Dear Dr. Marshall,
We appreciate very much your comments. Please see our responses below.

*This article documents the land biosphere prior and the optimized land biosphere and ocean posterior fluxes resulting from a 2010-2018 inversion using the Carbon Monitoring System (CMS) modelling system. The observational inputs are restricted to satellite measurements of XCO2, based on GOSAT for 2010-2014 and OCO-2 from 2015-2018.*

***Original:*** *My first hesitation is based on the appropriateness of publishing optimized fluxes in ESSD. These are not measurements, but rather, by definition, a model-based interpretation of measurements. In the description of the Aims and Scope of the journal it states that: "Any interpretation of data is outside the scope of regular articles." On some level this is a philosophical distinction, and it seems this article has made it through the first quick review process, so I have to assume that the editor does not see a major problem here.*

**Response**: This is a reanalysis dataset, not a pure model simulation. It is a combination of observations and an *apriori* based on their respective error statistics. Reanalysis products have been used more broadly in research than the raw observations. For example, the meteorology reanalysis data sets (e.g., MERRA and ERA-5) have many more users than weather station data or satellite radiances.

***Original***: *My next hesitation is on the criterion of "Completeness". This is one of the categories reviewers are asked to assess, stating that: "A data set or collection must not be split intentionally, for example, to increase the possible number of publications. It should contain all data that can be reviewed without unnecessary increase of workload and can be reused in another context by a reader." The current paper seems to be a classic case of withholding part of the dataset to release it in a future publication. The modelling system used has been well-documented in its ability to (quoting from the Introduction): "resolve regional fluxes, and also disentangle net biosphere exchange (NBE) into constituent carbon fluxes including plant gross primary productivity (GPP) and biomass burning through solar-induced fluorescence and carbon monoxide proxies, respectively (Bowman et al, 2017, Liu et al., 2017)." So is that what is reported here? No, they have decided to only report NBE, stating that" Subsequent papers will present the partitioning of the NBE into constituent gross fluxes." This seems like a clear infringement of the "Completeness" criterion. My recommendation would be to include the optimized GPP, biomass burning, and respiration fluxes in the same data release, and have an accompanying analysis paper (in another journal) that goes into the interpretation of the retrieved signals. One of the unique strengths of the CMS is its partitioning of the net land biosphere fluxes, which most modellers do not claim to be able to do with any confidence. It is this partitioning that would make the resultant fluxes more interesting for comparison against other approaches.*

**Response**: We respectfully disagree that the data are incomplete per ESSD guidance. The NBE can be reviewed independently of component fluxes and can be re-used in many applications by the reader, e.g., comparison to DGVM output, understanding the carbon-climate feedbacks etc. We agree that NBE can be more richly understood by partitioning it into component fluxes. However, there are multiple ways that this can be done, whether through independent data streams or additional data streams (e.g., Liu et al., 2017; Bowman et al., 2017) or through a more sophisticated land-surface assimilation, e.g., Quetin et al, 2020. We do not want to prejudge that methodology or the additional data that might be used.

With respect to NBE, we report all the elements from the inversion system, including gridded fluxes, uncertainties, and regionally aggregated fluxes. We evaluate both the mean fluxes and the uncertainty estimates with independent observations.

We will modify the introduction to reflect the fact that we have not withheld relevant datasets.

G. R. Quetin, A. A. Bloom, K. W. Bowman, A. G. Konings, Carbon Flux Variability From a Relatively Simple Ecosystem Model With Assimilated Data Is Consistent With Terrestrial Biosphere Model Estimates. *J Adv Model Earth Sy*. **12** (2020), doi:10.1029/2019ms001889.

***Original****: Finally, my third hesitation is related to the data quality. This is not related to anything that the authors themselves have done wrong, but there are (still) clear limitations to using only satellite data in an inversion. This has been well documented in the literature (e.g. Basu et al., 2013; Chevallier et al., 2014), and leads to an unexpectedly high source in northern Africa (and perhaps a too-large sink in Europe) that is hard to reconcile with bottom-up fluxes and inversions based on surface/in-situ measurements. The magnitude of this potential bias has decreased in more recent retrieval versions but has not disappeared. This discrepancy is clearly seen in the limited validation that is presented here, when the optimized concentrations are compared to the Atlantic ATom-1 and -2 flights. At least this inconsistency with independent data is documented: hopefully potential users of this dataset will not assume that their model is wrong simply because it disagrees with the CMS fluxes. One potential improvement here would be to include also fluxes optimized based on surface-based measurements, to give some idea of the uncertainty in the fluxes as a result of the choice of input data. (The estimated fluxes will most likely not agree within the stated uncertainties.) This is downplayed by comparing the global land biosphere budget to widely accepted values from the Global Carbon Project (Friedlingstein et al., 2019), rather than the regional breakdown. Comparing to Figure 8 of Friedlingstein et al. (2019) it seems that the tropics are a more substantial source and the extratropics a more substantial sink than is seen within the spread of inverse models included in the GCP analysis.*

**Response**: We agree with Dr. Marshall that the satellite-based NBE product is not perfect. However, neither is a surface-based inversion product nor is any assimilated product, e.g., ERA5. In particular, surface-based information used in the GCP analysis provides limited information on the tropics. Satellite-based NBE estimates have provided many new insights on the carbon cycle. For example, Basu et al. (2014) studied the flux seasonal variation over tropical Asia with top-down flux estimates based on GOSAT observations. Detmers et al. (2015) studied the 2011 anomalous carbon sink over Australia using NBE estimates based on GOSAT observations. Liu et al. (2018) CMS-Flux results showed excellent agreement with the North American carbon balance changes with in-situ approaches from Wolf et al. (2016). A snapshot of the differences between inversion systems has been documented in Crowell et al. (2019). Those differences will evolve even as a number of these systems converge on their inferences, (e.g., Gaubert et al., 2019). Sharing the data with the broader community will accelerate its use in scientific exploration, and at the same time, will help identify possible deficiencies that further feeds back on future development.

In this paper, we evaluate the reported fluxes and corresponding uncertainties with independent aircraft observations using rigorous methodology. As noticed by Dr. Marshall, we also point to any possible deficiencies in the products based on these evaluations.

