A global CO\textsubscript{2} flux dataset (2015–2019) inferred from OCO-2 retrievals using the Tan-Tracker inversion system

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Abstract. Accurate assessment of the various sources and sinks of carbon dioxide (CO\textsubscript{2}), especially terrestrial ecosystem and ocean fluxes with high uncertainties, is important for understanding of the global carbon cycle, supporting the formulation of climate policies, and projecting future climate change. Satellite retrievals of the column-averaged dry air mole fractions of CO\textsubscript{2} (XCO\textsubscript{2}) are being widely used to improve carbon flux estimation due to their broad spatial coverage. However, there is no consensus on the robust estimates of regional fluxes. In this study, we present a global and regional resolved terrestrial ecosystem carbon flux (NEE) and ocean carbon flux dataset for 2015–2019. The dataset was generated using the Tan-Tracker inversion system by assimilating Observing Carbon Observatory 2 (OCO-2) column CO\textsubscript{2} retrievals. The posterior NEE and ocean carbon fluxes were comprehensively validated by comparing posterior simulated CO\textsubscript{2} concentrations with OCO-2 independent retrievals and Total Carbon Column Observing Network (TCCON) measurements. The validation showed that posterior carbon fluxes significantly improved the modelling of atmospheric CO\textsubscript{2} concentrations, with global mean biases of 0.33 ppm against OCO-2 retrievals and 0.12 ppm against TCCON measurements. We described the characteristics of the dataset at global, regional, and Tibetan Plateau scales in terms of the carbon budget, annual and seasonal variations, and spatial distribution. The posterior 5-year annual mean global atmospheric CO\textsubscript{2} growth rate was 5.35 PgC yr\textsuperscript{-1}, which was within the uncertainty of the Global Carbon Budget 2020 estimate (5.49 PgC yr\textsuperscript{-1}). The posterior annual mean NEE and ocean carbon fluxes were −4.07 and −3.33 PgC yr\textsuperscript{-1}, respectively. Regional fluxes were analysed based on TransCom partitioning. All 11 land regions acted as carbon sinks, except for Tropical South America, which was almost neutral. The strongest carbon sinks were located in Boreal Asia, followed by Temperate Asia and North Africa. The entire Tibetan Plateau ecosystem was estimated as a carbon sink, taking up −49.52 TgC yr\textsuperscript{-1} on average, with the strongest sink occurring in eastern alpine meadows. These results indicate that our dataset captures surface carbon fluxes well and provides insight into the global carbon cycle. The dataset can be accessed at https://doi.org/10.11888/Meteoro.tpdc.271317 (Jin et al., 2021).
1 Introduction

Anthropogenic carbon dioxide (CO₂) emissions are dominant sources for increasing atmospheric CO₂ concentrations. Total emissions are partitioned among the atmosphere, land, and ocean. During the past decade (2010–2019), 31 % and 23 % of emissions were absorbed by the land and ocean, respectively (Friedlingstein et al., 2020). However, there is little agreement on the magnitude and interannual variability of land and ocean fluxes at regional scales (Hauck et al., 2020; Piao et al., 2020; Eldering et al., 2017; Piao et al., 2009). Precise knowledge of the various reservoirs within the carbon cycle is a prerequisite to monitor flux changes and make well-informed projections under future climate change (Zscheischler et al., 2017).

Atmospheric inversions provide important insight into the global carbon cycle through absorbing atmospheric CO₂ observations. Many inversion studies have utilized high-precision in situ and flask observations to infer surface CO₂ fluxes (Peters et al., 2007; Chevallier et al., 2010; Lauvaux et al., 2016). Although this is a useful way to quantify carbon fluxes at large scales, estimate uncertainty grows quickly as the scale shrinks due to the lack of observations outside of North America and Europe (Crowell et al., 2019; Byrne et al., 2017; Peylin et al., 2013). To improve spatial coverage and fill observation gaps of in situ CO₂ network, column-averaged CO₂ mole fraction (XCO₂) observations from satellites have been extensively applied to flux inversions. The Greenhouse gases Observing SATellite (GOSAT) was the first dedicated greenhouse gas satellite (Yokota et al., 2009), followed by Orbiting Carbon Observatory 2 (OCO-2) (Crisp et al., 2004). Inversions using GOSAT retrievals can significantly reduce the uncertainty of flux estimates in regions where surface CO₂ observations are sparse; however, no agreement is achieved on the estimates of regional fluxes (Chevallier et al., 2014; Basu et al., 2013; Takagi et al., 2011). Compared with GOSAT, OCO-2 has higher spatial resolution, broader spatial coverage, and collects more measurements per day (Eldering et al., 2017). Its higher measurement signal-to-noise ratio allows for higher-precision XCO₂ retrievals, and its higher spatial sampling density facilitates validation using the ground-based Total Carbon Column Observing Network (TCCON) (Liang et al., 2017; Wunch et al., 2017). Based on these characteristics, OCO-2 may provide better constraints on surface CO₂ fluxes inversions (Basu et al., 2018). Chevallier et al. (2019) indicated that large-scale annual fluxes estimated from bias-corrected OCO-2 land retrievals are within the uncertainty of fluxes estimated from the surface network. Villalobos et al. (2020) performed idealized flux inversion experiments over Australia using OCO-2 retrievals and found that the integrated flux uncertainty was greatly reduced and flux inversions at the unusually fine scale yielded useful information on the carbon cycle at continental and finer scales. With the refinement of instrument error characterization, retrieval algorithms, and bias correction procedures, the accuracy and precision of satellite-retrieved XCO₂ have improved significantly (O’dell et al., 2018; Kiel et al., 2019). The effectiveness and potential of these constantly updated satellite retrievals for inferring surface CO₂ fluxes requires further and persistent investigation.

In the global carbon cycle, the response of carbon fluxes in the Tibetan Plateau ecosystems play an important role (Nieberding et al., 2020; Li et al., 2016). The plateau’s crucial role is almost entirely due to its height, with an area of 2.5 million km² at an average elevation exceeding 4000 m above sea level (Qiu, 2008). The temperature on the Tibetan Plateau has increased by 0.35 °C per decade from 1970 to 2014, at a pace that is about three times the observed rate of global warming,
resulting in significant permafrost thawing and glacier retreat (Yao et al., 2019). These warming-induced environmental issues may enhance the productivity of grasslands and soil respiration, as well as substantial emissions of old CO2 (Ding et al., 2017; Du et al., 2018). However, there are many uncertainties in the Tibetan Plateau carbon cycle under climate change, which are further amplified by human activities (Chen et al., 2013; Piao et al., 2019). Previous studies on Tibetan Plateau carbon fluxes mainly relied on ground-based measurements; the application of satellite data is promising to compensate for ground-based findings and reveal new information about the carbon cycle.

In this study, we used the Tan-Tracker inversion system (Tian et al., 2014a, 2014b) to generate a global dataset containing terrestrial ecosystem carbon fluxes and ocean carbon fluxes from 2015 to 2019 by assimilating OCO-2 XCO2 retrievals. The Tan-Tracker inversion system adopts a dual-pass inversion strategy and the nonlinear least squares four-dimensional variational data assimilation (NLS-4DVar) method (Tian and Feng, 2015; Tian et al., 2018). The dual-pass strategy well distinguishes simulated CO2 errors from uncertainties in both the initial CO2 concentrations and carbon fluxes. The NLS-4DVar method comprising a fast localization module (Zhang and Tian, 2018) is able to assimilate large amounts of observations within an inversion window and obtain high accuracy inversion with low computational complexity. Compared with previous versions of Tan-Tracker, we improved the dual-pass strategy of Tian et al. (2014a), embedded the upgraded ensemble update scheme (Tian et al., 2020) to guarantee the system’s stable operation, and updated the GEOS-Chem transport model (Nassar et al., 2010) to v12.9.3 (http://www.geos-chem.org). In the dataset, we present optimized global daily gridded terrestrial ecosystem and ocean carbon fluxes with a spatial resolution of 2° latitude × 2.5° longitude. Corresponding fluxes from other sectors are also available (e.g., fossil fuel emissions, biomass burning emissions) to infer the global carbon budget. Besides, global model-simulated CO2 concentrations forced by optimized fluxes are provided. The optimized fluxes were comprehensively validated against independent OCO-2 retrievals and TCCON XCO2 observations. Data users can calculate the preferred carbon fluxes at a global or regional scale according to their needs for further analysis or comparison with other sources of flux information.

This paper is organized as follows: Sect. 2 describes the methods and data employed; Sect. 3 and 4 describe the dataset and its characteristics, respectively; Sect. 5 evaluates the posterior fluxes against OCO-2 retrievals and TCCON observations; Sect. 6 discusses the strengths and limitations of the method and dataset, as well as future developments; Sect. 7 introduces the data availability; the conclusion is presented in Sect. 8.

