A global surface CO_2 flux dataset (2015–2022) inferred from OCO-2 retrievals using the GONGGA inversion system

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Reply to reviewer 2

We would like to thank reviewer 2 for the constructive suggestions and insightful comments, which have helped us improve the manuscript. Please see below the point-to-point responses. All the line numbers indicated in this letter of response correspond to the revised version of text.

Reviewer 2:

The authors introduce a new inversion system (GONGGA) that assimilates total column CO_2 from NASA's OCO2 satellite to optimize terrestrial and oceanic carbon fluxes (NEE). The results are compared against a recent model inter-comparison project that assimilated an older version of this dataset. Results are also evaluated against a network of upward looking forward scattering radiometers as well as in-situ surface and aircraft observations.

The manuscript adds a novel inversion system to a growing list of similar simulations (global models that estimate CO_2 fluxes by assimilating total column CO_2 retrievals). The manuscript is generally well written. Therefore, I think this is suitable for publication in ESSD.

Response: We thank the reviewer for the positive evaluation of our study and the valuable suggestions to improve it. We have carefully revised our manuscript following the comments and suggestions.

I only have a few concerns at this point:

1. *Q: It isn't clear how XCO_2 uncertainties are treated in the inversion system. It is generally assumed that the reported XCO_2 uncertainty in the lite files is likely too low. Moreover, unlike in-situ observations, XCO_2 data exhibit high correlation (given that individual soundings are only 300 m apart). Therefore, the information content as well as errors are highly correlated for adjacent soundings. Generally, studies have relied on averaging. See Piero et al. 2022, Byrne et al. 2023, and Baker et al., 2022. I would recommend expanding the methods section to describe exactly how retrieval uncertainties are treated (given the context of the afore-mentioned studies) and perform some sensitivity analyses (e.g., tests where uncertainties are inflated) to estimate the impact of data error on retrieved fluxes.*

Response:

Thank you for mentioning the detailed procedure applied by the OCO-2 MIP project. In this inversion experiment, we used a different approach than the “super-obs” approach of the OCO-2 MIP project as explained below.

We applied an observation thinning algorithm to reduce the number of observations. Observation thinning is usually used in data assimilation for numerical weather prediction (NWP), and is efficient in reducing the error-correlation (Liu and Rabier, 2002; Campbell et al., 2017; Reale et al., 2018). During the whole period from September 6, 2014, to December 31, 2023, only one fifth of the total XCO_2 retrievals were assimilated. We added the reference for the rationality of observation thinning and explained the procedure in the revised Sec. 2.3:

- Line 147-153: “We applied a data thinning algorithm (Liu and Rabier, 2002; Campbell et al., 2017; Reale et al., 2018) to reduce the potential impacts of correlated errors in adjacent soundings. We set the threshold of the number of daily observations to 20,000. If the number of good retrievals exceeded the threshold within a single day, excess data were removed. For example, if there were 60,000 good retrievals in one day, one of every three sequential retrievals was selected according to sounding ID. Before data thinning, there were 203,368,424 XCO_2 retrievals with good quality from September 6, 2014, to December 31, 2022. After data thinning, 40,337,763 XCO_2 retrievals were actually assimilated in the inversion, about a fifth of total good retrievals.”

We are now working on adapting our system to use the “super-obs” approach following the OCO-2 MIP protocol, and will probably publish the results in the next version of GONGGA. We added a paragraph in the discussion section to outline the future development of GONGGA to align with the latest knowledge from OCO-2 science team:

- Line 422-427: “In addition, some parts of GONGGA’s inversion algorithm, such as the data selection, were partly different from those proposed by the OCO-2 Science Team (Peiro et al., 2022; Byrne et al., 2023; Baker et al., 2022), but GONGGA’s inversion results were broadly consistent with the ensemble of OCO-2 MIP inversions and GCB2023, and gave reasonable estimates of global and regional carbon budgets within the uncertainties. In the future, GONGGA will regularly publish new versions of inverted fluxes using the latest OCO-2 data on an annual basis. These updates will align with the latest suggestions from the OCO-2 Science Team, enabling the ongoing monitoring of CO_2 fluxes.”

