Global Terrestrial Ecosystem Carbon Flux Inferred from TanSat XCO₂ Retrievals

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Abstract

TanSat is China’s first greenhouse gases observing satellite. In recent years, substantial progresses have been achieved on retrieving column-averaged CO₂ dry air mole fraction (XCO₂). However, relatively few attempts have been made to estimate terrestrial net ecosystem exchange (NEE) using TanSat XCO₂ retrievals. In this study, based on the GEOS-Chem 4D-Var data assimilation system, we infer the global NEE from April 2017 to March 2018 using TanSat XCO₂. The inversion estimates global NEE at −3.46 PgC yr⁻¹, evidently higher than prior estimate and giving rise to an improved estimate of global atmospheric CO₂ growth rate. Regionally, our inversion greatly increases the carbon uptakes in northern mid-to-high latitudes, and significantly enhances the carbon releases in tropical and southern lands, especially in Africa and India peninsula. The increase of posterior sinks in northern lands is mainly attributed to the decreased carbon release during the non-growing season, and the decrease of carbon uptakes in tropical and southern lands basically occurs throughout the year. Evaluations against independent CO₂ observations and comparison with previous estimates indicate that although the land sinks in the northern middle latitudes and southern temperate regions are improved to a certain extent, they are obviously overestimated in northern high latitudes and underestimated in tropical lands (mainly northern Africa), respectively. These results suggest that TanSat XCO₂ retrievals may have systematic negative biases in northern high latitudes, and large positive biases over northern Africa, and further efforts are required to remove bias in these regions for better estimates of global and regional NEE.

Keywords: net ecosystem exchange, inverse modeling, TanSat XCO₂, GEOS-Chem

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1. Introduction

Satellite-based measurements of column averaged CO₂ dry air mole fraction (XCO₂) provide global coverage at high spatial resolution and support top-down estimates of surface CO₂ sinks and sources at global and regional scales, which is critical to future projections of climate change and effective carbon reduction strategy. In the past decade, a serial of satellite missions dedicated to measure XCO₂ have been launched and international measurement records have been greatly expanded. The Japanese Greenhouse Gases Observing Satellite (GOSAT), has been collecting data since 2009 [1]. The Orbiting Carbon Observatory 2 (OCO-2) launched by the US National Aeronautics and Space Administration (NASA) has been in operation since August of 2014 [2, 3]. The China’s greenhouse gas monitoring satellite mission (TanSat) [4] was launched in December of 2016, and followed by GOSAT-2 [5] in October of 2018 and OCO-3 [6] in May of 2019. These carbon satellites fly at low-orbit and measure near-infrared sunlight reflected from the surface in CO₂ spectral bands and the O₂ A band to retrieve XCO₂, with the primary scientific objective of monitoring of surface carbon sinks and sources.

Substantial progresses have been achieved in using XCO₂ data from GOSAT and OCO-2 to estimate terrestrial ecosystem carbon exchange (NEE) [7-15]. Attempts were also made to quantify anthropogenic CO₂ sources using XCO₂ retrievals [16-18]. These studies confirmed the advantages of satellite-based measurement of XCO₂ in estimating the major carbon sinks and sources, and shown that the use of XCO₂ retrievals could improve our understanding of the carbon cycle.

TanSat, supported by the Ministry of Science and Technology of China, the Chinese Academy of Sciences, and the China Meteorological Administration, was launched on 22 Dec 2016, and started collecting measurements operationally in March 2017 [19, 20]. It flies in a sun-synchronous low Earth orbit (LEO) that crosses the equator around 13:30 local time. There are two instruments onboard: the Atmospheric Carbon Dioxide Grating Spectrometer (ACGS) and the Cloud and Aerosol Polarimetry Imager (CAPI). The ACGS is a hyperspectral grating spectrometer that measures
backscattered sunlight in three NIR/SWIR bands. The CAPI is a multi-band imager that measures in five bands from UV to NIR. TanSat operates in three viewing modes: nadir, glint and target. The swath width of TanSat measurements is ~18 km across the satellite track and contains 9 footprints each with a size of 2 km × 2 km at nadir [11, 21].