Basu, S., Krol, M., Butz, A., Clerbaux, C., Sawa, Y., Machida, T., Matsueda, H., Frankenberg, C., Hasekamp, O. P., and Aben, I. (2014), The seasonal variation of the $CO_2$ flux over Tropical Asia estimated from GOSAT, CONTRAIL, and IASI, *Geophys. Res. Lett.*, 41, 1809– 1815, doi:10.1002/2013GL059105.

Detmers, R. G., Hasekamp, O., Aben, I., Houweling, S., van Leeuwen, T. T., Butz, A., Landgraf, J., Köhler, P., Guanter, L., and Poulter, B. (2015), Anomalous carbon uptake in Australia as seen by GOSAT, *Geophys. Res. Lett.*, 42, 8177– 8184, doi:10.1002/2015GL065161.

Crowell, S., Baker, D., Schuh, A., Basu, S., Jacobson, A. R., Chevallier, F., Liu, J., Deng, F., Feng, L., McKain, K., Chatterjee, A., Miller, J. B., Stephens, B. B., Eldering, A., Crisp, D., Schimel, D., Nassar, R., O'Dell, C. W., Oda, T., Sweeney, C., Palmer, P. I., and Jones, D. B. A.: The 2015–2016 carbon cycle as seen from OCO-2 and the global in situ network, Atmos. Chem. Phys., 19, 9797–9831, https://doi.org/10.5194/acp-19-9797-2019, 2019.

J. Liu, K. Bowman, N. C. Parazoo, A. A. Bloom, D. Wunch, Z. Jiang, K. R. Gurney, D. Schimel, Detecting drought impact on terrestrial biosphere carbon fluxes over contiguous US with satellite observations. *Environ Res Lett*. **13**, 095003 (2018).

B. Gaubert, B. B. Stephens, S. Basu, F. Chevallier, F. Deng, E. A. Kort, P. K. Patra, W. Peters, C. Rödenbeck, T. Saeki, D. Schimel, I. V. der Laan-Luijkx, S. Wofsy, Y. Yin, Global atmospheric CO2 inverse models converging on neutral tropical land exchange, but disagreeing on fossil fuel and atmospheric growth rate. *Biogeosciences*. **16**, 117–134 (2019).

S. Wolf, T. F. Keenan, J. B. Fisher, D. D. Baldocchi, A. R. Desai, A. D. Richardson, R. L. Scott, B. E. Law, M. E. Litvak, N. A. Brunsell, W. Peters, and I. T. van der Laan-Luijkx. Warm spring reduced carbon cycle impact of the 2012 US summer drought. Proceedings of the National Academy of Sciences, 113(21):5880–5885, 2016. doi: 10.1073/pnas.1519620113. URL http://www.pnas.org/content/113/21/5880.abstract.

***Original****: Another potential limitation to the usefulness of the data is the underwhelming resolution. Monthly fluxes at 4 x 5 degree resolution are no longer really state-of-the-art. One of the arguments for using satellite measurements is the higher spatial resolution of the signals that can be resolved compared to the rather sparse surface-based network. This dataset is not exploiting to this strength.*

**Response**: We chose 4º x 5º to reflect the information content of the current available space-based $CO_2$ data, rather than an arbitrary grid scale, and we note this spatial resolution has already been scientifically successful (e.g., Liu et al., 2017; Bowman et al., 2017; Liu et al., 2018; Sellers et al., 2018). Before the launch of GOSAT and OCO-2, the tropics had been basically treated as a whole (e.g., Gurney et al., 2002; Baker et al., 2006; Schimel et al., 2015). The 4º x 5º resolution has both scientific value and manageable uncertainties. The estimated posterior flux uncertainty reflects the actual uncertainty as shown in the comparison to aircraft $CO_2$ observations (Figure 9 in the text). Publishing the dataset will make the dataset easily accessible for more specific regional studies and thus will facilitate rapid progress.

Liu, J., Bowman, K. W., Schimel, D. S., et al. (2017). *Contrasting carbon cycle responses of the tropical continents to the 2015–2016 El Nino. Science, 358 eaam5690.*

Sellers, P. J., D. S. Schimel, B. Moore, J. Liu, and A. Eldering, Observing Carbon Cycle-climate feedbacks from space, Proceedings of the National Academy of Sciences Jul 2018, 115 (31) 7860-7868; DOI: 10.1073/pnas.1716613115

J. Liu, K. Bowman, N. C. Parazoo, A. A. Bloom, D. Wunch, Z. Jiang, K. R. Gurney, D. Schimel, Detecting drought impact on terrestrial biosphere carbon fluxes over contiguous US with satellite observations. *Environ Res Lett*. **13**, 095003 (2018).

Gurney KR, Law RM, Denning AS *et al*. (2002) Towards robust regional estimates of $CO_2$ sources and sinks using atmospheric transport models. *Nature*, **415**, 626– 630.

Baker, D. F., et al. (2006), TransCom 3 inversion intercomparison: Impact of transport model errors on the interannual variability of regional $CO_2$ fluxes, 1988–2003, *Global Biogeochem. Cycles*, 20, GB1002, doi:10.1029/2004GB002439.

Schimel D, Stephens BB, Fisher JB. 2015. Effect of increasing $CO_2$ on the terrestrial carbon cycle. *Proceedings of the National Academy of Sciences, USA* **112**: 436– 441.

Bowman, K. W., Liu, J., Bloom, A. A., Parazoo, N. C., Lee, M., Jiang, Z., … Wunch, D. (2017). Global and Brazilian carbon response to El Niño Modoki 2011–2010. *Earth and Space Science*, 4, 637– 660. https://doi.org/10.1002/2016EA000204

***Original:*** *Other comments:*
*Regarding the completeness of the dataset presented, I had some minor concerns. I tried to check the availability of the datasets linked to here, and found that I was not sure which version of the ECCO-Darwin fluxes had been used: the data portal lists several different options. I was not even entirely sure if the ocean fluxes had been optimized, but the netCDF gridded fluxes describe the ocean fluxes as "posterior ocean fluxes,2010-2014 constrained by GOSAT, 2015-2018 constrained by OCO2", so I assume that they are not identical to the prior. In any case, this could be clarified.*
**Response**: In the revision, we included the prior ocean fluxes, prior biosphere fluxes, and fossil fuel emissions in the gridded product, so the dataset is complete and the readers can calculate carbon budget of any defined region.