For the concern about the retrieval uncertainty, we used the xco2_unvertainty reported in the OCO-2 Lite file. To investigate the impacts of data error on inverted fluxes, we conducted three sensitivity tests. In the first and second experiments (E1 and E2), the reported XCO_2 uncertainties were enlarged by two and four folds, respectively. In the third experiment (E3), the XCO_2 uncertainties were added by 5 ppm. The three sensitivity tests adopted the same set-ups as the inversion in this study only except for the XCO_2 uncertainties. At the global scale, the inverted annual NBE and F_{OCEAN} from the original inversion, E1, and E2 are very close, but E3 has a different portioning between land and ocean fluxes than the other inversions, which amounts to about 0.2

Pg C yr^{-1} (Fig. R6). When it comes to the regional scale, the differences are larger in some regions and years but are still broadly consistent with the reference inversion (Fig. R7). In the revised manuscript, we added the results of these sensitivity tests and discussed the impacts of data errors:

- Line 406-416: "The processing of XCO_2 uncertainties also had an impact on the inversion results. We performed three sensitivity inversions with different XCO_2 uncertainties. The XCO_2 uncertainties were inflated two and four times in the first (E1) and second (E2) test, respectively. In the third test (E3), the XCO_2 uncertainties were increased by 5 ppm. The three sensitivity tests adopted the same configuration as the reference inversion in this study only except for the XCO_2 uncertainties. The distributions of different XCO_2 uncertainties were shown in Fig. S8. At the global scale, the inverted annual NBE and F_{OCEAN} from the original inversion, E1, and E2 were very close, but E3 had a different partitioning between land and ocean fluxes than the other inversions, which amounted to about 0.2 Pg C yr^{-1} (Fig. S9). When it comes to regional scale, the differences were larger in some regions and years but were still broadly consistent with the reference inversion (Fig. S10). These sensitivity tests highlighted the fact that the inversion results were indeed impacted by the assumption regarding XCO_2 uncertainty and careful assessment of uncertainties in satellite XCO_2 retrievals was necessary for accurate estimates of global and regional carbon fluxes."

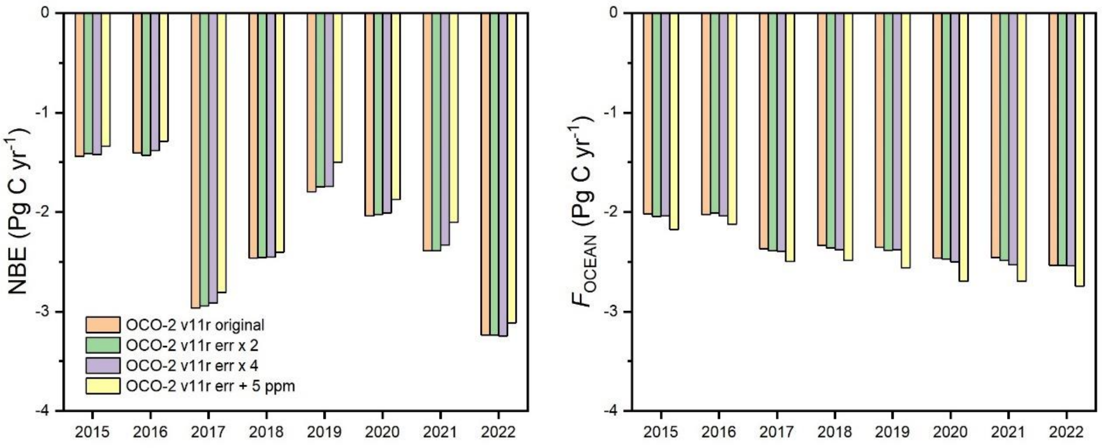

Figure R6. The global annual NBE and F_{OCEAN} from GONGGA posterior estimates with default OCO-2 v11r XCO_2 uncertainties (orange), doubled OCO-2 v11r original XCO_2 uncertainties (green), quadrupled OCO-2 v11r original XCO_2 uncertainties (purple), and OCO-2 v11r original XCO_2 uncertainties added by 5 ppm (yellow).

