropics to the north. Our investigation suggests that the difference can be attributed to differences in the surface correction we apply, which in turn suggests a need to better constrain the distribution of non-CO$_2$ carbon emissions from fossil fuel and biospheric sources. Even with the qualitatively different and relatively large flux shifts in our study, the chemical pump effects lie mostly within the 1σ uncertainty ranges of the flux estimates though, and are generally much smaller than the differences between the in situ and GOSAT inversions (figure 5). But it is worth keeping in mind that common assumptions in

Figure 5. As in figure 4, except comparing inversions with and without the chemical pump. All inversions shown here include vertically distributed international bunker emissions.
flux inversions that are known to be incorrect, such as emitting reduced carbon as CO2 at the surface, can cause definite biases in inferred natural fluxes with regional patterns. As posterior flux uncertainties decrease with greater coverage by in situ and satellite observations (from geostationary Nivitanont et al 2019 as well as low-Earth orbit platforms; Eldering et al 2017) and satellite retrieval biases continue to decrease in the future (with potentially active as well as passive measurement techniques; ASCENDS Ad Hoc Science Definition Team 2015), biases due to neglecting the chemical pump will increase in relative importance.

The above considerations provide another rationale for synergistic use of multiple species for carbon budget analysis (Palmer et al 2006). Specifically, current and future satellite (e.g. GOSAT-2; Imasu 2019) and surface observations of species such as CO, CH4, and NMVOCs in addition to CO2 could be used in joint inversions to simultaneously optimize surface fluxes of the different species and 3-D chemical CO2 production, extending the CO data assimilation work of Nassar et al (2010). This could provide better constraints on the global carbon cycle than can be achieved with CO2 observations alone. Once fundamental issues in inversions such as observation biases and coverage gaps have been better addressed, joint inversions do offer the promise of reducing uncertainties even in OH distributions, given that tracer observations can be used to constrain sinks as well as sources (as in the CH4 inversions of Wang et al 2004) and that the CO sink due to OH is essentially perfectly correlated with the chemical production source of CO2.

Acknowledgments

This work has been supported by the NASA Atmospheric CO2 Observations from Space program element, the NASA Carbon Monitoring System Program, and the NASA Carbon Cycle Science program (Grant No. NNX14AM76G, PI: T. Oda). The NASA Goddard High-End Computing Program and the Atmospheric Chemistry and Dynamics Laboratory provided access to supercomputing resources at the NASA Center for Climate Simulation and the GSFC Code 614 cluster, respectively. We are grateful to Ilan Chabay, Mark Lawrence, and Ortwin Renn at the IASS and Achim Maas and Judith von Pogrell in the IASS Fellowship program for travel funding to present the work at the 2019 EGU conference and for the time and space to finish work on the manuscript. Thanks go to Luke Oman for leading the production of the MERRA2-GMI simulation and making the results available. The ACOS GOSAT data were produced by the ACOS/OCO-2 project at the Jet Propulsion Laboratory, California Institute of Technology using spectra acquired by the GOSAT Project. We thank Chris O’Dell for providing the ACOS data to us, Luciana Gatti, John Miller, and Manuel Gloor for providing the Amazonica data, NOAA ESRL GMD CCGG for making their flask and continuous tower data publicly available, and JMA (including Yukio Fukuyama and Atsushi Takizawa) for making their in situ data publicly available on the WDCGG website. And many thanks go to G. James Collatz for providing CASA-GFED fluxes, Prabir Patra for CH4 emissions, Michael Manyin for modeling help, Martha Butler for inversion code and

| Domain | In situ obs (ppm) | GOSAT obs (ppm)* |
|--------|-----------------|-----------------|
| 90°–60°S | 0.004 | — |
| Ocean | — | — |
| Combined | 0.004 | — |
| 60°–30°S | —0.004 | —0.020 |
| land | 0.001 | —0.018 |
| Ocean | —0.002 | —0.019 |
| Combined | —0.108 | —0.033 |
| 30°–0°S | —0.22 | —0.030 |
| land | —0.052 | —0.032 |
| Ocean | —0.091 | —0.050 |
| Combined | —0.075 | —0.032 |
| 0°–30°N | —0.124 | —0.022 |
| land | —0.075 | 0.006 |
| Ocean | —0.120 | —0.021 |
| Combined | —0.061 | 0.004 |
| 30°–60°N | —0.047 | — |
| land | —0.057 | 0.004 |
| Ocean | —0.111 | —0.031 |
| Combined | —0.064 | —0.028 |
| 60°–90°N | —0.097 | —0.030 |

*Model profiles are weighted using ACOS column averaging kernels.

Table 2. Impact of chemical pump (chemical production–surface correction) on atmospheric CO2 averaged over different domains as sampled by surface and satellite observations (June 2009–May 2010 mean).
documentation, and Stephen Steenrod for computing help.

Data availability

The MERRA2-GMI simulation output that supports the findings of this study is openly available at https://opendap.nccs.nasa.gov/dods/merra2_gmi/ and also at https://portal.nccs.nasa.gov/datashare/merra2_gmi/.

The ODIAC2017 data product that supports the findings of this study is openly available from the data server hosted by the National Institute for Environmental Studies, http://db.cger.nies.go.jp/dataset/ODIAC/.

The 3-D chemical CO$_2$ production and surface correction data that support the findings of this study are available from the corresponding authors upon reasonable request.

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