***Original:*** *Similarly, the paper mentions that FLUXCOM-GPP is one of the inputs to CARDAMOM, but there is more than one version of this product as well. Even CARDAMOM comes in different flavours, I believe, based on the documentation in the cited papers. For completeness it would be suitable to include all the prior and posterior fluxes in the dataset - including the anthropogenic fluxes which are not optimised. Only then can the full budget be assessed.*
**Response**: In the revision, we specified the version of FLUXCOM GPP in the text: "In addition, mean GPP and fire carbon emissions from 2010 - 2017 are constrained by FLUXCOM RS+METEO version 1 GPP (Tramontana et al., 2016; Jung et al., 2017)".

In the revised dataset, we included all the prior and posterior fluxes in the dataset

***Original***: *I do not see the purpose of providing the monthly fluxes (with uncertainty) at 13 different FLUXNET sites. As far as I can tell, these are extracted directly from the model, and do not represent additional downscaling or enhanced temporal resolution. The benefit of this (and the rationale for the selection of these specific sites) is not clear to me. The measured monthly mean NBE at these sites is not included for comparison, nor is any validation using FLUXNET sites provided in the manuscript. It seems redundant.*
**Response**: We have removed the monthly fluxes at 13 different FLUXNET sites.

***Original:*** *I was surprised by the choice of the masks used for aggregation of fluxes. If two masks are included, why not include the broadly-applied TransCom mask? The benefit of such a common mask is the ease of comparison. Yes, a user may apply his or her own mask to the data, but it really does not add much in terms of space (22 regions with monthly resolution), and would facilitate comparison with already available model output. This is likely of more general application than the two custom masks given here.*
**Response**: In the revision, we added the monthly fluxes at TransCom regions (Figures 3, 5, and 8). We revised corresponding text to reflect the changes. In section 4.2, we added the following description: "The availability of flux estimates over the broadly used TransCom regions make it easy to

compare to previous studies. For example, we estimate that the annual net carbon uptake over North America is 0.7 ± 0.1 GtC/year with 0.2 GtC variability between 2010 and 2018, which agrees with 0.7 ± 0.5 GtC/year estimates based on surface $CO_2$ observations between 1996-2007 (Peylin et al., 2013).” In addition, we revised section 4.4: “We provide the regional mean NBE seasonal cycle, its variability, and uncertainty based on the three regional masks (Table 5). Here we briefly describe the characteristics of the NBE seasonal cycle over the 11 TransCom regions, and its comparison to three independent top-down inversion results based on surface $CO_2$, which are CT-Europe (e.g., van der Laan-Luijkx et al., 2017) CAMS (Chevallier et al., 2005), and Jena CarbonScope (Rödenbeck et al., 2003). CMS-Flux-NBE differs the most from surface $CO_2$-based inversions over the South American Tropical, Northern Africa, tropical Asia, and NH boreal regions. The CMS-Flux NBE has a larger seasonal cycle amplitude over tropical Asia and Northern Africa, where the surface $CO_2$ constraint is weak, while it has a smaller seasonal cycle amplitude over the boreal region; this may be due to the sparse satellite observations over the high latitudes and weaker seasonal amplitude of the prior CARDAMOM fluxes. The comparison to FluxSat GPP can only qualitatively evaluate the NBE seasonal cycle, but cannot differentiate among different estimates.”

***Original**: Minor/typographical comments:*
*L29: “from Greenhouse” -> “from the Greenhouse”*
*L30: remove “the” before NASA*
**Response:** We will correct the grammar**.**

**Original**: *L49: Crowell et al. 2019 is an odd choice as an example of inversions based on surface CO2 observations, as this was explicitly not the focus of the publication.*
**Response**: We replaced the reference with Chevallier et al., 2010.

***Original:** L55: The NBE are far -> NBE is far*
*L108: suggest “ North America (NA)” -> “North American” (abbreviation is established elsewhere, and adjectival form fits better here)*
*L122: Section 8 is -> Section 8 describes the*
*L128: “that no” -> “no”*
*L151: its -> their*
*L161: from2010 (missing space)*
*L169: CARDAMON -> CARDAMOM*
*L184: by ACOS -> by the ACOS*
*L185: maximize -> maximizes*
*L193: land nadir good quality observations -> land nadir observations flagged as being of good quality*
*L221: of OCO-2 -> of the OCO-2*
*L272: over Pacific, and -> over the Pacific, but*
*L277: its -> their*
*L279: each nine -> each of nine*
*L283: fractions sampled at ith aircraft locations -> fraction sampled at the ith aircraft location*
*L285: of mean -> of the mean*
*L287: either posterior fluxes or transport -> either the posterior fluxes or the transport*

*L288: posterior fluxes -> the posterior fluxes (twice)*
*L315: of RMSE to posterior flux using GEOS-Chem -> of the RMSE to the posterior flux using the GEOS-Chem âˇA*

*´l*
*L342: Please rewrite the first sentence.*
*L355 & L366: by NOAA -> by the NOAA*
*L360: of posterior -> of the posterior*
*L371: calculate -> calculated*
*L375: with GCP -> with the GCP (or, "with the range estimated by the GCP,")*
*L382: shows large -> shows that large*
*L382: Southern -> the Southern*
*L383: eastern -> the eastern*
*L409: or weakly -> or are weakly*
*L410: during 2015 -> during the 2015*
*L415: Pouter -> Poulter*
*L416: capitalisation weird in "tropical south America Savanna"âˇA*
*´l*
*L440: above planetary*
*-> above the planetary*
*L446: used NOAA -> used the NOAA*
*L448: is equal or above -> is greater than or equal toâˇA*
*´l*
*L450 & L482 & L497: Southern* Ocean -> the Southern Ocean (as an aside: the weaker seasonality *certainly plays a role, but this was also a "problem region" in comparison to Atom-1 measurements, so perhaps there is something else going on there: : :)*

**Response**: In the revision, we have revised the text accordingly.

***Original***:: *Figure 2: It is really difficult to tell the regions apart on this map. The blues in North America, for instance, really blend together.*

**Response**: We remade Figure 2.

***Original:*** *Figure 9: This figure seems unnecessarily cramped. Perhaps split it into two? For instance, I could barely tell that the bars were really blue without zooming way in, as they are so tiny.*

**Response**: In the revision, we removed the bars, since the number of observations has very little information. We believe that the new figure is clearer.