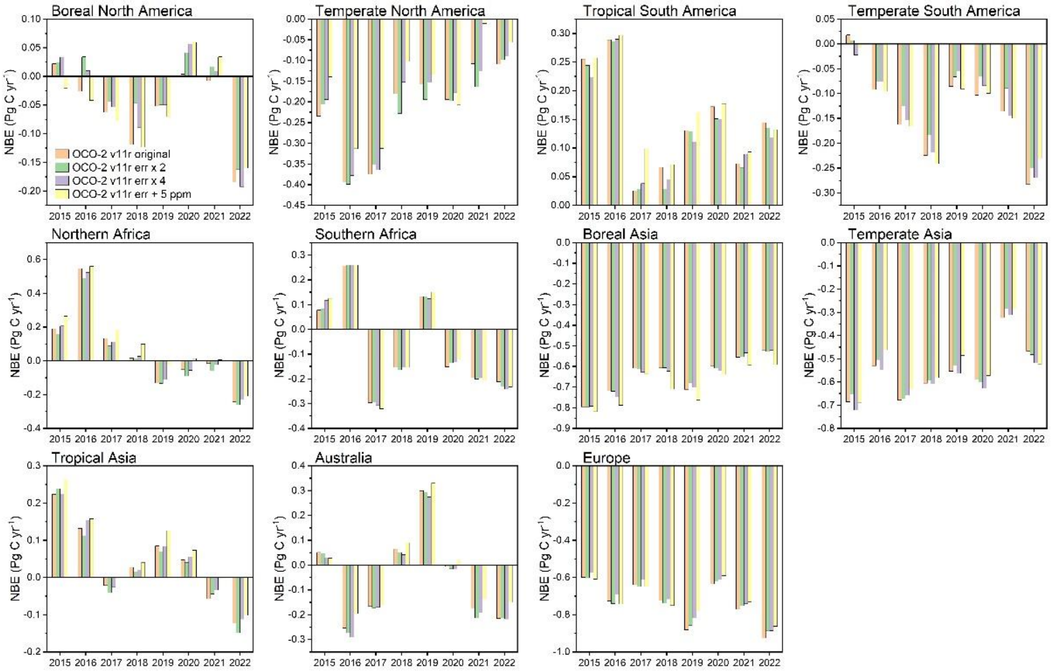

Figure R7. NBE in 11 TransCom land regions from GONGGA posterior estimates with default OCO-2 v11r XCO$_2$ uncertainties (orange), doubled OCO-2 v11r original XCO$_2$ uncertainties (green), quadrupled OCO-2 v11r XCO$_2$ uncertainties (purple), and OCO-2 v11r XCO$_2$ uncertainties added by 5 ppm (yellow).

2. *Q: The authors note that the main differences from the OCO v10 MIP arise in the high northern latitudes. At one point this was due an issue with the OCO-2 retrievals in the v11 dataset. I wonder if the retrievals used in the inversion system are impacted by this. I would check with the dataset providers to see if the authors are using a version that is known to have issues. Also see the data quality statement: https://docserver.gesdisc.eosdis.nasa.gov/public/project/OCO/OCO2_L2_Data_Release_Statement_v11.1_Lite_Files.pdf*

Response:

We noticed that in v11r Lite dataset, the XCO$_2$ data may have a bias of about -0.4 ppm due to the impact of a different DEM data used in the retrieval algorithm (Jacobs, et al., 2024). It was found that this negative bias would introduce a larger sink in the northern high latitudes. To check the impact of such biases in XCO$_2$, we run the inversion with the latest v11.1r product for the period from 2015 to 2018. The results show that the inverted sink north of 60°N using v11.1r are smaller than that using v11r by 90 to 140 Tg C yr^{-1}, and accompanied by a compensating increase in ocean carbon uptake in the northern mid- and low- latitudinal band (Fig. R8). That means the sink in Boreal North America from GONGGA will be even smaller than that from the OCO-2 MIP if v11.1r data are used. Thus, the difference between GONGGA and OCO-2 MIP in the estimates of sink in Boreal North America seems not due to the negative biases in v11r Lite XCO$_2$ retrievals but is likely due to other differences, such as the inversion algorithm, the prior fluxes, and the associated prior uncertainty. In particular, we found that Boreal North America was a carbon source in the prior flux of GONGGA, while it was a carbon sink in the OCO-2 MIP prior. After assimilating the observations, Boreal North America emerged as a carbon sink in both GONGGA and OCO-2 MIP, but the sink size was smaller in GONGGA than OCO-2 MIP. In the revised manuscript, we added a paragraph to discuss the potential impacts of using different versions of OCO-2 retrieval products on inverted fluxes, and emphasized that we would regularly update the GONGGA results with the latest OCO-2 dataset:

- Line 417-427: "In the current version of GONGGA, we assimilated the OCO-2 v11r Lite XCO_2 dataset. A recent paper found that the v11r Lite product has a bias of -0.4 to -0.8 ppm across regions north of 60°N due to the variations of digital elevation model (DEM) used in the retrieval algorithm (Jacobs et al., 2024), and this bias introduces a ~ 100 Tg C shift in the partitioning of carbon fluxes for the latitudinal bands. A preliminary test of GONGGA using the latest v11.1r Lite product showed the inverted terrestrial carbon sink tends to be 90 to 140 Tg C yr^{-1} lower north of 60° N than using the v11r Lite product, consistent with the previous findings. In addition, some parts of GONGGA's inversion algorithm, such as the data selection, were partly different from those proposed by the OCO-2 Science Team (Peiro et al., 2022; Byrne et al., 2023; Baker et al., 2022), but GONGGA's inversion results were broadly consistent with the ensemble of OCO-2 MIP inversions and GCB2023, and gave reasonable estimates of global and regional carbon budgets within the uncertainties. In the future, GONGGA will regularly publish new versions of inverted fluxes using the latest OCO-2 data on an annual basis. These updates will align with the latest suggestions from the OCO-2 Science Team, enabling the ongoing monitoring of CO_2 fluxes."

We also expanded the discussion about the regional differences in inverted fluxes between GONGGA and OCO-2 MIP in Sec. 4.2:

- Line 260-269: "GONGGA showed good agreement with OCO-2 MIP inversions for most regions, and divergences occurred mainly in Boreal North America and Northern Africa. The difference between GONGGA and OCO-2 MIP inversions may be related to the prior NBE adopted and retrieval pre-processing methods utilized. In Boreal North America, GONGGA's prior emerged as a carbon source, whereas OCO-2 MIP's prior was a carbon sink (Fig. S1). After assimilating OCO-2 retrievals, GONGGA and OCO-2 MIP consistently showed Boreal North America was a carbon sink, but the sink in GONGGA was smaller than OCO-2 MIP. The same situation happened in Northern Africa. Both GONGGA's prior and OCO-2 MIP's prior estimated Northern Africa as a terrestrial carbon sink, but the sink from GONGGA was stronger than that from OCO-2 MIP (Fig. S1). Constrained by OCO-2 retrievals, both GONGGA and OCO-2 MIP estimated it as a carbon source, and the source from GONGGA was weaker than that from OCO-2 MIP, aligning with the sizes of their prior sinks."