Since launch, several research teams in China have made tremendous efforts to retrieve XCO₂ from TanSat measurements. Overcoming the challenges of eliminating the systematic calibration biases, and addressing the instrument degradation and the weak signal-to-noise ratio for certain spectral bands as well, they have successfully produced XCO₂ products. Yang et al. [4] developed the Institute of Atmospheric Physics Carbon dioxide retrieval Algorithm for Satellite measurement (IAPCAS) and produced the first global XCO₂ product from TanSat observations. To further improve the retrieval accuracy, Yang et al. [22] developed a spectrum correction method and applied the University of Leicester Full Physics (UoL–FP) algorithm for TanSat nadir mode XCO₂ retrievals. Evaluated against TCCON retrievals, the TanSat XCO₂ retrievals have a mean bias and RMSE of −0.08 ppm and 1.47 ppm, respectively. Applying this correction method, a new TanSat XCO₂ product that retrieved by IAPCAS algorithm shows an improvement on accuracy and precision [23]. Wang et al. [24] implemented NASA Atmospheric CO₂ Observations from Space (ACOS) algorithm with TanSat measurements to retrieve XCO₂. Hong et al. [25] retrieved XCO₂ at TanSat glint mode with spectral recalibration and using the Iterative Maximum A Posteriori Differential Optical Absorption Spectroscopy (IMAP-DOAS) algorithm.

The major scientific goal of the TanSat mission is to quantify carbon sinks and sources at global and regional scales. However, relatively few attempts have been made to utilize TanSat XCO₂ retrieval to estimate surface carbon fluxes. Yang et al. [26] took the initial step to derive surface carbon flux from TanSat XCO₂ retrievals, focusing on net carbon budget over land and without evaluating inversion results using independent CO₂ observations. In this study, we conduct the inversion using the GEOS-Chem Adjoint 4D-Var assimilation system, which has been successfully
applied with GOSAT and OCO-2 XCO\textsubscript{2} retrievals [27]. Different from Yang et al. [26], we focus on
the optimization of NEE, which has the largest uncertainty among all carbon components in the
carbon cycle, and has aroused great interest in the carbon cycle research community. And most pre-
vious inversion studies focused on NEE. Therefore, by comparing with previous studies, we can
analyze and discuss the rationality of our inversion results. We explore the potential of TanSat
XCO\textsubscript{2} retrievals in improving the estimates of NEE in different regions, and evaluate the inversion
results using surface flask CO\textsubscript{2} observations and Total Carbon Column Observing Network
(TCCON) XCO\textsubscript{2} retrievals. The paper is organized as follows: Section 2 briefly introduces TanSAT
XCO\textsubscript{2} retrievals, and the inversion methodology and settings. Section 3 presents results and discus-
sions. Conclusions are given in Section 4.

2. Data and Method

2.1 The GEOS-Chem inverse modeling framework

The GEOS-Chem model [28] is a global three-dimensional chemistry transport model (CTM),
which enables atmospheric composition simulations on local to global scales. It is developed and
used by hundreds of research groups worldwide (http://geos-chem.org). The original CO\textsubscript{2} simula-
tion in the GEOS-Chem model was developed by Suntharalingam et al. [29] and updated by Nassar
et al. [30]. In this study, the GEOS-Chem model was run from March 1, 2017 to April 1, 2018 in a
horizontal resolution of 4°×5° for 47 vertical layers. The posterior CO\textsubscript{2} field on Mar 1, 2017 from
NOAA's CarbonTracker, version CT2019 [31] was taken as the initial concentration. The first
month was treated as spin-up, and the results from April 2017 to March 2018 were analyzed in this
study.