2 Methods and Data

2.1 Tan-Tracker inversion system

Figure 1 shows the frame of the Tan-Tracker inversion system. The fluxes to be optimized are terrestrial ecosystem carbon fluxes (i.e., net ecosystem exchange, NEE) and atmosphere-ocean carbon exchange, whereas other fluxes (e.g., fossil fuel emissions and biomass burning emissions) are assumed to have no errors. This assumption is commonly adopted in global flux inversion systems (Peters et al., 2007; Nassar et al., 2011; Crowell et al., 2019; Jiang et al., 2021). The core of Tan-Tracker is
a novel dual-pass inversion strategy with modifications to Tian et al. (2014a, 2014b) and the NLS-4DVar method (Tian and Feng, 2015; Tian et al., 2018). This dual-pass strategy performs assimilations twice within an inversion window. First, the CO₂ assimilation pass is performed using the prior fluxes within a short time (5 days) to obtain the optimized initial CO₂ concentrations; then, the flux assimilation pass is performed using the optimized initial CO₂ concentrations within a longer time (14 days) to obtain the optimized fluxes. This strategy well distinguishes the CO₂ simulation deviation caused by errors from initial CO₂ concentrations and carbon fluxes. When assimilation of the current inversion window is complete, the prior initial CO₂ concentrations before assimilation and the posterior fluxes are used to actuate the atmospheric chemistry transport model, which simulates the period from the initial moment of the current window to the initial moment of the next window to obtain the initial CO₂ concentrations of the next window. Then, the previous steps are repeated, performing cyclic data assimilation.

The Tan-Tracker optimization procedure is realized using the NLS-4DVar method (Tian and Feng, 2015; Tian et al., 2018). The optimization minimizes the following cost function:

\[
J(x) = \frac{1}{2} (x - x_a)^T (B^{\text{prior}})^{-1} (x - x_a) + \frac{1}{2} (y - h(x))^T R^{-1} (y - h(x)),
\]

where \(x\) is the state variable (i.e., the variable to be optimized) and \(x_a\) is the prior state variable, \(B^{\text{prior}}\) is the prior error covariance matrix, \(y\) is the observed CO₂ concentrations, \(h()\) is the observation operator, and \(R\) is the observation error covariance matrix. The state variable of the CO₂ assimilation pass is CO₂ concentrations, whereas that of the flux assimilation pass is the scaling factor, that is:

\[
F_{i,j}^{\text{post}} = \lambda_{i,j}^{\text{post}} \times F_{i,j}^{\text{prior}}.
\]

where \(F_{i,j}^{\text{post}}\) is the posterior carbon flux, \(\lambda_{i,j}^{\text{post}}\) is the posterior scaling factor, and \(F_{i,j}^{\text{prior}}\) is the prior carbon flux, \(i = 1, 2, \ldots, I, j = 1, 2, \ldots, J\), and \(I\) and \(J\) denote the numbers of grids in longitude and latitude, respectively. Both of fluxes and scaling factors are gridded variables.

The Tan-Tracker inversion system uses the global three-dimensional (3D) atmospheric chemistry transport model GEOS-Chem to simulate CO₂ concentrations in the atmosphere (Suntharalingam et al., 2004; Nassar et al., 2010, 2013). The spatial resolution of GEOS-Chem is 2° latitude × 2.5° longitude, with 47 layers in the vertical direction. The model is driven by the various carbon fluxes, initial CO₂ concentrations, and Modern-Era Retrospective analysis for Research and Applications 2 (MERRA-2) meteorological data provided by the Goddard Earth Observing System (GEOS) of the National Aeronautics and Space Administration (NASA) Global Modeling and Assimilation Office (Gelaro et al., 2017). The observations assimilated are OCO-2 column CO₂ (XCO₂) retrievals (O’dell et al., 2012; O’dell et al., 2018). In this study, we optimized the global NEE and atmosphere-ocean carbon fluxes during 2015–2019 using the Tan-Tracker inversion system. The configurations of Tan-Tracker are described in Table 1.

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Figure 1. Flowchart of the Tan-Tracker inversion system.

Table 1. Configurations of the Tan-Tracker inversion system.

| System setup       | Configuration                                      | Reference                                |
|--------------------|----------------------------------------------------|-----------------------------------------|
| Inversion setup    | Inversion strategy                                  | Dual pass                               |
|                    | Optimized fluxes                                    | Terrestrial ecosystem carbon flux (NEE) and atmosphere-ocean carbon exchange |
|                    | Assimilated data                                    | OCO-2 XCO₂ retrievals                  |
|                    | Inversion method                                    | NLS-4DVar method                        |
|                    | State variable                                      | CO₂ concentration for CO₂ pass; scale factor for flux pass |
|                    | Assimilation window                                 | 5 days for CO₂ pass; 14 days for flux pass |

Tian et al. (2014a); Tian et al. (2014b); Han and Tian (2019)  
Peters et al. (2007); Jiang et al. (2021)  
O'dell et al. (2012); O'dell et al. (2018)  
Tian and Feng (2015); Tian et al. (2018)  
−
Transport model  GEOS-Chem  Version 12.9.3  Suntharalingam et al. (2004); Nassar et al. (2010); Nassar et al. (2013)

Spatial scale  Global  –

Spatial resolution  2° latitude × 2.5° longitude, 47 vertical levels  –

Meteorological forcing  MERRA-2  (Gelaro et al., 2017)

| Flux Type | Inventory name/abbreviation | Description | References |
|-----------|-----------------------------|-------------|------------|
| NEE       |                             |             |            |
| Fossil fuel emissions |                     |             |            |
| Biomass burning emissions |                  |             |            |
| Ship emissions |                         |             |            |
| Aviation emissions |                     |             |            |
| Biofuel burning emissions |                  |             |            |
| Chemical production of CO2 |           |             |            |

2.2 Prior CO2 fluxes

The various carbon fluxes required to drive GEOS-Chem to simulate atmospheric CO2 concentrations included NEE, ocean carbon fluxes, fossil fuel emissions, biomass burning emissions, ship emissions, aviation emissions, biofuel burning emissions, and chemical production of CO2 (Table 2). The 3D chemical source of CO2 includes the oxidation of CO, CH4 and other carbon gases. As fossil fuel emission and biospheric inventories used to count CO2 precursor species (CO, CH4 and other carbon gases) as direct CO2 emissions at the surface, whereas real chemical production of CO2 from these species occurs at different times and locations from emission, model implementation of CO2 chemical production requires adjustments to these surface emission inventories (Nassar et al., 2010).

The optimized fluxes were NEE and ocean-atmosphere exchange. The prior NEE was obtained from CarbonTracker CT2019B (Jacobson et al., 2020), which provides data from January 2000 until March 2019, with a spatial resolution of 1° × 1° and temporal resolution of 3 h. CarbonTracker is a CO2 measurement and modeling system developed by the National Oceanic and Atmospheric Administration (NOAA) that tracks CO2 sources and sinks worldwide. CarbonTracker uses ground-based atmospheric CO2 observations from a host of collaborators and simulates atmospheric transport to estimate surface CO2 fluxes (Peters et al., 2007). The prior ocean carbon fluxes were obtained from Takahashi et al. (2009), which contains monthly data from 2000 to 2013 with a horizontal resolution of 4° × 5°. As the original ocean flux dataset does not cover the simulation period of this study, we used NOAA Marine Boundary Layer (MBL) Reference data of CO2 (https://www.esrl.noaa.gov/gmd/ccgg/mlb/index.html, last accessed: 26 April 2021) to extend the ocean flux to 2018. NOAA MBL Reference is a data product derived directly from measurements of weekly air samples collected by the Cooperative Air Sampling Network; the zonally-averaged MBL reference can be used to identify large-scale trends in atmospheric greenhouse gases (Conway et al., 1994). According to the correlation of MBL CO2 concentration and ocean carbon fluxes described in Takahashi et al. (2009), we constructed the ocean fluxes for 2014–2018 using corresponding MBL data. Due to a lack and deficiency of data for 2019, prior NEE and ocean carbon fluxes for 2018 were used as 2019 prior estimates.

Table 2. Summary of inventories used for the GEOS-Chem CO2 simulation in this work.
2.3 OCO-2 column CO$_2$ observations

The OCO-2 Level 2 Lite (v9r) carbon dioxide column-averaged dry-air mole fraction (XCO$_2$) products retrieved by the Atmospheric Carbon Observations from Space (ACOS) algorithm (Connor et al., 2008) were used in this study (O’dell et al., 2012; O’dell et al., 2018). The OCO-2 satellite carries high-resolution spectrometers that return high-precision measurements of reflected sunlight received within the CO$_2$ and O$_2$ bands in the short-wave infrared spectrum (Crisp et al., 2012). The OCO-2 spacecraft flies in a 705-km-altitude sun-synchronous orbit, with a 16-day (233 orbits) ground track repeat cycle. OCO-2 has a footprint of 1.29 × 2.25 km$^2$ at nadir mode and acquires eight cross-track footprints, creating a swath width of 10.3 km. After filtering and bias correction, the OCO-2 XCO$_2$ retrievals (v7) agree well when aggregated around and coincident with ground-based TCCON data in nadir, glint, and target observation modes, with absolute median differences of < 0.4 ppm and root-mean-square differences of < 1.5 ppm (Wunch et al., 2017). O’dell et al. (2018) demonstrated that OCO-2 retrieval error variance with respect to TCCON was reduced by 20 % over land and 40 % over ocean between versions 7 and 8, with improved nadir and glint observation consistency over land.