***Original***: *General figure comment: Something is a bit off with the rendering of the digits in your colour bars, making the bottom bar of "2"s disappear and making a gap in the bottom of round digits.*
**Response:** we have remade Figures 10 and 11.

***Original:{*** *L466: from Monte -> from the Monte*
*L478: What is meant here? "either transport or low of posterior flux uncertainty estimates": Perhaps, "either transport errors or too low values for posterior flux uncertainties"?*
*L480: of flight -> of the flight*
*L493: defined -> as defined*
*L496: These -> The, also, specify which ratio you mean "between RMSE and RMSEMC"*
*L500: Pacific -> the Pacific*
*L503: these -> the*
*L504: with 4_x 5_resolution transport model -> using a transport model with only 4_x*

*5_resolution*
*L513-515: A bit awkward, please rephrase.*
*L516: indicates small -> indicates a small*
*L518: of posterior -> of the posterior*
*L533: to FLUXSAT -> to the FLUXSAT*
*L541: “needs caution” -> perhaps better: “calls for caution”*
*L556: by GCP -> by the GCP*
*L562: atmospheric -> the atmospheric*
*L563: level -> levels*
*L576: provide support the monitoring of the regional contributions to the changes inÂ˘aatmospheric: : : I’m not sure about this, perhaps: “support the monitoring of the regional (biospheric) contributions to changes in atmospheric: : :”?*
*L580 & L582: data is -> data are*
*L582: ensemble posterior -> ensemble of posterior*
**Response**: We have incorporated all these comments in the revision.

Thanks for the constructive comments. Please see our response below.
Anonymous Referee #2
***Original****: The authors present a brief description and evaluation results for the inverse model estimated CO2 fluxes for 2010-2018, based on observations by GOSAT and OCO-2 satellites. The data presented in the dataset are produced with the same model that was applied in several research papers and have mostly been used for estimating the variability and anomalies in the global carbon cycle at the regional and global scale. The satellite-based flux inversions proved to be useful in constraining large regional scale response of the natural carbon cycle to climate anomalies, droughts, heatwaves, such as those driven by the El-Nino cycle. In this context, the presented data can become a useful asset for those studying the carbon cycle variability at regional scale and its connection to the climate anomalies.*

*On the negative side, there are desirable components in the evaluation, such as analysis of the CO2 flux seasonal cycle, its comparison with inverse model estimates made with ground-based observations, or other independent estimates, such as based on flux tower data. The same can be said on comparison with observed CO2 concentration at background monitoring sites, such as the NOAA flask sampling network. In case there are identified biases in such comparison, it would be possible to advise the users to restrict the use of the data to studying the flux anomalies rather than using the fluxes for forward simulations, comparing with surface fluxes and using in ecosystem model optimization, where seasonal cycle performance is important. The authors should clearly state such limitations so that the users can have enough information on how to make best use of the provided data. The paper is well written and can be accepted after minor revision addressing the comments and suggestions.*

**Response**: We appreciate the constructive comments. In the revision, we added the comparison to NOAA marine boundary layer reference sites, and compared the seasonal cycle to three publicly available surface CO2 constrained top-down flux inversions. Please see our detailed response below.

Detailed comments.
***Original****: Notable deficiency: NBE flux evaluation looks somewhat qualitative. Based on data presented in the paper, and data provided on the data distribution site it is difficult to compare the NBE fluxes to alternative estimates. The 28-region data is provided, but it doesn't look directly mappable to widely used Transcom-3 22 region map. Recommend adding comparison figure (similar to Figure 8) of the seasonal flux climatology on Transcom3 22 regions or the authors-proposed 28 regions to other available estimates such as CAMS inversion fluxes (based on Chevallier et al. 2010) or FLUXCOM fluxes (Jung et al. 2020).*
**Response**: In the revision, we added monthly fluxes at TransCom 3 regions as part of the dataset in addition to the monthly fluxes at the original two regional masks we used in the first version. We revised Figure 3 to include the TransCom 3 region mask, and Figure 5 to include climatological NBE fluxes, variability, and uncertainties at TransCom 3 regions.

We replaced Figure 8 with NBE seasonal cycle comparisons between CMS-Flux NBE and the three publicly available surface $CO_2$ constrained top-down NBE estimates, which are CAMS, Jena CarbonScope, and CT-Europe. We revised section 4.4 based on the new Figure 8: "We provide the regional mean NBE seasonal cycle, its variability, and uncertainty based on the three regional masks (Table 5). Here we briefly describe the characteristics of the NBE seasonal cycle over the 11 TransCom regions, and its comparison to three independent top-down inversion results based on surface $CO_2$, which are CT-Europe (e.g., van der Laan-Luijkx et al., 2017) CAMS (Chevallier et al., 2005), and Jena CarbonScope (Rödenbeck et al., 2003). CMS-Flux-NBE differs the most from surface $CO_2$-based inversions over the South American Tropical, Northern Africa, tropical Asia, and NH boreal regions. The CMS-Flux NBE has a larger seasonal cycle amplitude over tropical Asia and Northern

Africa, where the surface $CO_2$ constraint is weak, while it has a smaller seasonal cycle amplitude over the boreal region; this may be due to the sparse satellite observations over the high latitudes and weaker seasonal amplitude of the prior CARDAMOM fluxes. The comparison to FluxSat GPP can only qualitatively evaluate the NBE seasonal cycle, but cannot differentiate among different estimates. In general, the months that have larger productivity corresponds to months with a net uptake of carbon from the atmosphere, especially over the NH (Figure 8). More research is still needed to understand the seasonal cycles of NBE, including its phase (i.e., transition from source to sink) and amplitude (peak-to-trough difference), and its relationships between GPP and respiration."