The inverse modeling of CO\textsubscript{2} flux was implemented using the 4D-Var data assimilation ap-
proach based on the GEOS-Chem Adjoint model [32]. The prior carbon fluxes used in this study
consist of fossil fuel emission, biomass burning emission, terrestrial NEE, and CO\textsubscript{2} exchanges over
the ocean surface. Fossil fuel emission is from CT2019, which is an average of Carbon Dioxide In-
formation Analysis Center (CDIAC) product [33] and Open-source Data Inventory of Anthropogenic CO₂ (ODIAC) emission product [34]. NEE is from the simulations of the Simple-Biosphere-Model-Carnegie- Ames Stanford Approach (SiBCASA) biogeochemical model [35]. Biomass burning CO₂ emission is also from the simulations of SiBCASA model based on the Global Fire Emissions Database version 4 (GFEDv4) [36]. CO₂ exchanges over the ocean surface are from the Jena CarboScope sea-air CO₂ flux dataset estimated from the Surface Ocean CO₂ Atlas (SOCAT) data set of pCO₂ observations [37]. Due to their relatively small uncertainties at global and continental scales, the fossil fuel emission and the biomass burning emission in our inversion are prescribed. The NEE and ocean CO₂ fluxes are optimized on monthly scale and a global 4° × 5° grid. The scaling factors of the NEE and ocean CO₂ fluxes are optimized monthly in each model grid by minimizing the cost function, $J$, given by:

$$J(c) = \frac{1}{2} \sum_{i=1}^{N} (XCO₂^{m}_{i} - XCO₂^{obs}_{i})R^{-1}_{obs,i} (XCO₂^{m}_{i} - XCO₂^{obs}_{i}) + \frac{1}{2} (s - s_a)Q^{-1}_s(s - s_a)$$

where $N$ is total number of satellite-based XCO₂ observations; $XCO₂^{m}_{i}$ and $XCO₂^{obs}_{i}$ are the modeled and retrieved XCO₂, respectively; $s_a$ and $s$ are the prior and posterior scaling factors; $R_{obs,i}$ is the model-data mismatch error covariance matrix; $Q_s$ is the scaling factor error covariance matrix. The $R_{obs,i}$ is constructed using the retrieval errors, which are provided along with the TanSat XCO₂ data. Following Wang et al. [27], the $Q_s$ is constructed using the uncertainties of scaling factors in each grid, meanwhile, a spatial correlation is considered, which is assumed to be decayed exponentially with distance, and the temporal correlation is neglected. The scale lengths assigned along longitudinal and latitudinal directions are 500 and 400 km for the NEE and 1000 and 800 km for the ocean exchange, respectively. The prior scaling factor $s_a$ is typically set as unity in each month and each grid. The uncertainty of prior scaling factor represents the uncertainty of prior flux, which is assumed to be uniform globally, and do not change over time. We followed Deng et al. [38] to take global annual uncertainties of NEE and ocean flux as 100% and 40%, respectively, which are the square root of the sum of variances of monthly fluxes at all land and ocean grids, respectively. After
a series of testing, the uncertainties of the prior scaling factors for monthly land and ocean fluxes at the grid cell level are calculated to be 3 and 5, respectively. The modeled XCO$_2$ is calculated using the modeled CO$_2$ concentration profile and retrieval averaging kernels according to equation (2).

\[ XCO_2^m = XCO_2^a + \sum_j h_j a_j (A(x) - y_{a,j}) \]  

(2)

where $j$ denotes the retrieval level, $x$ is the modeled CO$_2$ profile; $A(x)$ is a mapping matrix, which maps the modeled CO$_2$ concentration profile into the satellite retrieval levels; XCO$_2^a$ is a prior XCO$_2$, $h_j$ is the pressure weighting function, $a_j$ is the satellite averaging kernel and $y_{a,j}$ is the prior CO$_2$ profile for retrieval.