Considering the quality and large amount of OCO-2 XCO$_2$ observations, we performed quality control and observation thinning to filter out some retrievals (Han and Tian, 2019). The observation preprocessing procedure included three steps. In

| Source                          | Resolution          | Description                                                                 | Reference                                    |
|---------------------------------|---------------------|------------------------------------------------------------------------------|----------------------------------------------|
| Fossil fuel emissions           | ODIAC               | 1° × 1° monthly global emissions                                            | Oda and Maksyutov (2011); Oda et al. (2018b) |
| Net ecosystem exchange (NEE)    | CarbonTracker       | 1° × 1° 3-hourly averaged data                                              | Jacobson et al. (2020)                       |
| Ocean carbon fluxes             | CT2019B             | 4° × 5° climatology of monthly ocean-atmosphere CO$_2$ fluxes               | Takahashi et al. (2009)                      |
| Biomass burning emissions       | GFED v4             | 0.25° × 0.25° monthly data scaled with daily factors                         | Van Der Werf et al. (2017); Randerson et al. (2017) |
| Ship emissions                  | CEDS                | 0.5° × 0.5° monthly ship emissions                                          | Hoesly et al. (2018)                         |
| Aircraft emissions              | AEIC                | 1° × 1° with 47 vertical levels, aviation fuel burning from AEIC            | Olsen et al. (2013); Simone et al. (2013)    |
| Biofuel burning emissions       | Yevich & Logan      | 1° × 1° annual inventory of biofuel CO$_2$ emissions for 1985 and scaled to 1995 | Yevich and Logan (2003)                      |
| Chemical source                 | GEOS-Chem CO$_2$    | Chemical production of CO$_2$ based on CO loss rates from GEOS-Chem 4° × 5° simulations | Nassar et al. (2010)                         |
the first step, observations were filtered according to the xco2_quality_flag and xco2_uncertainty parameters provided by the OCO-2 Lite product. xco2_quality_flag = 0 denotes the retrieval quality is good whereas xco2_quality_flag = 1 denotes the quality is bad. We selected only observations with xco2_quality_flag = 0. The xco2_uncertainty parameter represents the posterior uncertainty of XCO₂ retrieval, and observations with xco2_uncertainty > 1.5 ppm were filtered out. In the second step, differences between OCO-2 XCO₂ and corresponding model-simulated XCO₂ were considered. The observation was discarded when the absolute difference exceeded 2 ppm, or the difference was beyond the range of two standard deviations above or below the daily mean difference. In the third step, if the number of observations remaining after the first two filtering steps exceeded 20,000, then the observation too close to the previous one was eliminated to maintain a number of observations around 20,000. Figure 2 shows the OCO-2 observations in the first inversion window before and after quality control and thinning. After the preprocessing procedure, extremely large and small observations were excluded. Observations over the Antarctic were generally discarded due to poor quality (xco2_quality_flag = 1), perhaps because of a small solar altitude angle (O’dell et al., 2018).

Figure 2. Spatial distributions of (a) all OCO-2 XCO₂ observations and (b) observations after quality control and thinning in the first inversion window (2015.1.1–2015.1.14).
During the optimization procedure, simulated and satellite observations were used to calculate the second term in Eq. (1). The xco2_uncertainty parameter provided by the OCO-2 Level 2 Lite product was used to construct the observation error covariance matrix $\mathbf{R}$; observation errors were assumed to be independent of each other. We used an observation operator to project the model-simulated 3D atmospheric CO$_2$ concentration to the satellite column-averaged concentration. According to Connor et al. (2008), the observation operator is expressed as follows:

$$XCO_2^p = XCO_2^m + h^T A (x - x_a).$$

(3)

where $XCO_2^m$ is the model simulated column concentration, $XCO_2^p$ is the prior column concentration, $h$ is the pressure weighting function, $A$ is the averaging kernel matrix, $x$ is the modeled CO$_2$ profile, and $x_a$ is the prior profile.

2.4 Uncertainty quantification and ensemble update

As a hybrid method based on 4DVar and the ensemble Kalman filter (EnKF), the NLS-4DVar method applies an ensemble to approximate the prior error covariance matrix (Tian et al., 2018) as follows:

$$\mathbf{B}^{prior} = \left( \frac{\mathbf{p}_x^{prior} \mathbf{p}_x^{prior}}{} \right)_{N-1}^T,$$

(4)

where $\mathbf{p}_x^{prior} = (x'_1, x'_2, ..., x'_N)$ is an ensemble of prior perturbations, $x'_j = x_j - x_a, j = 1, 2, ..., N$, $x_j$ is the $j$th perturbation, and $N$ is the number of prior perturbations. According to Evensen (2009), the ensemble of posterior perturbations after assimilation is calculated as follows:

$$\mathbf{p}_x^{post} = \mathbf{p}_x^{prior} \sqrt{\mathbf{I} - \mathbf{Z}^T \mathbf{Z}},$$

(5)

where

$$\mathbf{U}_2 \mathbf{Z}_2^T = \mathbf{X}_2,$$

(6)

$$\mathbf{X}_2 = \Lambda^{-1/2} \mathbf{Z}^T \mathbf{p}_y,$$

(7)

$$\mathbf{Z}^T \mathbf{Z} = \left[ \left( \mathbf{p}_y \right) \left( \mathbf{p}_y \right)^T + (N - 1) \mathbf{R} \right]^{-1}.$$  

(8)

and $\Phi$ is a random orthogonal matrix, $\mathbf{p}_y = h(\mathbf{p}_x^{prior}) - h(x_a)$. Then, the prior ($\mathbf{B}^{prior}$) and posterior ($\mathbf{B}^{post}$) error covariance matrices can be calculated using $\mathbf{B}^{prior}_x$ and $\mathbf{B}^{post}_x$, respectively, according to Eq. (4). $\mathbf{B}^{prior}$ and $\mathbf{B}^{post}$ represent the prior and posterior uncertainties of scaling factors, respectively. In the flux assimilation pass, the prior perturbations of the scaling factor in the first inversion window were obtained through historical sampling, and prior perturbations in the following windows were generated through ensemble updating. Compared with previous versions (Tian et al., 2014a, 2014b), the current Tan-Tracker system adopts an upgraded ensemble update method that well maintains the ensemble dispersion during cyclic assimilation (Tian et al., 2020). The new ensemble update equation is as follows:

$$\mathbf{p}_{x,r+1}^{prior} = \mathbf{p}_{x,r}^{prior} \mathbf{V}_2 \Phi^T.$$  

(9)
After obtaining the prior and posterior uncertainties of the scaling factors, the prior and posterior total flux uncertainties (\(\sigma_{\text{total}}^{\text{prior}}\) and \(\sigma_{\text{total}}^{\text{post}}\)) can be calculated according to the correlation between fluxes and scaling factors as follows (Niwa and Fujii, 2020):

\[
\sigma_{\text{total}}^{\text{prior}} = \sqrt{(F_{\text{prior}})^T B_{\text{prior}} (F_{\text{prior}})},
\]

\[
\sigma_{\text{total}}^{\text{post}} = \sqrt{(F_{\text{prior}})^T B_{\text{post}} (F_{\text{prior}})},
\]

where we assume that the flux uncertainties are time independent.

The uncertainty reduction (UR) rate is an important indicator of inversion system performance. Following Deng et al. (2007), the UR is defined as follows:

\[
\text{UR} = \left(1 - \frac{\sigma_{\text{total}}^{\text{post}}}{\sigma_{\text{total}}^{\text{prior}}}\right) \times 100\%.
\]

The magnitudes of the UR rates indicate the degree to which the final inverted fluxes are constrained by atmospheric CO\(_2\) observations.

2.5 Evaluation of posterior fluxes

Generally, it is impossible to directly verify the posterior fluxes due to the lack of flux observations. Instead, we compared the simulated CO\(_2\) concentrations driven by posterior fluxes with CO\(_2\) observations to achieve indirect verification (e.g., Wang et al. (2019); Wu et al. (2020); Liu et al. (2021)). The evaluation of posterior fluxes consists of two parts. First, the simulated CO\(_2\) concentrations were compared with unassimilated OCO-2 XCO\(_2\) retrievals, that is, independent observations. Second, the simulated CO\(_2\) concentrations were validated by comparisons with TCCON XCO\(_2\) observations. TCCON is a network of ground-based Fourier Transform Spectrometers that record direct solar spectra in the near-infrared spectral region. From these spectra, accurate and precise column-averaged CO\(_2\) abundances are retrieved and reported (Wunch et al., 2011). In this study, we used GGG2014 version data from 30 TCCON sites (Wunch et al., 2015); the site locations are shown in Fig. 3.