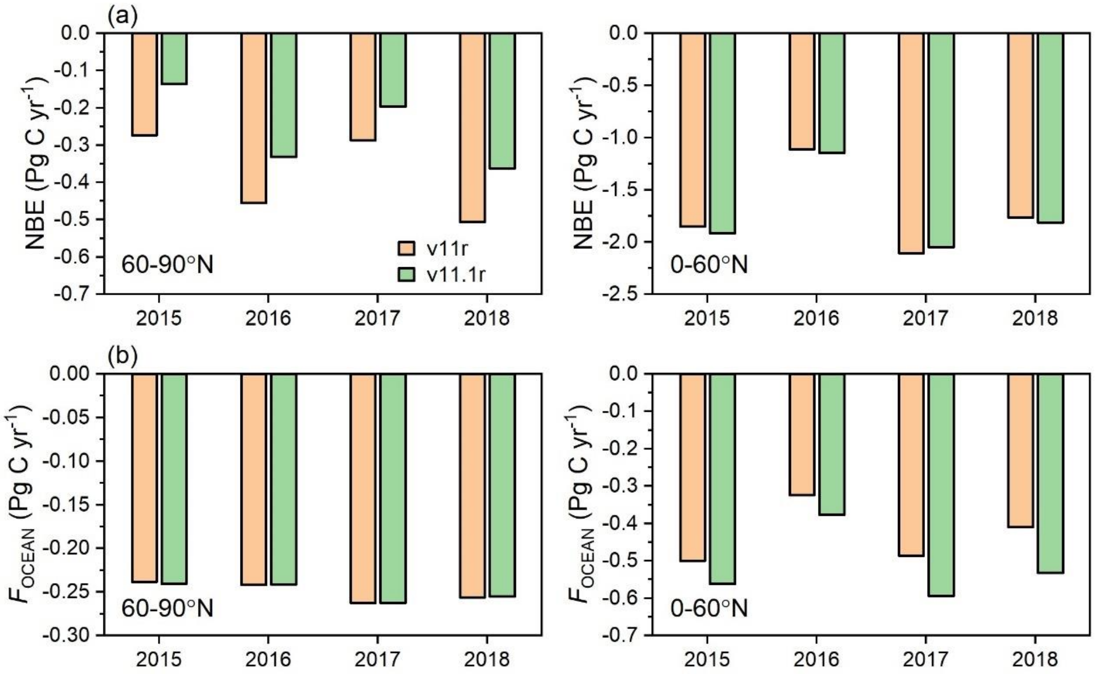

Figure R8. The inverted (a) NBE and (b) F_{OCEAN} in regions north of 60°N and 0-60°N from GONGGA inversions using OCO-2 v11r retrievals (orange bars) and v11.1r (green bars) retrievals during 2015-2018.

Minor comments:

1. Lines 99-100: Biomass burning carbon emissions are also terrestrial ecosystem fluxes, so I would just define NEE instead (i.e., balance of photosynthesis and respiration).

Response:

Thank you for the suggestion. We used NEE in the revised manuscript.

2. Line 153- Cite ObsPack and also specify which version was used.

Response:

The ObsPack data we used were CO_2 GLOBALVIEW plus v8.0 and NRT v8.1. Version information and citations were added in Line 164-165.

3. Line 176-178: CARVE aircraft observations may not be appropriate for evaluation, given that CARVE flight tracks did not intend to sample regions that were representative of large areas. I would recommend removing CARVE, or discussing this when you discuss results for Fig. 12.

Response:

We removed CARVE aircraft observations in our evaluations and added data from NASA's ATom Mission.

4. Line 190-92: Earlier it was stated that fossil fuel and biomass burning CO_2 emissions were not optimized. So it would be incorrect to say that E_{FOS} and E_{FIRE} were quantified. Instead they were specified.

Response:

Thank you for the suggestion. We included the fossil fuel and biomass burning CO_2 emissions, although not optimized, in the dataset for readers who may be interested in all the carbon budgets. To be clearer, we revised the sentence: "Here, we present the five major components of the global carbon budget, including the fossil fuel CO_2 emissions (E_{FOS}), biomass burning emissions (E_{FIRE}), atmospheric CO_2 concentration growth rate (G_{ATM}), ocean-atmosphere carbon fluxes (F_{OCEAN}), and NEE." in Line 203-205.

5. Line 192: S_{LAND} generally refers to NEE + BMB fluxes. I would suggest changing this to NEE throughout. You could then call the sum of NEE and BMB S_{LAND} or NBE.

Response:

Thank you for the suggestion. We agree that the Global Carbon Budget report also used S_{LAND} and S_{OCEAN}, but they mainly represent the carbon stock changes, which are different from the inverted fluxes. To be clearer, we changed the notations in the revised manuscript. We used NEE for the inverted land fluxes excluding biomass burning and fossil fuel emissions, NBE for the sum of NEE and biomass burning emissions, and F_{OCEAN} for the inverted atmosphere-ocean fluxes.