2.2 TanSat XCO$_2$ retrievals

We use TanSat XCO$_2$ retrievals produced from the Nadir mode measurements by a retrieval scheme based on the IAPCAS retrieval algorithm [23]. It is a joint CO$_2$ weak band and O$_2$ A band retrieval. A spectra correction method was developed to remove spectrum artifacts in the fitting residual of the O$_2$ A band by applying an 8-orders Fourier series model. Using XCO$_2$ retrievals from 20 TCCON sites as a reference dataset, a genetic algorithm was applied to select quality filters. The bias-correction strategy was constructed from a multiple regression for those selected quality filters. An inter-comparison with UoL-FP TanSat XCO$_2$ retrieval indicate a good agreement, with a standard deviation of 1.28 ppm and a bias of $-0.35$ ppm [23]. The global transport model we used is unable to resolve the details of individual pixel level retrieval. In addition, individual pixel level retrievals close in time and space are likely to be strongly correlated. Therefore, following Wang et al. [27], we construct a single representative XCO$_2$ value and retrieval error for the model grid cell (4°x5°) by averaging all XCO$_2$ retrievals and errors falling inside that grid cell. TanSat XCO$_2$ retrievals used in our inversion are over land only and spans from 1 March 1 2017 to 1 May 2018.

2.3 Evaluation data and method

The inversion results were independently evaluated by comparing the forward-simulated CO$_2$
mixing ratios against surface flask measurements of CO₂ mixing ratio and TCCON XCO₂ retrievals. The CO₂ flask measurements are from the GLOBALVIEWplus v6.0 ObsPack [39], which contains a collection of discrete and quasi-continuous measurements at surface, tower and ship sites contributed by national and universities laboratories around the world. Following the criteria described in Wang et al. [27], we choose flask observations from 52 surface sites among Obspack dataset. TCCON is a network of ground-based Fourier Transform Spectrometers that measure direct near-infrared solar absorption spectra [40]. In this study, we use XCO₂ retrievals from 26 stations from TCCON GGG2014R1 dataset [41 - 67]. The locations of the flask and TCCON sites used in this study are shown in Figure 1.

![Figure 1. Distributions of the observation sites used in this study. Solid circles are surface flask sites, red cross marks are TCCON sites, the shaded area shows the 11 TRANSCOM regions](image)

We run the GEOS-Chem model with both prior and posterior fluxes to obtain their corresponding CO₂ mixing ratios. The simulated CO₂ mixing ratios are sampled at flask site location and within half an hour of observation time. For the comparisons with TCCON retrievals, we firstly mapped the simulated prior and posterior CO₂ concentrations at 47 model levels into 71 TCCON levels, and then, calculated the modeled XCO₂ values at those TCCON sites according to the approach of Wunch et al. [40]. Mean biases and standard deviation of the biases (STDEV) between the modeled
and observed CO$_2$ mixing ratios and XCO$_2$ were calculated to evaluate the inversion results.

3. Results and Discussions

3.1 Global carbon budget

Table 1 presents the prior and posterior CO$_2$ fluxes, which are globally aggregated over land and oceans for the period from Apr 2017 to Mar 2018. The optimized global NEE and ocean flux for the 1-year period are -3.46 PgC and -2.77 PgC, respectively. With 10.0 PgC from fossil fuel and cement production and 2.40 PgC from biomass burning released into the atmosphere, the inversion estimates that the global net carbon flux is 6.15 PgC. During this 1-year period, the global mean atmospheric CO$_2$ mixing ratio estimated by NOAA/ESRL increase by 2.46 ppm (Ed Dlugokencky and Pieter Tans, NOAA/ESRL, www.esrl.noaa.gov/gmd/ccgg/trends/), which is the equivalent of a net carbon increase of 5.2 PgC in the atmosphere [68]. The global mean atmospheric growth rate (AGR) reflects well the total net CO$_2$ flux added into the atmosphere. On global scale, the uncertainties of carbon emissions from fossil fuel and cement production ($E_{ff}$) and biomass burning ($E_{bb}$) are relatively small, thus the global total land and ocean sinks can be estimated directly ($E_{ff} + E_{bb} - AGR$), which is generally used as a benchmark to evaluate the global inversion results. The posterior total sink of land and ocean is larger than the prior sink (see Table 1), but it is still lower than the benchmark, indicating that the inversion using TanSat XCO$_2$, albeit improves to some extent compared to the prior, but still underestimates the total land and ocean CO$_2$ sink to a certain extent. The differences of ocean fluxes between the prior and the posterior flux are small since the TanSat XCO$_2$ retrievals are only available over land.