To statistically evaluate the inversion results, we calculated four statistics: the root mean square error (RMSE), mean bias (BIAS), mean absolute error (MAE), and correlation coefficient (CORR). These four statistics represent the bias, error variance, and linear correlation between the simulated and observed CO\(_2\) concentrations, and are formulated as follows:

\[
\text{RMSE} = \frac{1}{M} \sum_{j=1}^{M} (h(x)_j - y_j)^2 ;
\]

\[
\text{BIAS} = \frac{1}{M} \sum_{j=1}^{M} (h(x)_j - y_j) ;
\]

\[
\text{MAE} = \frac{1}{M} \sum_{j=1}^{M} |h(x)_j - y_j| ;
\]

\[
\text{CORR} = \frac{\sum_{j=1}^{M} (h(x)_j - \bar{h}(x))(y_j - \bar{y})}{\sqrt{\sum_{j=1}^{M} (h(x)_j - \bar{h}(x))^2 \sum_{j=1}^{M} (y_j - \bar{y})^2}}
\]

where \(h(x)_j\) and \(y_j\) are the \(j\)th simulated observation and real observation, respectively. \(M\) is the number of observations and the overbar denotes the average.
Figure 3. Distribution of 30 TCCON sites used for validation in this study (red circles). Shaded areas indicate the 11 TansCom land regions.

3 Dataset description

Here we present a global gridded dataset containing various carbon fluxes and simulated CO$_2$ concentrations from 2015 to 2019 (inclusive). The posterior NEE and ocean carbon fluxes were generated using the Tan-Tracker inversion system inferred from OCO-2 XCO$_2$ retrievals. Apart from these two optimized fluxes, all other emissions listed in Table 2 plus net carbon fluxes are included in the flux files. The global gridded fluxes are daily with a resolution of 2° latitude × 2.5° longitude at 47 vertical levels. The vertical layers are set using the hybrid sigma-pressure grid from GEOS-Chem (http://wiki.seas.harvard.edu/geos-chem/index.php/GEOS-Chem_vertical_grids, last accessed: 14 May 2021). The fluxes are distributed in 47 layers due to the presence of aircraft emissions and chemical sources; the remaining fluxes are surface fluxes. The GEOS-Chem simulated instantaneous CO$_2$ concentrations actuated by posterior NEE and ocean fluxes were generated every 3 h, at the same spatial resolution as the fluxes. The surface pressure and pressure at each vertical level are provided in the concentration files. The aggregated global annual and monthly fluxes with corresponding uncertainties are provided in tabular format. Users can aggregate the gridded fluxes on their preferred regions and compare the results with other available datasets. The characteristics of the dataset are described in Sect. 4.
4 Characteristics of the dataset

4.1 Global fluxes

4.1.1 Global carbon budget

The annual atmospheric CO₂ growth rate (AGR) is the net difference between total CO₂ emissions and uptake over land and ocean (Jiang et al., 2021). Table 3 presents the annual and annual mean AGR during 2015–2019 estimated from prior and posterior fluxes in this study. For comparison, the AGRs from Global Carbon Budget 2020 (GCB2020; Friedlingstein et al., 2020), CarbonTracker CT2019B (Jacobson et al., 2020), and Jena CarboScope (JCS; Rödenbeck, 2005) (http://www.bgc-jena.mpg.de/CarboScope/?ID=s, last accessed: 26 May 2021) are also included. The AGR of GCB2020 was estimated directly from atmospheric CO₂ concentration measurements, which are provided by the NOAA Earth System Research Laboratory (ESRL; https://www.esrl.noaa.gov/gmd/ccgg/ggrn.php, last accessed: 23 April 2021); it can be considered a true value. The uncertainty of the GCB2020 AGR is around 0.2 PgC yr⁻¹. CT2019B does not contain complete data for 2019; therefore, we have omitted the 2019 annual and annual mean estimates of CT2019B data. JCS provides estimates of surface-atmosphere CO₂ exchange based on atmospheric measurements using atmospheric transport inversion. In this study, we used version s10oc_v2020 of the JCS product. Table 3 shows that prior AGR evaluations were generally greater than those of GCB2020, except for 2018, contributing to a positive annual mean deviation of 0.43 PgC yr⁻¹, mainly due to prior results for 2016 and 2017, which were 0.61 and 1.14 PgC yr⁻¹, respectively. The positive sign of the deviation indicates that prior carbon sources were overestimated, or sinks were underestimated. After absorbing the satellite observations, the posterior AGR weakened every year, with an annual mean of 5.33 PgC yr⁻¹, which was within the uncertainty range of the GCB2020 estimate (5.49 PgC yr⁻¹). The AGRs of CT2019B were generally smaller than those of GCB2020. A comparison of the AGR of CT2019B and GCB2020 throughout 2015–2018 showed a negative deviation of 0.12 PgC yr⁻¹. The AGRs of JCS during 2015–2017 were quite close to the GCB2020 evaluations. The largest deviation in the JCS data occurred in 2019, with a positive deviation of 0.4 PgC yr⁻¹ compared with GCB2020. Overall, posterior AGRs were clearly refined compared to the prior, indicating the effectiveness of the flux inversions. Notably, although the annual mean result is comparatively accurate, the annual AGRs still require improvement, which imposes higher requirements on inversion systems.

Table 3. Annual and annual mean global atmospheric CO₂ growth rates (AGR) during 2015–2019 estimated in this study and in three flux products: GCB 2020, CT2019B, and JCS.

|                      | Atmospheric CO₂ growth rate (PgC yr⁻¹) |
|----------------------|----------------------------------------|
|                      | Prior | Posterior | GCB2020 | CT2019B | JCS     |
| 2015                 | 6.71  | 5.81      | 6.28    | 5.94    | 6.26    |
| 2016                 | 6.71  | 6.11      | 6.07    | 6.24    | 5.98    |
| 2017                 | 5.75  | 4.98      | 4.58    | 4.46    | 4.55    |
| 2018                 | 5.02  | 4.38      | 5.09    | 4.87    | 4.81    |
Figure 4 presents the interannual variations and corresponding uncertainties of global NEE and ocean carbon fluxes from prior and posterior estimates as well as GCB2020, CT2019B, and JCS. It should be noted that JCS products contain only the net biosphere exchange (NBE), which is the sum of NEE and biomass burning emissions; therefore, to obtain the NEE of JCS, we subtracted the biomass burning emissions used in this study, such that JCS NEE data represent NBE minus GFED4 v4. The annual mean prior NEE was \(-3.53\) PgC yr\(^{-1}\). Posterior NEE were consistently stronger than prior NEE, varying from \(-3.17\) to \(-4.73\) PgC yr\(^{-1}\) in 2016 and 2018, with an annual mean of \(-4.07\) PgC yr\(^{-1}\). The enhancements were obvious during 2015–2018, exceeding 0.5 PgC yr\(^{-1}\). Posterior NEE were generally greater than GCB2020 except for 2016; the largest discrepancy occurred in 2015. However, posterior and GCB2020 estimates of NEE were comparable considering their uncertainties. JCS NEE were basically greater than those of GCB2020, except for 2016, but generally weaker than the posterior ones.

For the ocean fluxes, differences between the posterior and prior sinks were moderate during 2015–2019, within 0.15 PgC yr\(^{-1}\). The posterior sinks were strengthened in 2015, 2017, and 2018, and weakened in 2016 and 2019. The posterior ocean sink had an annual value of \(-3.33\) PgC yr\(^{-1}\), slightly stronger than the prior value of \(-3.29\) PgC yr\(^{-1}\). The ocean formed a sink for CO\(_2\) because the gas is highly soluble in seawater, a property that is critical to the ocean’s ability to absorb atmospheric CO\(_2\) (Mckinley et al., 2017). During the past two decades, sufficient evidence has been gathered to support the conclusion that the global integrated ocean carbon sink has grown as atmospheric carbon content increases (Khatiwala et al., 2013; Watson et al., 2020). Posterior ocean sinks showed an increasing trend, especially from 2015 to 2018. The GCB2020 ocean flux estimates were quite stable, with an annual mean of \(-2.60\) PgC yr\(^{-1}\) and standard deviation of 0.06 PgC yr\(^{-1}\). Posterior ocean sinks were universally greater than the GCB2020 estimates, with the largest deviation occurring in 2018 (1.08 PgC yr\(^{-1}\)). Posterior ocean fluxes were more consistent with the CT2019B estimates; both were stronger than the GCB2020 estimates, and those of CT2019B were even stronger than the posterior fluxes. Compared with the posterior and CT2019B results, JCS had smaller ocean sinks and better coherence with GCB2020.