6. Line 231: The OCO-MIP V10 citations should be Byrne et al., (2023). I think here it should also be noted that the v10 MIP assimilated v10 OCO-2 retrievals while in this study OCO-2 v11r retrievals are assimilated.

Response:

Thank you for the correction. We corrected the citations for OCO-MIP v10 and revised the sentence to: "Here, we present the GONGGA-estimated annual mean (2015–2022) NBE for 11 TransCom land regions and their comparison with OCO-2 model intercomparison project (MIP) v10 inversions (Fig. 5). OCO-2 MIP v10 (Byrne et al., 2023; Baker et al., 2023) includes an ensemble of 14 atmospheric inversions over the period of 2015–2020 assimilating OCO-2 v10r retrievals, and each of them is characterized by distinct transport models, data assimilation algorithms, and prior fluxes (Table S1)." in Line 250-254.

7. Lines 258-263: This is citing previous work and should go in a discussion section rather than the results, since it reads like it is a result of this study, which it is not. Finally, given that biomass burning fluxes were not optimized, I think these should be discussed in terms of how their magnitude is relative to the NEE fluxes (that were optimized).

Response:

Thank you for your suggestion. We moved the paragraph to the discussion section and revised the text:

- Line 394-405: “Regarding the regional carbon budget, we found that fire emission, although it was not optimized in the inversion, largely impacted the net CO_2 fluxes from terrestrial ecosystem, i.e. NBE, in equatorial regions and Australia. With the frequent occurrence of wildfires in these regions, carbon emissions from wildfires may exceed regional NEE and make these regions net carbon sources (Fig. S7). For the past few decades, ~50% of fire-related carbon emissions and ~70% of global burned areas occurred across African subtropical savannah systems (Andela and Van Der Werf, 2014; Giglio et al., 2013). In the Amazon, despite the decline in deforestation rate during 2003-2015, carbon emissions from drought-induced fires had increased very quickly (Aragão et al., 2018). Southeast Australia also experienced intensive and geographically extensive wildfires during the 2019–2020 summer season, and the fires released substantial amounts of CO_2 into the atmosphere (Van Der Velde et al., 2021; Byrne et al., 2021; Wang et al., 2020). As a result, the 8-yr mean biomass burning emissions in Tropical South America, Northern Africa, and Tropical Asia amounted to 0.17, 0.33, and 0.13 Pg C yr^{-1}, and were 6.2, 1.2, and 1.4 times higher than regional NEE, respectively, resulting in net carbon sources in these regions. The increasing fire emissions thus present a great challenge to climate mitigation efforts.”

8. *Fig. 6: The caption for this figure should say NBE, not IAV of NBE, since each point on the figure refers to a value not an IAV. Also it seems from this figure that most of the IAV comes from North Extra tropics, but in lines 273-76 the authors say that tropics contribute 100% to global IAV. I think this should be clarified.*

Response:

We changed the caption for Fig. 6 as “Annual NBE over the globe, northern extra-tropics (30–90°N), tropics (30°S–30°N), and southern extra-tropics (90–30°S) during 2015–2022.” Figure 6 shows that although the total global land carbon sink was mainly located in the northern extra-tropics (green line), the shape of global year-to-year fluctuations (black line) tightly follows that of the tropics (red line). For example, the enhanced global NBE in 2017 and 2022 compared to other years was mainly caused by an increased NBE in the tropics, while the NBE in the northern extra-tropics in these two years was close to other years. In addition, using Eq. (1) from Ahlström et al. (2015), which accounts for the synchronicity of the sign and magnitude in the NBE change between regions and the globe, we found the tropics contribute about 100% of the global NBE IAV. To be clearer, we changed this figure to show the NBE anomalies in different regions rather than the absolute values.

9. *Q: In all figures with labels “PgC” should be changed to “Pg C”.*

Response:

We changed all the “PgC” and “PgC yr^{-1}” to “Pg C” and “Pg C yr^{-1}” in the figures, as suggested.