**Table 1.** Global carbon budget from Apr 2017 to Mar 2018 (PgC yr$^{-1}$)

<table>
<thead>
<tr>
<th></th>
<th>Fossil fuel and cement production</th>
<th>Biomass burning</th>
<th>NEE</th>
<th>Ocean flux</th>
<th>Global net flux</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prior flux</td>
<td>10.0</td>
<td>2.40</td>
<td>-2.98</td>
<td>-2.84</td>
<td>6.58</td>
</tr>
<tr>
<td>Posterior flux</td>
<td></td>
<td></td>
<td>-3.46</td>
<td>-2.77</td>
<td>6.15</td>
</tr>
</tbody>
</table>


3.2 Regional carbon flux

Figure 2 shows the distributions of annual posterior and prior land and ocean carbon fluxes for the 1-year period (excluding the carbon emissions from fossil fuel combustion, cement production and biomass burning). Compared with the prior flux, the posterior land sinks increase significantly in most part of Eurasia boreal region, eastern part of China, western part of North America boreal region, midwestern and eastern regions of the US. Contrastingly, the inferred land sinks decrease remarkably in Africa, Latin America, and India peninsula (Fig. 1c), and even turn to significant carbon sources in Sahel, eastern Africa and India peninsula (Fig.1a).
**Figure 2.** Global distributions of (a) the posterior flux, (b) the prior flux, and (c) the differences between posterior and prior fluxes.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Prior</th>
<th>Posterior</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>-0.15</td>
<td>-0.95</td>
</tr>
<tr>
<td>Boreal N. America</td>
<td>-0.10</td>
<td>-0.55</td>
</tr>
<tr>
<td>Temperate N. America</td>
<td>-0.23</td>
<td>-0.71</td>
</tr>
<tr>
<td>Boreal Asia</td>
<td>-0.05</td>
<td>-1.10</td>
</tr>
<tr>
<td>Temperate Asia</td>
<td>-0.22</td>
<td>-0.50</td>
</tr>
<tr>
<td>Tropical Asia</td>
<td>-0.34</td>
<td>-0.35</td>
</tr>
<tr>
<td>Europe</td>
<td>-0.03</td>
<td>-1.25</td>
</tr>
<tr>
<td>Tropical S. America</td>
<td>-0.70</td>
<td>-0.17</td>
</tr>
<tr>
<td>Temperate S. America</td>
<td>-0.42</td>
<td>-0.26</td>
</tr>
<tr>
<td>Northern Africa</td>
<td>-0.34</td>
<td>1.53</td>
</tr>
<tr>
<td>Southern Africa</td>
<td>-0.55</td>
<td>-0.05</td>
</tr>
<tr>
<td>Australia</td>
<td>0.00</td>
<td>-0.04</td>
</tr>
<tr>
<td>Northern boreal land</td>
<td>-0.15</td>
<td>-1.65</td>
</tr>
<tr>
<td>Northern temperate land</td>
<td>-0.48</td>
<td>-2.46</td>
</tr>
<tr>
<td>Tropical land</td>
<td>-1.38</td>
<td>1.01</td>
</tr>
<tr>
<td>Southern temperate land</td>
<td>-0.97</td>
<td>-0.35</td>
</tr>
</tbody>
</table>

Table 2. The prior and posterior carbon fluxes in different regions (PgC yr\(^{-1}\))