| Year | Prior NEE | Posterior NEE | Annual Mean NEE |
|------|-----------|---------------|-----------------|
| 2019 | 5.51      | 5.49          | –               |
| Annual mean | 5.94 | 5.35 | 5.49 | – | 5.49 |

The annual mean posterior NEE was \(-3.17\) PgC yr\(^{-1}\).
Combining the NEE and ocean fluxes, the total posterior annual mean sink was $-7.40$ PgC yr$^{-1}$, which is strengthened compared to the prior estimate of $-6.82$ PgC yr$^{-1}$, and contributed to a decrease in net carbon emissions that was consistent with the aforementioned AGR estimates. Notably, CO$_2$ emissions and uptake were classified differently among different inversion systems and GCB2020, preventing NEE and ocean flux estimates from being perfectly equivalent. GCB2020 contains fossil CO$_2$ emissions, land-use change emissions, and terrestrial and ocean CO$_2$ sinks. CT2019B includes fossil CO$_2$ emissions, biomass burning emissions, and terrestrial and ocean CO$_2$ sinks. In this study, apart from the above mentioned sources and sinks, we additionally considered emissions from shipping, aviation, biofuel burning, and chemical production from CO oxidation (Table 2), providing a more comprehensive consideration of the global carbon cycle. Table A1 shows the annual CO$_2$ emissions and uptake from all considered sectors. The uncertainties of carbon emissions other than NEE and ocean fluxes are unclear and therefore omitted, but these uncertainties actually exist and should be well described. Both the improvements of inversion methods and accompanying emissions estimates are necessary to obtain more accurate NEE and ocean carbon fluxes.

### 4.1.2 Seasonal cycle

Figure 5 shows the seasonal cycle and corresponding uncertainties of global NEE and ocean carbon fluxes from prior and posterior estimates during 2015–2019. For NEE, the terrestrial ecosystem emitted CO$_2$ in winter (December to February) and autumn (September to November), and taken up CO$_2$ in spring (March to May) and summer (June to August). The prior annual
NEE means for winter, spring, summer, and autumn were 1.74, –0.31, –6.66, and 1.70 PgC, respectively. After inversion, the corresponding posterior fluxes were 1.41, –0.55, –6.32, and 1.39 PgC, respectively. The magnitudes of posterior fluxes in winter, summer, and autumn decreased by 19%, 5%, and 18%, respectively, whereas the magnitude in spring increased by 79%, which was the most obvious flux modification. Overall, the annual net sink of terrestrial ecosystems increased. The CO₂ emissions in winter and autumn were roughly equivalent. The largest emissions occurred in October or November, and the posterior range was 0.72 PgC in 2018 to 1.16 PgC in 2015. The net terrestrial ecosystem sinks mainly owed to the large uptake in summer. The largest uptake occurred in July, up to –2.62 ± 0.07 PgC in posterior estimates. Spring uptake was much smaller than in summer, and the posterior estimate in 2016 was nearly neutral (–0.04 PgC).

Unlike terrestrial ecosystems, the ocean acted as a carbon sink year-around. The prior annual mean ocean uptake values for winter, spring, summer, and autumn were –0.99, –0.86, –0.68, and –0.77 PgC, respectively. The inversion modifications were not significant, generating posterior estimates of –1.01, –0.89, –0.69, and –0.75 PgC, respectively. The largest and smallest uptakes occurred in winter and summer, respectively. Seasonal changes in the ocean flux field are attributed to the combined effects of seasonal changes in water temperature, biological utilization of CO₂, water mixing, and wind speeds (Takahashi et al., 2002).

![Graph](https://doi.org/10.5194/essd-2021-210)

Figure 5. Monthly variations and corresponding uncertainties of global (a) NEE and (b) ocean carbon fluxes from prior and posterior estimates during 2015–2019.
4.1.3 Uncertainty evaluation

Figure 6 shows the global 5-year mean monthly prior and posterior uncertainties for NEE and ocean fluxes. Monthly means were calculated because uncertainties exhibit clear monthly characteristics. Figure A1 includes the daily uncertainties from prior and posterior estimates. The uncertainties were calculated from the ensemble of perturbations and prior fluxes using Eqs. (4), (10), and (11). As the prior ensemble dispersion was maintained when updated over time, the variation in uncertainties mainly depended on the prior fluxes and flux correlations between different grids. The pattern of NEE monthly uncertainties was consistent with NEE monthly variation (Fig. 5a), with the largest sinks (June, July, and August) contributing to the largest uncertainties in the same months. For the ocean fluxes, uncertainties were much smaller than NEE. Because the flux initial ensemble of perturbations was generated through historical sampling, small uncertainties indicated relatively stable ocean fluxes over time. Large ocean uncertainties were concentrated in winter and summer. Large uncertainties in winter were related to the large ocean sink during that season, whereas large uncertainties in summer were caused by the high spatial correlations between gridded fluxes.

Figure 7 shows the daily UR rates for NEE and ocean fluxes from 2015 to 2019, which varied prominently over time. The estimated URs depended strongly on the number of observations and specification of the observation errors, as well as the a priori error covariance matrix (Deng et al., 2014; Jiang et al., 2021). The UR values reflect the decrease of posterior uncertainties constrained by OCO-2 XCO₂ retrievals. The NEE URs ranged from 0.00 % to 27.90 %. The 0.00 % URs were caused because no OCO-2 retrievals were provided in the inversion windows from April 21, 2015 to May 6, 2015 and from August 10, 2017 to September 6, 2017. Ocean URs were comparable to those over land, ranging from 0.00 % to 25.13 %. Due to the monthly prior ocean fluxes and 14-day inversion window, dates within the same month and the same inversion window shared common URs. Table 4 presents the global annual and annual mean prior uncertainties as well as the UR rates of NEE and ocean sinks during 2015–2019. Temporal correlations in the error covariance matrix were neglected, resulting in discrepancies among the annual uncertainties and URs (Deng et al., 2014). The annual differences in uncertainty and UR decreased greatly when integrated over a year. The annual prior uncertainty of NEE was ~0.55 PgC yr⁻¹, and URs ranged from 7.28 % in 2015 to 8.45% in 2018. The annual prior uncertainties associated with ocean sinks were much smaller than those of NEE, and the annual total uncertainties of different years were probably consistent with each other. URs for ocean sinks were generally higher than those of NEE, with larger interannual variability, ranging from 6.59 % in 2014 to 10.49 % in 2016.
Figure 6. Global 5-year mean monthly prior and posterior uncertainties for (a) NEE and (b) ocean carbon fluxes.
Figure 7. Daily uncertainty reduction (UR) rates for (a) NEE and (b) ocean carbon fluxes from 2015 to 2019.

Table 4. Global annual and annual mean prior uncertainties and URs of NEE and ocean sinks during 2015–2019.

|          | NEE             | Ocean sink      |
|----------|-----------------|-----------------|
|          | Prior uncertainty (PgC yr⁻¹) | UR (%) | Prior uncertainty (PgC yr⁻¹) | UR (%) |
| 2015     | 0.54            | 7.28            | 0.028            | 7.37   |
| 2016     | 0.53            | 8.14            | 0.028            | 10.49  |
| 2017     | 0.56            | 7.36            | 0.029            | 6.59   |
| 2018     | 0.56            | 8.45            | 0.029            | 10.07  |
| 2019     | 0.56            | 7.48            | 0.029            | 7.99   |
| Annual mean | 0.55            | 7.74            | 0.029            | 8.50   |

4.2 Regional fluxes

Figure 8 shows the global distributions of the prior and posterior annual mean NEE and ocean carbon fluxes during 2015–2019. For the prior NEE, carbon sinks mainly occurred over central and eastern North America, the central Amazon, southern South America, central Europe, most of Russia and China, central and southern Africa, and most of Australia. The area of the terrestrial ecosystem carbon sources was much smaller than that of the sinks, which mainly occurred over western and southern
North America, northern South America, small areas in southern South America, northern and southern Europe, western Russia, scattered areas of northwestern and southwestern China, the Malay Archipelago, and the southern coast of Australia. After assimilating OCO-2 XCO₂ retrievals, sinks of central and northeastern North America were impaired whereas sinks of western, southeastern, and southern North America were strengthened. Meanwhile, sinks of the southern Amazon and eastern Brazil were weakened. In Europe, the source was weaker and sink was stronger than prior ones. A widespread weakening of sink occurred in central Russia. Sinks of northeastern and eastern China as well as Australia were reinforced, sinks of Indochinese Peninsula were weakened nevertheless.