***Original****: Line 208 It looks like presented bias figures (below 0.1 ppm) are related to global mean bias, are the bias values available as seasonal mean values by latitude or TCCON site? Are retrieved and bias-corrected concentrations consistent with model simulations optimized with ground-based observations?*

**Response:** O'Dell et al. (2018) compared OCO-2 $X_{CO2}$ with observations from TCCON sites and the model simulations optimized with ground-based CO2. In the revision, we cited O'Dell et al. (2018), and added the following discussion in section 2.3: "O'Dell et al. (2018) showed that the OCO-2 $X_{CO2}$ land nadir retrievals has a mean bias ~0.3 ppm and RMS ~1.1 ppm when compared to TCCON retrievals; the differences between OCO-2 $X_{CO2}$ retrievals and surface $CO_2$ constrained model simulations are well within 1.0 ppm over most of the locations in the Northern Hemisphere (NH), where most of the surface $CO_2$ observations are located."

O'Dell, C. W., Eldering, A., Wennberg, P. O., Crisp, D., Gunson, M. R., Fisher, B., Frankenberg, C., Kiel, M., Lindqvist, H., Mandrake, L., Merrelli, A., Natraj, V., Nelson, R. R., Osterman, G. B., Payne, V. H., Taylor, T. E., Wunch, D., Drouin, B. J., Oyafuso, F., Chang, A., McDuffie, J., Smyth, M., Baker, D. F., Basu, S., Chevallier, F., Crowell, S. M. R., Feng, L., Palmer, P. I., Dubey, M., García, O. E., Griffith, D. W. T., Hase, F., Iraci, L. T., Kivi, R., Morino, I., Notholt, J., Ohyama, H., Petri, C., Roehl, C. M., Sha, M. K., Strong, K., Sussmann, R., Te, Y., Uchino, O., and Velazco, V. A.: Improved retrievals of carbon dioxide from Orbiting Carbon Observatory-2 with the version 8 ACOS algorithm, Atmos. Meas. Tech., 11, 6539–6576, https://doi.org/10.5194/amt-11-6539-2018, 2018.

***Original:*** *Line 1031 Figure 8. Although the seasonally varying fluxes look to be in a reasonable range it is very much advisable to compare/plot along with observed or observation-based fluxes, such as FLUXCOM NEE product (Jung et al. 2020).*

**Response:** See our response above.

Technical corrections.

***Original****: Line 191 Looks anomalous, to have 2000 good quality retrievals available on a single day in the ACOS-GOSAT dataset (appears significantly larger than average).*

**Response**: The number 2000 is the number of soundings that are processed by retrieval algorithm, not the number of good quality observations. The number of good quality retrievals is between ~100-300 daily.

***Original:*** *Line 193 Need to state how good quality is defined (what value of the quality flag is used)?*

**Response**: We clarified in the revision: "We only assimilate ACOS-GOSAT land nadir good quality observations, which are the retrievals with quality flag equal to 1."

***Original****: Line 199 Is 'super observations' a good term to name 100 km (_12 sec) average data?*

**Response**: This term was originated from numerical weather prediction. In the revision, we cited a relevant reference to further clarify the term: "To reduce the sampling error due to the resolution differences between the transport model and OCO-2 observations, we generate super observations by aggregating the observations within ~100 km (along the same orbit) (Liu et al., 2017). The super-obbing strategy was first proposed in numerical weather prediction (NWP) to assimilate dense observations (Lorenc, 1981), and is still broadly used in NWP (e.g., Liu and Rabier, 2003)."

***Original****: Line 228 The statement "For large-order systems, the posterior errors cannot be explicitly calculated" can be argued. Posterior flux uncertainty projected to regions can be estimated analytically using recipes provided by (Fisher and Courtier, 1995) or (Meirink et al, 2008), using either flux singular vectors or flux increments obtained on course of the iterative optimization (eg Niwa and Fujii, 2020). Using random perturbations is simpler and is used widely, but that doesn't mean that the more accurate method is impossible to apply.*

**Response**: In section 2.4, we incorporated the above comments when we discuss the posterior flux uncertainty estimation: "Posterior flux uncertainty projected to regions can be estimated analytically based on the methods described in Fisher and Courtier (1995) or Meirink et al. (2008), using either flux singular vectors or flux increments obtained during the iterative optimization (e.g., Niwa and Fujii, 2020). In this study, we rely on a Monte Carlo approach to quantify posterior flux uncertainties following Chevallier et al. (2010) and Liu et al. (2014), which is simpler and widely used."

***Original****: Line 240 Common perception is that tower footprint size is less than 1 km, based on estimates by Baldocchi, (1997) and others. The citation by Running et al (1999) of 'several km2' may refer to the upper range. They (Running et al 1999) also consider 1–3 km2 and 1 km2 as typical values throughout their paper.*

**Response**: We revised the description to: "Direct NBE estimates from flux towers only provide a spatial representation of roughly 1 – 3 kilometers (Running et al., 1999),…".

# Carbon Monitoring System Flux Net Biosphere Exchange 2020 (CMS-Flux NBE 2020)

Junjie Liu[1,2*], Latha Baskaran[1], Kevin Bowman[1], David S. Schimel[1], A. Anthony Bloom[1], Nicholas C. Parazoo[1], Tomohiro Oda[3,4], Dustin Carroll[5], Dimitris Menemenlis[1], Joanna Joiner[6], Roisin Commane[7], Bruce Daube[8], Lucianna V. Gatti[9], Kathryn McKain[10,11], John Miller[10], Britton B. Stephens[12], Colm Sweeney[10], Steven Wofsy[8],