Table 2 summarizes the annually aggregated NEE in China, the 11 TRANSCOM land regions, and the regions of different latitudes. Our inversion estimates most land regions in Northern Hemisphere as strong carbon sinks. Especially in Europe and boreal Asia, the prior flux shows weak carbon sinks, while the posterior flux presents strong sinks up to 1.25 and 1.1 PgC, respectively. The difference between posterior and prior flux in tropical Asia is small since there are few satellite observations over this region. Most noticeably, the inversion gives northern Africa as a relatively large carbon source of 1.53 PgC. In Southern Hemisphere, southern Africa and temperate S. America also have obvious reductions of carbon sinks, with NEE decreasing from -0.55 and -0.42 to -0.05 and -
0.26 PgC yr\(^{-1}\), respectively, while the NEE in Australia shifts to a weak carbon sink. Using the same TanSat XCO\(_2\) retrievals to infer the net carbon budget over land without differentiating biosphere flux from other components, Yang et al. [26] also found large reductions of carbon flux in northern mid-to-high latitudes and strong enhancements of carbon flux in tropical S. America and Africa compared to prior flux. Since different inversion methods and settings were applied, this similar flux adjustment pattern between two inversions is likely induced by TanSat XCO\(_2\) retrievals.

Our estimated land sinks in temperate N. America (-0.71 PgC yr\(^{-1}\)) and temperate Asia (-0.50 PgC yr\(^{-1}\)) are in the range of previous inverse modeling studies of -0.5 ~ -0.9 PgC yr\(^{-1}\) [27, 31, 69-71], and -0.4 ~ -0.7 PgC yr\(^{-1}\) [27, 31, 69, 70, 72], respectively. In Europe, the carbon sink is significantly stronger than those from recent EUROCOM inversions using surface in situ observations [73], but close to those from the inversions using an earlier version of GOSAT XCO\(_2\) retrievals [7, 69]. In China, although the carbon sink is two times higher than a previous comprehensive estimate based on both top-down and bottom-up approaches [74], it is lower than that from a most recent inversion using China’s surface in situ CO\(_2\) measurements [75]. In boreal lands, our estimated sinks are stronger than previous studies, especially in Boreal Asia, where previous studies showed a moderate sink in the range of -0.11 to -0.76 PgC yr\(^{-1}\) [70, 76-79]. In tropical and southern lands, the inverted NEE in S. America, Australia, and tropical Asia are roughly close to those from previous studies [70], but the inverted NEE in Africa has a great difference from previous studies. For example, Ciais et al. [80] presented a synthesis of estimates for Africa’s carbon balance, giving a sink of -0.2 PgC yr\(^{-1}\) (excluding land use change emissions), and CarbonTracker inversions usually show a stronger sink in the range of -0.6 ~ -1.4 PgC yr\(^{-1}\) [31]. It is worth mentioning that, compared to the previous studies, we here just present 1-year estimates which can be largely influenced by climate inter-annual variability [81-83].
Figure 3. Seasonal variations of the prior and posterior fluxes in 11 TRANSCOM regions and all land.

This flux change pattern derived from TanSat XCO₂, of apparent strengthening of carbon sinks in northern mid-to-high latitudes and weakening in tropical and southern lands, is also not consistent with our previous inverse modeling using the same system with GOSAT and OCO-2 XCO₂ retrievals [27]. To further understand how prior flux was adjusted by TanSat data, we examine the seasonal variations of prior and posterior fluxes as shown in Figure 3. In temperate and boreal land regions, posterior fluxes are generally in phase with prior fluxes in growing season, with small adjustment of prior flux in Europe and N. America and apparent enhancement of carbon uptake in
Eurasia region. However, starting from November 2017, posterior fluxes in all these regions decrease gradually, namely the non-growing season carbon release exhibits relatively large reduction. It is difficult to find an ecological answer for this apparent decrease of non-growing season carbon release across northern mid-to-high latitudes. Most likely, after November 2017, the TanSat XCO₂ retrievals possess systematic negative biases, resulting in an underestimate of carbon release in these regions.