By contrast, the ocean carbon flux distribution was much simpler, with a clear characteristic that fluxes varied with latitude. The ocean flux sources mainly occurred in tropical oceans and high-latitude Southern Ocean, and the equatorial Pacific was the most prominent source area for atmospheric CO₂. Sinks mainly occurred in mid-latitude regions of both hemispheres and high latitude Northern Ocean. After inversion, the overall pattern of ocean fluxes was preserved. The tropical sources were generally impaired, especially the eastern equatorial Pacific. Sinks of North Pacific were strengthened whereas sinks of southern Pacific were weakened. Besides, the northern and southern sinks of Atlantic as well as southern sinks of Indian Ocean were basically weaker than prior estimates. In general, the spatial distribution of NEE was far more complicated than that of ocean carbon fluxes (Fig. 8), and the interannual variation of NEE was also stronger (Fig. A2). Therefore, the regional NEE requires more detailed analysis and attribution.

Table 5 lists the prior and posterior NEE for the 11 TransCom land regions. In each region, the prior NEE indicated a carbon sink. The powerful sinks occurred mainly in Asia, Africa, and North America, accounting for 45 %, 27 %, and 18 % of the total carbon sink. Among these regions, Boreal Asia had the strongest sink, followed by Temperate Asia, and the weakest sink occurred in Tropical South America. After inversion, the posterior sinks of most regions were reinforced, except in Tropical South America and Boreal Asia. The European sink showed the largest increase of 0.29 PgC yr⁻¹. Clear sink enhancement also occurred in Temperate Asia and Northern Africa, of 0.17 and 0.10 PgC yr⁻¹, respectively. By contrast, Tropical South America shifted from a weak sink to a weak source. Harris et al. (2021) has pointed out that forests in the Brazilian Amazon were a net carbon source of 0.22 GtCO₂ yr⁻¹ between 2001 and 2019, and estimated that commodity-driven deforestation was the largest source of gross forest-related emissions. In Boreal Asia, the sink was weakened by 0.14 PgC yr⁻¹, but remained the strongest sink worldwide, followed by Temperate Asia and Northern Africa, accounting for 40 %, 27 %, and 17 % of the posterior global total sink. The interannual variability differed greatly for different regions. The Tropical South America had the most obvious interannual variability, followed by Temperate North America and Southern Africa (Fig. A3). The flux uncertainties in the Northern Hemisphere were generally higher than those in the Southern Hemisphere because of the more complicated distribution of carbon sources and sinks in the Northern Hemisphere (Fig. 8). The four regions with the greatest uncertainties were Boreal Asia, Europe, Temperate North America, and Temperate Asia. Under the constraint of OCO-2 satellite observations, the posterior uncertainties of all 11 regions decreased. Australia, South Africa, and Tropical South America showed the clearest improvements where ground-based CO₂ observations are insufficient.
Figure 8. Global distributions of 5-year annual mean NEE and ocean carbon fluxes: (a) prior, (b) posterior, and (c) their differences (posterior – prior).
Table 5. Prior and posterior NEE values, and corresponding UR rates for the 11 TransCom land regions.

| Region           | NEE Prior (PgC yr⁻¹) | NEE Posterior (PgC yr⁻¹) | UR (%) |
|------------------|----------------------|-------------------------|--------|
| Boreal North America | -0.23 ± 0.078       | -0.24 ± 0.072           | 7.7    |
| Temperate North America | -0.37 ± 0.125       | -0.42 ± 0.115           | 7.9    |
| Tropical South America | -0.01 ± 0.046       | 0.01 ± 0.042            | 9.5    |
| Temperate South America | -0.17 ± 0.049       | -0.17 ± 0.045           | 8.9    |
| Northern Africa   | -0.53 ± 0.046       | -0.63 ± 0.042           | 8.7    |
| Southern Africa   | -0.40 ± 0.025       | -0.41 ± 0.023           | 9.7    |
| Boreal Asia       | -0.88 ± 0.201       | -0.74 ± 0.185           | 7.9    |
| Temperate Asia    | -0.56 ± 0.082       | -0.73 ± 0.075           | 8.5    |
| Tropical Asia     | -0.07 ± 0.020       | -0.08 ± 0.018           | 9.0    |
| Australia         | -0.05 ± 0.011       | -0.09 ± 0.010           | 9.9    |
| Europe            | -0.12 ± 0.138       | -0.41 ± 0.127           | 8.0    |

4.3 Tibetan Plateau fluxes

The Tibetan Plateau was demonstrated to act as a carbon sink through remote sensing observations, ecosystem models, and atmospheric inversions during the 1980s and 1990s (Piao et al., 2009). Recent flux observations and field soil carbon data have also confirmed the carbon sink function of the Tibetan Plateau (Kato et al., 2006; Li et al., 2016; Ding et al., 2017). The carbon estimates of the Tibetan Plateau reported in this study are consistent with those reported in previous studies. The prior annual mean NEE was −52.65 TgC yr⁻¹, whereas the posterior NEE was weakened to −49.52 TgC yr⁻¹ during 2015–2019. Figure 9 shows the 5-year annual and seasonal variations of NEE on the Tibetan Plateau. The prior NEE ranged from −38.35 TgC yr⁻¹ in 2015 to −67.47 TgC yr⁻¹ in 2017, whereas the posterior NEE ranged from −30.39 TgC yr⁻¹ in 2015 to −68.87 TgC yr⁻¹ in 2017. The posterior NEE were impaired every year except in 2017, with the largest change occurring in 2015. The prior uncertainties of annual NEE on the Tibetan Plateau were 14.83, 13.54, 15.92, 15.77, and 15.77 TgC yr⁻¹, respectively, during 2015–2019. After inversion, these uncertainties were reduced by 8.54 %, 9.06 %, 8.20 %, 8.70 %, and 6.94 %, respectively. The UR rates on the Tibetan Plateau were comparable to that observed globally and regionally.

The NEE on the Tibetan Plateau showed a clear seasonal cycle. The ecosystem acted as a carbon sink from May to September and as a carbon source from January to April and October to December, with the peak monthly uptake occurring in July. The prior annual mean sink from May to September and source from January to April and October to December were estimated to be −101.65 and 49.00 TgC yr⁻¹, which contributed to forming a net annual sink. The corresponding posterior values were −104.40 and 54.88 TgC yr⁻¹, respectively. Both the posterior seasonal sink and source were amplified, whereas the increased amplitude of the source was stronger than that of the sink, resulting in a decrease in the posterior annual net sink.
Figure 9. Prior and posterior NEE on the Tibetan Plateau during 2015–2019. (a) Annual variation. (b) Seasonal cycle.

Figure 10 shows the 5-year mean spatial distribution of NEE on the Tibetan Plateau during 2015–2019. Previous studies have reported clear regional heterogeneity in the spatial distribution of carbon sinks on the Tibetan Plateau, with significantly stronger carbon sinks in eastern alpine meadows than in western alpine steppes (Jin et al., 2015; Ding et al., 2017). Our estimates were consistent with these findings. Overall, the Tibetan Plateau ecosystem tended to take up carbon; the eastern plateau was the strongest carbon sink, whereas small parts of the southeastern and northern regions emitted CO₂. The eastern distribution was dramatically modified after inversion, with impaired central sinks and amplified surrounding sinks. The central and northern sinks of the plateau were weakened, and the western and southern sinks were slightly strengthened. This spatial heterogeneity in the distribution of carbon sources and sinks on the Tibetan Plateau is related to water conditions. Alpine meadows face lower drought stress than alpine steppes; therefore, the increased vegetation productivity of alpine meadows due to warming is greater than that of alpine steppes, in turn leading to more organic carbon fixation by vegetation input into the soil (Ding et al., 2017; Du et al., 2018; Hopping et al., 2018). The results of field control experiments on the Tibetan Plateau have also shown that warming promotes the net exchange of carbon fluxes in meadow ecosystems with better water conditions, whereas it inhibits carbon fixation in arid steppes (Ganjurjav et al., 2018).
Figure 10. Five-year mean spatial distributions of NEE on the Tibetan Plateau during 2015–2019 based on (a) prior NEE, (b) posterior NEE, and (c) their difference (posterior – prior).

5 Dataset evaluation

5.1 Evaluation using independent OCO-2 observations

We evaluated model simulated XCO$_2$ against independent OCO-2 retrievals to indirectly verify the posterior NEE and ocean carbon fluxes. Figure 11 compares prior and posterior simulated XCO$_2$ with independent OCO-2 XCO$_2$ observations. The simulated and observed XCO$_2$ values were daily averages; daily statistics were calculated using all observations within a single day. The prior simulated XCO$_2$ were generally higher than OCO-2 observations, and the deviation accumulated with forward model integration. Since 2016, RMSE, BIAS, and MAE remained above 1.5, 1.0, and 1.5 ppm, respectively. By 2018, these statistics reached 2.3, 2.0, and 2.0 ppm, respectively. Table 6 shows the 5-year annual mean statistics. After inversion,
simulated \( \text{CO}_2 \) concentrations decreased, especially at the surface (Fig. A4); posterior RMSE, BIAS, and MAE were greatly improved, with RMSE decreasing from 2.12 to 1.27 ppm, BIAS from 1.62 to 0.33 ppm, and MAE from 1.80 to 0.95 ppm. There were no significant changes in CORR before or after inversion. These results show that satellite observations were well absorbed by the inversion system, such that the NEE and ocean carbon fluxes were corrected effectively.