1. Jet Propulsion Laboratory, Caltech, CA
2. Caltech, CA
3. Global Modeling and Assimilation Office, NASA Goddard Space Flight Center
4. Goddard Earth Sciences Technology and Research, Universities Space Research Association, Columbia, MD
5. Moss Landing Marine Laboratories, San José State University, California, CA
6. Laboratory for Atmospheric Chemistry and Dynamics, NASA Goddard Space Flight Center
7. Lamont-Doherty Earth Observatory of Columbia University, NY
8. Harvard University, Cambridge, MA
9. LaGEE, CCST, INPE- National Institute for Space Researc, Brazil
10. NOAA, Global Monitoring Laboratory, Boulder, CO 80305
11. University of Colorado, Cooperative Institute for Research in Environmental Sciences, Boulder, CO
11. National Center for Atmospheric Research, Boulder, CO 80301

Correspondence: Junjie Liu (junjie.liu@jpl.nasa.gov)

**Abstract**. Here we present a global and regionally-resolved terrestrial net biosphere exchange (NBE) dataset with corresponding uncertainties between 2010–2018: CMS-Flux NBE 2020. It is estimated using the NASA Carbon Monitoring System Flux (CMS-Flux) top-down flux inversion system that assimilates column $CO_2$ observations from the Greenhouse gases Observing SATellite (GOSAT) and the NASA's Observing Carbon Observatory -2 (OCO-2). The regional monthly fluxes are readily accessible as tabular files, and the gridded fluxes are available in NetCDF format. The fluxes and their uncertainties are evaluated by extensively comparing the posterior $CO_2$ mole fractions with $CO_2$ observations from aircraft and the NOAA marine boundary layer reference sites. We describe the characteristics of the dataset as global total, regional climatological mean, and regional annual fluxes and seasonal cycles. We find that the global total fluxes of the dataset agree with atmospheric $CO_2$ growth observed by the surface-observation network within uncertainty. Averaged between 2010 and 2018, the tropical regions range from close-to neutral in tropical South America to a net source in Africa; these contrast with the extra-tropics, which are a net sink of 2.5 ± 0.3 gigaton carbon per year. The regional satellite-constrained NBE estimates provide a unique perspective for understanding the terrestrial biosphere carbon dynamics and monitoring changes in regional contributions to the changes of atmospheric $CO_2$ growth rate. The gridded and regional aggregated dataset can be accessed at: https://doi.org/10.25966/4v02-c391 (Liu et al., 2020).



**Deleted:** Carroll[5]
**Deleted:** Joiner[3]
**Deleted:** Commane[6]
**Deleted:** Daube[7]
**Deleted:** Gatti[8]
**Deleted:** McKain[9]
**Deleted:** [10]
**Deleted:** Miller[9]
**Deleted:** Stephens[11]
**Deleted:** Sweeney[9]
**Deleted:** Wofsy[7]
**Deleted:** <#>Global Modeling and Assimilation Office, NASA Goddard Space Flight Center, Greenbelt, MD¶
**Moved (insertion) [4]**
**Deleted:** ¶
**Formatted:** Normal (Web), Indent: First line: 0"
**Moved up [4]:** <#>Moss Landing Marine Laboratories, San José State University, California, CA¶
**Deleted:** the
**Deleted:** uncertainty
**Deleted:** estimates
**Deleted:** $CO_2$ observations

## Introduction

New "top-down" inversion frameworks that harness satellite observations provide an important complement to global aggregated fluxes (e.g., Global Carbon Project, Friedlingstein et al., 2019) and inversions based on surface $CO_2$ observations (e.g., Chevallier et al., 2010), especially over the tropics and the Southern Hemisphere (SH) where conventional surface $CO_2$ observations are sparse. The net biosphere exchange (NBE) is far more variable than ocean fluxes (Lovenduski and Bonan, 2017) or fossil fuel emissions (Yin et al, 2019), and is thus the focus of this dataset estimated from a top-down atmospheric $CO_2$ inversion of satellite column $CO_2$ dry-air mole fraction ($X_{CO2}$). Here, we present the global and regional NBE as a series of maps, time series and tables, and disseminate it as a public dataset for further analysis and comparison to other sources of flux information. The gridded NBE dataset and its uncertainty, air-sea fluxes, and fossil fuel emissions are also available, so that users can calculate carbon budget from regional to global scale. The NBE can be subsequently decomposed into individual fluxes using ancillary measurements (i.e., gross primary production (GPP), respiration, fires, fossil fuel, etc.) to provide process understanding on regional carbon flux variability (e.g., Liu et al., 2017; Bowman et al., 2017). Finally, we provide a comprehensive evaluation of both mean and uncertainty estimates against the $CO_2$ observations from independent airborne datasets and the NOAA marine boundary layer (MBL) reference sites (Conway et al., 1994).

Global top-down atmospheric $CO_2$ flux inversions have been historically used to estimate regional terrestrial NBE, which is the net carbon flux of all the land-atmosphere exchange processes except fossil fuel emissions. They make uses of the spatiotemporal variability of atmospheric $CO_2$, which is dominated by NBE, to infer net carbon exchange at the surface (Chevallier et al., 2005; Baker

**Deleted:** Page Break ¶

**Deleted:**

**Deleted:** Crowell et al., 2019

**Deleted:** .

**Deleted:** These satellite-constrained estimates resolve regional fluxes, and also disentangle net biosphere exchange (NBE) into constituent carbon fluxes including plant gross primary productivity (GPP) and biomass burning through solar-induced fluorescence and carbon monoxide proxies, respectively (Bowman et al, 2017, Liu et al., 2017). Both the spatial and process resolution are critical for evaluating models and reducing uncertainties about future carbon-climate feedbacks (e.g., Friedlingstein et al., 2014).

**Deleted:** NBE

**Deleted:** are

**Deleted:** are

**Deleted:**

**Deleted:** W

**Deleted:** dataset

**Formatted:** Subscript

**Deleted:** an

**Deleted:** Subsequent papers will present the partitioning of the NBE into constituent gross fluxes.

**Deleted:** ¶

**Deleted:** is a sum of net ecosystem exchange and biomass burning carbon fluxes et al., 2006; Liu et al., 2014). The accuracy of the NBE from top-down flux inversion is determined by the density and accuracy of the $CO_2$ observations, the accuracy of modeled atmospheric transport, and knowledge of the prior uncertainties of the flux inventories.