In tropical regions and Southern Africa, except tropical Asia, the posterior fluxes are also in phase with the prior flux, but the posterior fluxes have stronger carbon release basically throughout the year. For tropical Asia and Australia, the adjustment of prior flux made by TanSat XCO₂ is not significant. In temperate S. America, the posterior flux is out of phase with the prior flux, with carbon release peak in November other than in May as of prior flux. Compared to the seasonal cycles recovered by the other systems like CT [31], CMS-Flux [84] and GCASv2 [70], the changes of monthly NEE constrained by TanSat XCO₂ adjust the seasonal cycles in temperate S. America, tropical S. America and Southern Africa much closer to the previous estimates. In Northern Africa, although the seasonal cycle of the posterior fluxes are basically the same as those of the prior fluxes, except for the weak carbon sinks in September and October, the remaining months are all carbon sources in the posterior fluxes. Palmer et al. [85] showed that even in extremely dry years (2015/16), there are strong sink during the wet seasons. Liu et al. [84] showed the multi-year (2010–2017) averaged seasonal cycles of net biosphere exchange (NBE, including biomass burning carbon emissions) in Northern Africa from 4 inversion systems (e.g., CAMS, CT-Europe, CarboScope, and CMS-Flux). All the 4 system show significant sinks in this area. Therefore, we believe that the posterior monthly fluxes in Northern Africa in this study is unreasonable.

3.3 Evaluation for the inversion results

As shown in Table 3, the mean bias between the prior CO₂ mixing ratio and flask measurements is 0.97 ppm, with a standard deviation of 2.19 ppm, while the mean biases between the poste-
rior CO₂ mixing ratio and flask measurements are reduced to 0.08 ppm, with a standard deviation of 2.24 ppm. The reduction of overall posterior bias relative to the prior bias suggests that the inversion improves the global estimate of total carbon sink, while the slight increase of posterior STDEV relative to the prior one shows that the inversion has not improved carbon flux estimates consistently at regional scales. At TCCON sites, the overall bias and STDEV of the XCO₂ simulated using the posterior flux are both reduced. The posterior XCO₂ yields a smaller STDEV of the differences, which is not surprising since the TanSat XCO₂ retrievals were bias corrected using the TCCON retrievals.

Table 3. Statistics of the model-data mismatches at the 52 surface flask sites and the 26 TCCON sites (ppm)

<table>
<thead>
<tr>
<th>Flask</th>
<th>TCCON</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pri- or Posterior</td>
<td>Pri- or Posterior</td>
</tr>
<tr>
<td>Bias</td>
<td>0.97</td>
</tr>
<tr>
<td>Stdev</td>
<td>2.19</td>
</tr>
</tbody>
</table>

Figure 4 depicts the biases at each flask and TCCON site in their corresponding latitude. For most of flask sites, prior CO₂ mixing ratios have positive biases, indicating the prior flux underestimates carbon sinks in both Northern and Southern Hemisphere. As for posterior CO₂ mixing ratios, the biases become larger at sites in Southern Hemisphere and tropical regions, and turns to relatively large negative value at sites in northern high latitude (> 40°N) regions, while in northern middle latitude (10°N to 40°N) regions, the biases are significantly reduced. This suggests that the inversion underestimates carbon sinks in Southern Hemisphere and tropical regions, overestimates the carbon sinks significantly in northern high latitude regions, and improves the estimates of NEE in northern middle latitude regions. The latitudinal distributions of the mean biases of the prior and posterior XCO₂ at the TCCON sites located in Southern Hemisphere and northern middle and low latitudes are very similar to those at flask sites, while in northern high latitudes, the posterior
matches well with TCCON but shows a large negative bias in respective to flasks. The different performances of the posterior concentrations against flask and TCCON observations in northern high latitudes may be related to the simulations of vertical CO₂ profile in these areas, which should be paid attention to in the future. The biases of prior XCO₂ are positive at most of the TCCON sites. Relative to the prior XCO₂, the bias of posterior XCO₂ become larger in Southern Hemisphere and tropical regions. In northern mid-to high latitude regions, overall, though positive bias of posterior XCO₂ at 16 sites are greatly reduced and fall within -0.8 to 0.8 ppm interval, there are still 4 sites with relatively large negative bias. Evaluation results at TCCON sites are in general comparable to those at surface flask sites, further suggesting the underestimation of carbon flux in Southern Hemisphere and tropical regions and improvement of the carbon sinks in northern middle latitude regions.