![Figure 11](https://doi.org/10.5194/essd-2021-210)

**Figure 11.** Comparison of prior and posterior simulated \( \text{XCO}_2 \) with independent OCO-2 \( \text{XCO}_2 \) observations. (a) Time series of simulated and observed \( \text{XCO}_2 \), (b) RMSE, (c) BIAS, and (d) MAE of simulated and observed \( \text{XCO}_2 \).

**Table 6.** Statistics for simulated \( \text{XCO}_2 \) and OCO-2 independent \( \text{XCO}_2 \) observations.

|            | RMSE (ppm) | BIAS (ppm) | MAE (ppm) | CORR  |
|------------|------------|------------|-----------|-------|
| Prior      | Posterior  | Prior      | Posterior | Prior | Posterior |
| 2.12       | 1.27       | 1.62       | 0.33      | 1.80  | 0.95       | 0.95 | 0.95 |

**5.2 Evaluation using TCCON observations**

Table 7 lists the statistics for simulated \( \text{XCO}_2 \) and TCCON observed \( \text{XCO}_2 \). The prior model-simulated \( \text{XCO}_2 \) were generally higher than TCCON observations except at the HeiFei site, and BIAS exceeded 2 ppm at many sites (e.g., Ny Ålesund, Garmisch, and Nicosia sites). RMSE, BIAS, and MAE between prior simulated and observed \( \text{XCO}_2 \) were 1.89, 1.51, and 1.63 ppm worldwide. This result agrees with the flux analysis presented in Sec. 4.1, which indicated that the global carbon sink was underestimated. The error of model simulations was generally larger in the Northern Hemisphere than in the Southern
Hemisphere, due to the more complex carbon flux pattern in the Northern Hemisphere (Wang et al., 2019). After inversion, the global carbon sink was reinforced, contributing to a more reasonable atmospheric CO$_2$ simulation. The posterior RMSE, BIAS, and MAE were 1.06, 0.12, and 0.81 ppm, decreasing by 44 %, 92 %, and 50 %, respectively, compared to the prior statistics, demonstrating the optimization of posterior fluxes through absorbing OCO-2 satellite observations.

Figure 12 shows the time series of prior and posterior simulated XCO$_2$ and observed XCO$_2$ at 30 TCCON sites. The global CO$_2$ concentrations generally increased over time. In the Northern Hemisphere, CO$_2$ concentrations showed a strong seasonal cycle. The strong source in winter caused high CO$_2$ concentrations, whereas the strong sink in summer caused low CO$_2$ concentrations. In the Southern Hemisphere, the seasonal cycle was much weaker than in the Northern Hemisphere, and became less clear as latitude increased. The Southern Hemisphere is mainly covered by ocean, and the seasonal variation in ocean fluxes was much less pronounced than NEE (Fig. 5), with a less complex spatial distribution than that over land (Fig. 8), contributing in turn to the weak seasonal cycle of CO$_2$ concentrations in the Southern Hemisphere. Generally, posterior simulated XCO$_2$ characterized the temporal variation characteristics of CO$_2$ observations.

At most sites, prior simulated XCO$_2$ were larger than TCCON observations. The overestimation of winter CO$_2$ concentrations in the Northern Hemisphere was very clear, especially in the mid- and high latitudes. After inversion, the simulated concentrations agreed better with TCCON observations (Fig. 13). The overestimation of winter CO$_2$ concentrations at mid- and high latitudes of the Northern Hemisphere was also well mitigated due to the weakening of winter carbon sources (Sec. 4.1.2). The inversion results were not ideal at the Jet Propulsion Laboratory, Caltech, and HeFei sites. At these three sites, prior simulated XCO$_2$ were close to the TCCON observations, whereas posterior simulations were about 1 ppm smaller than the TCCON observations, suggesting that carbon sinks were overestimated or carbon sources were underestimated. This may be related to biases of OCO-2 retrievals (O’Dell et al., 2018). Besides, the resolution of the Tan-Tracker inversion system is 2° latitude × 2.5° longitude; therefore, it cannot achieve ideal results at every site worldwide. Improvements of inversion resolution and observation quality are necessary to infer fluxes at finer regional scales.

**Table 7.** Geographic locations of TCCON sites used for validation, and statistics used to compare simulated XCO$_2$ and TCCON XCO$_2$ observations. Sites are listed according to latitude from north to south.

| Station    | Lat. | Long.  | RMSE (ppm) | BIAS (ppm) | MAE (ppm) |
|------------|------|--------|------------|------------|-----------|
|            |      |        | Prior      | Posterior  | Prior     | Posterior |
| Eureka     | 80.05| –66.42 | 1.57       | 1.13       | 1.02      | –0.61     | 1.30 | 0.86 |
| Ny Ålesund | 78.90| 11.92  | 2.62       | 1.27       | 2.47      | 0.96      | 2.47 | 1.08 |
| Sodankylä  | 67.37| 26.63  | 2.46       | 1.15       | 2.28      | 0.81      | 2.31 | 0.94 |
| East Trout Lake | 54.35| –104.99 | 2.46    | 1.05       | 2.25      | 0.42      | 2.28 | 0.81 |
| Bialystok  | 53.23| 23.02  | 1.90       | 0.93       | 1.68      | 0.51      | 1.70 | 0.73 |
| Bremen     | 53.10| 8.85   | 2.19       | 1.09       | 1.96      | 0.55      | 1.98 | 0.87 |
| Karlsruhe  | 49.10| 8.44   | 2.21       | 1.07       | 1.92      | 0.48      | 1.96 | 0.87 |
| Location                  | Value1 | Value2 | Value3 | Value4 | Value5 | Value6 | Value7 | Value8 | Value9 | Value10 | Value11 |
|---------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|---------|---------|
| Paris                     | 48.97  | 2.36   | 1.96   | 1.46   | 1.06   | –0.32  | 1.58   | 1.14   |
| Orléans                   | 47.97  | 2.11   | 2.45   | 1.17   | 2.26   | 0.86   | 2.26   | 0.95   |
| Garmisch                  | 47.48  | 11.06  | 2.56   | 1.19   | 2.34   | 0.84   | 2.35   | 1.00   |
| Zugspitze                 | 47.42  | 10.98  | 1.49   | 0.80   | 1.20   | –0.21  | 1.25   | 0.62   |
| Park Falls                | 45.95  | –90.27 | 1.85   | 0.81   | 1.48   | 0.10   | 1.57   | 0.59   |
| Rikubetsu                 | 43.46  | 143.77 | 2.20   | 1.09   | 1.83   | 0.32   | 1.87   | 0.75   |
| Lamont                    | 36.60  | –97.49 | 1.60   | 0.70   | 1.37   | –0.02  | 1.42   | 0.55   |
| Anmeyondo                 | 36.50  | 126.33 | 1.35   | 1.00   | 0.91   | –0.10  | 1.11   | 0.77   |
| Tsukuba                   | 36.05  | 140.12 | 2.06   | 1.24   | 1.64   | 0.14   | 1.77   | 0.92   |
| Nicosia                   | 35.14  | 33.38  | 2.52   | 0.74   | 2.46   | 0.11   | 2.46   | 0.61   |
| Edwards                   | 34.96  | –118.18| 0.98   | 1.40   | 0.49   | –1.10  | 0.80   | 1.16   |
| Jet Propulsion Laboratory | 34.20  | –118.13| 1.13   | 1.66   | 0.17   | –1.24  | 0.90   | 1.37   |
| Caltech                   | 34.14  | –118.13| 1.13   | 1.66   | 0.17   | –1.24  | 0.90   | 1.37   |
| Saga                      | 33.24  | 130.29 | 1.62   | 1.10   | 1.09   | –0.51  | 1.30   | 0.89   |
| Hefei                     | 31.91  | 117.17 | 1.21   | 1.74   | –0.08  | –1.24  | 0.93   | 1.47   |
| Izana                     | 28.30  | –16.48 | 1.72   | 0.85   | 1.46   | –0.32  | 1.50   | 0.72   |
| Burgos                    | 18.53  | 120.65 | 2.01   | 0.92   | 1.83   | 0.00   | 1.84   | 0.71   |
| Manaus                    | –3.21  | –60.60 | 1.12   | 0.97   | 0.64   | 0.36   | 0.89   | 0.79   |
| Ascension Island          | –7.92  | –14.33 | 2.05   | 1.20   | 1.83   | 0.89   | 1.83   | 0.98   |
| Darwin                    | –12.46 | 130.89 | 1.56   | 0.99   | 1.39   | 0.17   | 1.43   | 0.76   |
| Réunion Island            | –20.90 | 55.49  | 1.53   | 1.01   | 1.27   | 0.18   | 1.32   | 0.77   |
| Wollongong                | –34.41 | 150.88 | 1.34   | 0.86   | 1.09   | –0.12  | 1.20   | 0.66   |
| Lauder                    | –45.04 | 169.68 | 1.73   | 0.57   | 1.55   | 0.34   | 1.56   | 0.47   |
| Global mean               | –      | –      | 1.89   | 1.06   | 1.51   | 0.12   | 1.63   | 0.81   |
Figure 12. Time series of prior and posterior simulated XCO$_2$ and XCO$_2$ observations at 30 TCCON sites. Sites are sorted according to latitude from north to south.
Figure 13. Scatter plots of prior and posterior simulated XCO$_2$ and XCO$_2$ observations at 30 TCCON sites. Sites are sorted according to latitude from north to south.
6 Discussion