For $CO_2$ flux inversions based on high precision *in situ* and flask observations, the measurement error is low (<0.2 parts per million (ppm)) and not a significant source of error; however, these observations are limited spatially, and are concentrating primarily over North America (NA) and Europe (Crowell et al., 2019). Satellite $X_{CO2}$ from $CO_2$-dedicated satellites, such as the Greenhouse Gases Observing Satellite (GOSAT) (launched in July 2009) and the Observing Carbon Observatory 2 (OCO-2) (Crisp et al., 2017) have much broader spatial coverage (O'Dell et al., 2018), which fill the observational gaps of conventional surface $CO_2$ observations, but they have up to an order of magnitude higher single-sounding uncertainty and potential systematic errors compared to the *in situ* and flask $CO_2$ observations. Recent progress in instrument error characterization, spectroscopy, and retrieval methods have significantly improved the accuracy and precision of the $X_{CO2}$ retrievals (O'Dell et al., 2018; Kiel et al., 2019). The single sounding random error of $X_{CO2}$ from OCO-2 is ~1.0 ppm (Kulawik et al., 2019). A recent study by Byrne et al. (2020) shows less than a 0.5 ppm difference between posterior $X_{CO2}$ constrained by a recent data set, ACOS-GOSAT b7 $X_{CO2}$ retrievals, and those constrained by conventional surface $CO_2$ observations. Chevallier et al. (2019) also showed that OCO-2 based flux inversion had similar performance to surface $CO_2$ based flux inversions when comparing posterior $CO_2$ mole fractions to aircraft $CO_2$ in the free troposphere. Results from these studies show that systematic uncertainties in $CO_2$ retrievals from satellites are comparable to, or smaller than, other uncertainty sources in atmospheric inversions (e.g. transport).

**Deleted:** and

A newly-developed biogeochemical model-data fusion system, CARDAMOM, made progress in producing NBE uncertainties, along with mean values that are consistent with a variety of observations assimilated through a Markov Chain Monte Carlo (MCMC) method (Bloom et al., 2016; 2020). Transport model errors in general have also been reduced relative to earlier transport model intercomparison efforts, such as TransCom 3 (Gurney et al., 2004; Gaubert et al., 2019). Advancements in satellite retrieval, transport, and prior terrestrial biosphere modeling have led to more mature inversions constrained by satellite $X_{CO2}$ observations.

**Deleted:** TRANSCOM

Two satellites, GOSAT and OCO-2, have now produced more than 10 years of observations. Here we harness the CMS-Flux inversion framework (Liu et al., 2014; 2017; 2018; Bowman et al., 2017) to generate an NBE product: CMS-Flux NBE 2020, by assimilating both GOSAT and OCO-2 from 2010–2018. The dataset is the longest satellite-constrained NBE product so far. The CMS-Flux framework exploits globally available $X_{CO2}$ to infer spatially-resolved total surface-atmosphere exchange. In combination with constituent fluxes, e.g., GPP, NBE from CMS-Flux framework have been used to assess the impacts of El Niño on terrestrial biosphere fluxes (Bowman et al, 2017; Liu et al, 2017) and the role of droughts in the North American carbon balance (Liu et al, 2018). These fluxes have furthermore been ingested into land-surface data assimilation systems to quantify heterotrophic respiration (Konings et al., 2019), evaluate structural and parametric uncertainty in carbon-climate models (Quetin et al., 2020), and inform climate dynamics (Bloom et al., 2020). We present the regional NBE and its uncertainty based on three types of regional masks: (1) latitude and continent, 2) distribution of biome types (defined by plant functional types), and continent, and 3) TransCom regions (Gurney et al., 2004).

**Deleted:** , which can be subsequently decomposed into individual fluxes using ancillary measurements (i.e., GPP, respiration, fires, fossil fuel, etc.)

**Deleted:** The flux estimates from the

**Deleted:** (NA)

**Deleted:** two

**Deleted:** ;

**Deleted:** and )

**Deleted:** .

**Deleted:** The gridded NBE dataset and its uncertainty are also available, so that users can aggregate the fluxes and uncertainties based on self-defined regions.

The outline of the paper is as follows: Section 2 describes methods, and Sections 3 and 4 describe the dataset and the major NBE characteristics, respectively. We extensively evaluate the posterior fluxes and uncertainties by comparing the posterior $CO_2$ mole fractions against aircraft observations and the NOAA MBL reference $CO_2$, and a gross primary production (GPP) product (section 5). In Section 6, we discuss the strength and weakness, and potential usage of the data. A summary is provided in Section 7, and Section 8 describes the dataset availability and future plan.

# 2 Methods

## 2.1 CMS-Flux inversion system

The CMS-Flux framework is summarized in Figure 1. The center of the system is the CMS-Flux inversion system, which optimizes NBE and air-sea net carbon exchanges with a 4D-Var inversion system (Liu et al., 2014). In the current system, we assume no uncertainty in fossil fuel emissions, which is a widely adopted assumption in global flux inversion systems (e.g., Crowell et al., 2019), since the uncertainty in fossil fuel emissions at regional scales is substantially less than the NBE uncertainties. The 4D-Var minimizes a cost function that includes two terms:

$$J(\mathbf{x}) = (\mathbf{x}-\mathbf{x}_b)^T \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}^b) + (\mathbf{y}-h(\mathbf{x}))^T \mathbf{R}^{-1}(\mathbf{y}-h(\mathbf{x})) \quad (1)$$

The first term measures the differences between the optimized fluxes and the prior fluxes normalized by the prior flux error covariance **B**. The second term measures the differences between observations ($\mathbf{y}$) and the corresponding model simulations ($h(\mathbf{x})$) normalized by the observation error covariance **R**. The term $h(\cdot)$ is the observation operator that calculates observation-equivalent model-simulated $X_{CO2}$. The 4D-Var uses the adjoint (i.e., the backward integration of the transport model) (Henze et al., 2004) of the GEOS-Chem transport model to calculate the

**Formatted:** Subscript
**Deleted:** observations
**Deleted:** and
**Deleted:** is
**Deleted:** that
**Moved (insertion) [1]**
**Deleted:** .
**Deleted:** ,
**Moved up [1]:** which is a widely adopted assumption in global flux inversion systems (e.g., Crowell et al., 2019).
**Deleted:** include
**Deleted:** the sum of
**Field Code Changed**
**Deleted:** , and
**Deleted:** t
**Deleted:** simulated value
**Field Code Changed**
**Field Code Changed**

sensitivity of the observations to surface fluxes. The configurations of the inversion system are summarized in Table 1. We run both the forward and adjoint at 4° x 5° spatial resolution, and optimize monthly NBE and air-sea carbon fluxes at each grid point from January 2010 to December 2018. Inputs for the system include prior carbon fluxes, meteorological drivers, and the satellite $X_{CO2}$ (Figure 1). Section 2.2 (Table 2) describes the prior flux and its uncertainties, and section 2.3 (Table 3) describes the observations and the corresponding uncertainties.