Overall, the overestimation of carbon sinks in high latitudes implies that the TanSat XCO₂ retrievals have systematic negative biases over this region, while the underestimates of carbon sinks in Southern Hemisphere and tropical regions indicates the systematic positive biases.

![Figure 4](image.png)

**Figure 4.** Biases of the simulated CO₂ mixing ratios against (a) the flask measurements and (b) the TCCON XCO₂ retrievals in different latitudes (Bias equals modeled minus observed)
4. Conclusions

In this study, based on the GEOS-Chem 4D-Var data assimilation system, we use TanSat XCO\(_2\) retrievals to constrain terrestrial NEE from April 2017 to March 2018. The annual and monthly posterior NEE at both global and regional scales are shown and discussed. The posterior carbon fluxes are evaluated by comparing the posterior CO\(_2\) mixing ratios against observations from 52 surface flask sites and 26 TCCON sites.

The inversion estimates global land carbon sink at \(-3.46\) PgC yr\(^{-1}\), evidently higher than prior estimate and giving rise to an improved estimate of global atmospheric CO\(_2\) growth rate. Regionally, in northern mid-high latitudes, the land sinks were greatly increased, while in tropical and southern lands, carbon sinks were significantly reduced, and even turned into carbon sources, especially over Africa and India peninsula. In northern lands, the enhancement of posterior carbon sinks is mainly attributed to the decreased carbon release during the non-growing season, and in tropical and southern lands, the decrease of carbon uptake or increase of carbon release basically occurs throughout the year.

Evaluations of the inversions using CO\(_2\) concentrations from flask measurements and TCCON retrievals show that the inversion overestimates the land sinks in northern high latitude regions, significantly underestimates those in tropical and southern lands, and improves the NEE in the northern middle latitude regions to a certain extent. These suggest that TanSat XCO\(_2\) still have systematic negative biases in northern high latitude regions, and positive biases over tropical and southern lands, especially in Northern Africa. These systematic biases are probably caused by the bias-correction process of the TanSat XCO\(_2\) retrievals. Generally, the bias-correction strategy removes parameter-dependent biases using a linear combination of identified bias parameters such as CO\(_2\) gradient between 700 hPa and surface, surface pressure difference between prior and retrieval, surface albedo of CO\(_2\) weak band etc. The coefficients are determined by the linear regression of differences between TanSat XCO\(_2\) and TCCON measurements and those parameters. Since most of
TCCON sites locates in northern middle latitudes (Figure 1), the obtained coefficients work well to remove bias in those regions. However, there are fewer TCCON sites in northern high latitudes, tropical and southern land, the regression relationship obtained in northern middle latitudes might not hold well in those regions, thus the biases-correction process might not remove biases effectively and even produce more biases.

Effective bias correction is critical for the quality of XCO$_2$ data. The TCCON based bias correction needs to be complemented with using other sources such as Small Area Approximation and model-based truth proxies as adopted by OCO-2 products [86]. Effort should be dedicated to develop new truth proxies since the combination of aforementioned sources are still not adequate. A more complete bias correction scheme could not only further improve the accuracy of current TanSat retrievals, but also facilitate the development of retrieval algorithm for China’s planned carbon satellite missions as well.

**Data Availability**

The global terrestrial ecosystem carbon flux inferred in this study is free to access at doi: 10.5281/zenodo.5720212, the TanSat v2 XCO$_2$ data product can be obtained from the CASA TanSat data and science service (www.chinageoss.org/tansat).

**Conflicts of Interest**

The authors declare that there is no conflict of interest regarding the publication of this article.

**Authors’ Contributions**

H. Wang conducted the inversion and wrote the draft, F. Jiang designed the experiment and revised the manuscript, Y. Liu, D. Yang and Jing Wang provided the TanSat XCO$_2$ data and helped to revised the manuscript; M. Wu, W. He, Jun Wang, W. Ju and J. Chen provided important comments
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