The atmospheric CO$_2$ observations assimilated in this study were OCO-2 XCO$_2$ retrievals. Although satellite observations have better spatial coverage than ground-based observations, they remain unable to continuously monitor CO$_2$ concentrations with global coverage, resulting in observational gaps. Spatial and temporal gaps in ground- and space-based observations can introduce artifacts into flux estimates, leading to difficulties in constraining carbon fluxes at regional scales (Basu et al., 2018; Byrne et al., 2017; Liu et al., 2014). Advances in satellite retrieval algorithms allow significant improvements in the consistency of space- and surface-based flux constraints (Byrne et al., 2020). The simultaneous assimilation of ground- and space-based atmospheric CO$_2$ observations will be carried out in the Tan-Tracker inversion system, expecting more precise estimation of regional fluxes.

In this study, we optimized terrestrial ecosystem carbon fluxes and ocean carbon fluxes, while assuming no error in other emission inventories. As the largest emission sector, global fossil CO$_2$ emissions are estimated with an uncertainty at ±5% according to GCB2020 (Friedlingstein et al., 2020). However, uncertainties of national bottom-up fossil fuel emissions vary across countries according to data collection and management practices (Andres et al., 2014; Marland, 2008; Oda et al., 2018a). Inaccuracies in fossil CO$_2$ emissions are added to NEE optimization based on our assumption, which may cause bias in NEE estimates. Fossil CO$_2$ emissions are anthropogenic, whereas NEE are natural emissions or uptakes; both have different emission characteristics and spatial distributions. In a future study, we plan to simultaneously optimize fossil emissions and NEE to distinguish errors from anthropogenic and natural sectors.

The treatment of various errors during inversion also requires improvement. The transport model is assumed to have no error, and all errors associated with simulated CO$_2$ are attributed to the initial CO$_2$ concentrations and carbon fluxes. An independent and comprehensive quantification of the systematic errors of transport models is required to distinguish CO$_2$ simulation errors from different sources. To account for prior flux uncertainties, we used 36 samples to approximate the prior error covariance matrix and updated the matrix over time. To date, there is no consensus on the accurate calculation of prior uncertainties. In this study, when gridded flux uncertainties were integrated over space and time, only the spatial correlation of gridded fluxes was considered, whereas the temporal correlation was omitted. However, the gridded fluxes were correlated in time according to their diffusive and accumulative characteristics, resulting in underestimated monthly or yearly uncertainties. Further efforts are required to improve confidence in the resulting posterior fluxes and corresponding uncertainties.

The global-scale flux inversion performed in this study had a spatial resolution of 2° latitude × 2.5° longitude. Inversions with this resolution are feasible and effective for large and global regions. However, the requirements for fine and accurate regional inversions are increasing, and the present resolution cannot meet the stricter standards anticipated in the future. Therefore, we plan to perform finer inversions at regional scales to obtain a better understanding of regional carbon cycles.
7 Data availability

The dataset is available in the National Tibetan Plateau/Third Pole Environment Data Center and can be accessed at https://doi.org/10.11888/Meteoro.tpdc.271317 (Jin et al., 2021). As the satellite XCO₂ retrievals, carbon fluxes, and meteorological data are persistently improving and updating, we plan to update the dataset annually in the future, aiming to support current scientific research and policy making.

8 Conclusion

Here we present a global and regional resolved NEE and ocean carbon flux dataset during 2015–2019. The dataset was generated by the Tan-Tracker inversion system constrained by OCO-2 XCO₂ retrievals. We qualitatively validated the posterior fluxes by comparing the posterior simulated CO₂ concentrations with OCO-2 independent retrievals and TCCON observations. After inversion, posterior RMSE, BIAS, and MAE for simulated and OCO-2 XCO₂ were greatly improved, with RMSE decreasing from 2.12 to 1.27 ppm, BIAS from 1.62 to 0.33 ppm, and MAE from 1.80 to 0.95 ppm. The posterior RMSE, BIAS, and MAE for simulated and TCCON XCO₂ were 1.06, 0.12, and 0.81 ppm, decreasing by 44 %, 92 %, and 50 %, respectively, compared to the prior statistics. Both validations demonstrated the optimization of posterior fluxes through absorbing OCO-2 satellite observations. We described the characteristics of the dataset at the global, regional and Tibetan Plateau scales from aspects of carbon budget, annual and seasonal variations, and spatial distribution. Also, the posterior fluxes were assessed through comparisons with other flux estimates, such as GCB2020, CT2019B, and JCS data. The posterior 5-year annual mean global AGR was 5.35 PgC yr⁻¹ and within the uncertainty of the GCB2020 estimate. The posterior annual mean NEE and ocean carbon fluxes were −4.07 and −3.33 PgC yr⁻¹, respectively. Regional fluxes are analysed based on TransCom partition. All 11 land regions acted as carbon sinks apart from Tropical South America, which was almost neutral. The strongest carbon sinks were seen in Boreal Asia, followed by Temperate Asia and North Africa. The Tibetan Plateau ecosystem was estimated as a carbon sink as a whole, absorbing −49.52 TgC yr⁻¹ for the annual mean. The sinks in the eastern alpine meadows were much stronger than that in the western steppes, while sporadic areas in the southeastern and northern regions acted as sources. This dataset can help understand global and regional carbon distribution and its variability, support the formulation of climate policies, and make well-informed projections under future climate change.

Appendix A

In the Appendix, we include the table and figures to support the main text.

Table A1. Global annual carbon flux estimates from various sectors and AGR during 2015–2019. The NEE and ocean carbon fluxes here refer to posterior values.

| CO₂ emissions and uptakes (PgC yr⁻¹) | 2015  | 2016  | 2017  | 2018  | 2019  |
|--------------------------------------|-------|-------|-------|-------|-------|
|                                      |       |       |       |       |       |
### Table 1: Daily Uncertainties for Various Emissions from 2015 to 2019

|                  | 2015   | 2016   | 2017   | 2018   | 2019   |
|------------------|--------|--------|--------|--------|--------|
| NEE              | -4.05  | -3.17  | -4.15  | -4.73  | -4.28  |
| Ocean carbon fluxes | -2.90  | -3.17  | -3.47  | -3.64  | -3.47  |
| Fossil fuel emissions | 9.31   | 9.35   | 9.45   | 9.67   | 9.72   |
| Biomass burning emissions | 2.10   | 1.74   | 1.79   | 1.70   | 2.14   |
| Biofuel burning emissions | 0.82   | 0.82   | 0.82   | 0.82   | 0.82   |
| Ship emissions    | 0.27   | 0.27   | 0.27   | 0.27   | 0.27   |
| Aircraft emissions | 0.28   | 0.29   | 0.31   | 0.32   | 0.32   |
| Chemical source   | 1.11   | 1.11   | 1.11   | 1.11   | 1.11   |
| Surface correction | -1.14  | -1.14  | -1.14  | -1.15  | -1.15  |
| AGR              | 5.81   | 6.11   | 4.98   | 4.38   | 5.49   |

**Figure A1.** Daily uncertainties for (a) prior NEE, (b) posterior NEE, (c) prior ocean carbon fluxes, and (d) posterior ocean carbon fluxes from 2015 to 2019.
Figure A2. Spatial distributions of prior and posterior NEE plus ocean carbon fluxes from 2015 to 2019. The first column plots (a, c, e, g, i) denote the prior distributions and the second column plots (b, d, f, h, j) denote the posterior distributions.
Figure A3. Prior and posterior interannual variations of NEE in the 11 TransCom land regions from 2015 to 2019.
Figure A4. Spatial distributions of prior and posterior simulated surface CO$_2$ concentrations from 2015 to 2019. The first column plots (a, c, e, g, i) denote the prior distributions and the second column plots (b, d, f, h, j) denote the posterior distributions.
Author contributions. TX conceptualized, administrated, and supervised the research, and acquired funds for it. JZ, HR, and FY made investigations, constructed the inversion system, and visualized the data. JZ created the dataset. JZ and FY made formal analysis of it. TX and LX developed the methodology. TX, LX, and MH provided necessary resources. JZ and CC validated the data. JZ wrote the original manuscript draft. TX, LX, and FY reviewed and edited the original manuscript draft.

Competing interest. The authors declare that they have no conflict of interest.

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