10. Line 317: Observed XCO$_2$ should be changed to retrieved XCO$_2$ given that XCO$_2$ cannot be observed directly.

Response:

We changed the “observed XCO$_2$” to “TCCON XCO$_2$ retrievals” in this sentence and other places where necessary.

11. Figures 11 and 12. RMSE folds in both random and systematic error (bias). See Rastogi et al., (2021) for discussion of bias and random error evaluation of OCO-2 relative to in-situ aircraft observations. For vertical profile data, I think it would be useful to look at errors in the column. For instance, the model may have errors that cancel in the column (e.g., high bias near the surface and a low-bias aloft).
Instead, I would recommend the authors to report random error and bias separately. Also, why is bias capitalized?

Response:

Thank you for the suggestion. We separately reported biases and random errors in the revised manuscript.

Regarding the vertical profile, we added the evaluations in Fig. S6 in the revised manuscript, which is also shown here as Fig. R9. The random errors, which were quantified by the standard deviation of the mismatch between observations and modelled CO$_2$, were typically within 1 ppm. Large biases, up to 2 ppm, were seen in the high latitudes and above 9 km. This is consistent with the comparisons against the TCCON observations (Fig. 8 in the manuscript). The reason for such large biases can be attributed to the underestimation of land carbon sink in the high latitudes as compared to OCO-2 MIP, or the biases in the atmospheric transport. We added the following texts to the revised manuscript:

- Line 385-388: “We also compared the vertical distribution of modelled CO$_2$ against the observations. Figure S6 shows that the random errors were typically within 1 ppm, showing a good agreement between the simulations and observations. However, large biases, up to 2 ppm, were seen in the high latitudes and above 9 km, consistent with the comparisons against the TCCON retrievals (Fig. 8).”

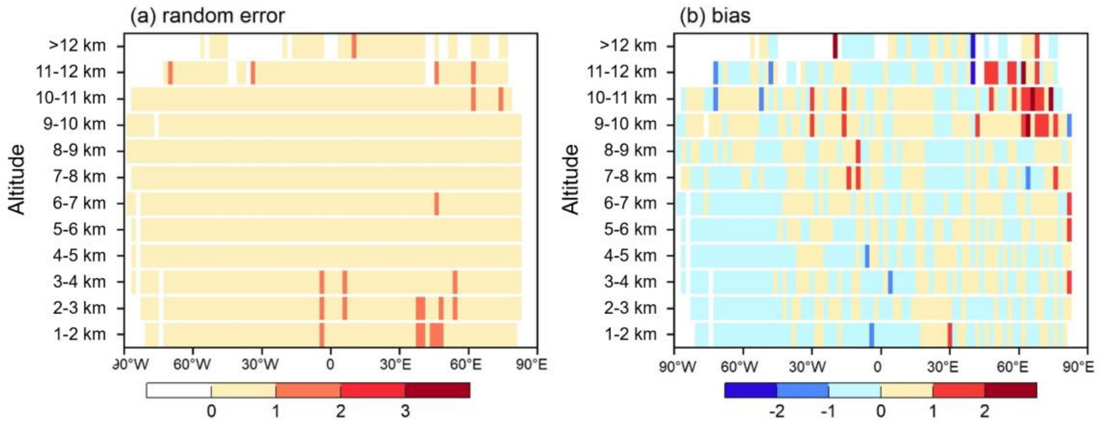

Figure R9. (a) random error and (b) bias between posterior CO_2 simulations and aircraft observations as a function of latitude and altitude (posterior simulations minus observations; unit: ppm). The altitudes are binned every kilometer from 1 km to 12 km, and for altitudes above 12 km.

12. In this section there are other datasets such as the atmospheric tomography mission (ATom) aircraft campaigns would have been valuable for evaluation. See Gaubert et al., (2023) for details. I would also advise the authors to look at the OCO MIP website for evaluation against observations (surface and partial columns).

Response:

Thank you for the suggestion. We added the atmospheric tomography mission (ATom) aircraft data to our evaluation. We changed Fig. 1(b) to include the distribution of ATom observations, and Fig. 12 in the revised manuscript gave the evaluation including Atom observations.

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