**2.2 The prior $CO_2$ fluxes and uncertainties**

The prior $CO_2$ fluxes include NBE, air-sea carbon exchange, and fossil fuel emissions (see Table 2). The data sources for the prior fluxes are listed in Table 7 and provided in the gridded fluxes. Methods to generate prior ocean carbon fluxes and fossil fuel emissions are documented in Brix et al., (2015), Caroll et al. (2020), and Oda et al. (2018). The focus of this dataset is optimized terrestrial biosphere fluxes, so we briefly describe the prior terrestrial biosphere fluxes and its uncertainties.

**Deleted:** P

**Deleted:** net carbon fluxes

We construct the NBE prior using the CARDAMOM framework (Bloom et al., 2016). CARDAMOM data assimilation system explicitly represents the time-resolved uncertainties in the NBE. The prior estimates are already constrained with multiple data streams accounting for measurement uncertainties following a similar Bayesian approach used in the 4D-variational approach. We use the CARDAMOM setup as described by Bloom et al. (2016, 2020) resolved at monthly timescales; data constraints include GOME-2 solar-induced fluorescence (Joiner et al., 2013), MODIS Leaf Area Index (LAI), and biomass and soil carbon (details on the data assimilation are provided in Bloom et al. (2020)). In addition, mean GPP and fire carbon emissions from 2010 - 2017 are constrained by FLUXCOM GPP (Tramontana et al., 2016) and GFEDv4.1s (Randerson et al., 2018), respectively, both assimilated with an uncertainty of 20%. We use the Olsen and Randerson (2001) approach to downscale monthly GPP and respiration fluxes to 3-hourly timescales, based on ERA-interim re-analysis of global radiation and surface temperature. Fire fluxes are downscaled using the GFEDv4.1 daily and diurnal scale factors on monthly emissions (Giglio et al., 2013). Posterior CARDAMOM NBE estimates are then summarized as NBE mean and standard deviation values.

The NBE from CARDAMOM shows net carbon uptake of 2.3 GtC/year over the tropics and close to neutral in the extratropics (Figure S1). The year-to-year variability (i.e., interannual variability, IAV) estimated from CARDAMOM from 2010 –2017 is generally less than 0.1 gC/m$^2$/day outside of the tropics (Figure S1). Because of the weak interannual variability estimated by CARDAMOM, we use the same 2017 NBE prior for 2018.

**Deleted:** N

CARDAMOM generates uncertainty along with the mean state. The relative uncertainty over the tropics is generally larger than 100%, and the magnitude is between 50% and 100% over the extra-tropics (Figure S2). We assume no correlation in prior flux errors in either space or time. The temporal and spatial error correlation estimates can in principle be computed by CARDAMOM. We anticipate incorporating these error correlations in subsequent versions of this dataset.

**Deleted:** T

**2.3 Column $CO_2$ observations from GOSAT and OCO-2**

We use satellite-column $CO_2$ retrievals from Atmospheric Carbon Observations from Space (ACOS) team for both GOSAT (version 7.3) and OCO-2 (version 9) (Table 3). The use of the same retrieval algorithm and validation strategy adopted by the ACOS team to process both

GOSAT and OCO-2 spectra maximizes the consistency between these two datasets. Both GOSAT and OCO-2 satellites carry high-resolution spectrometers optimized to return high precision measurements of reflected sunlight within $CO_2$ and $O_2$ absorption bands in the shortwave infrared (Crisp et al., 2012). Both satellites fly in a sun-synchronous orbit. GOSAT has a 13:00 ± 0.15 hours local passing time and a three-day ground track repeat cycle. The footprint of GOSAT is ~10.5 km in diameter in sun-nadir view (Crisp et al., 2012). The daily number of soundings processed by the ACOS-GOSAT retrieval algorithm is between a few hundreds to ~2000. Further quality control and filtering reduce the ACOS-GOSAT $X_{CO2}$ retrievals to ~100 – 300 daily (Figure S5 in Liu et al., 2017). We only assimilate ACOS-GOSAT land nadir observations flagged as being good quality, which are the retrievals with quality flag equal to zero.

OCO-2 has a 13:30 local passing time and 16-day ground track repeat cycle. The nominal footprints of the OCO-2 are 1.25 km wide and ~2.4 km along the orbit. Because of their small footprints and sampling strategy, OCO-2 has many more $X_{CO2}$ retrievals than ACOS-GOSAT. To reduce the sampling error due to the resolution differences between the transport model and OCO-2 observations, we generate super observations by aggregating the observations within ~100 km (along the same orbit) (Liu et al., 2017). The super-obing strategy was first proposed in numerical weather prediction (NWP) to assimilate dense observations (Lorenc, 1981), and is still broadly used in NWP (e.g., Liu and Rabier, 2003). More detailed information about OCO-2 super observations can be found in Liu et al. (2017). OCO-2 has four observing modes: land nadir, land glint, ocean glint, and target. Following Liu et al. (2017), we only use land nadir observations. The super observations have more uniform spatial coverage and are more comparable to the spatial

**Deleted:** cro

**Deleted:** observations

**Deleted:** .

**Deleted:** crossing

**Deleted:** its

**Moved (insertion) [2]**

**Deleted:** from OCO-2 to generate a set of super observations by aggregating the observations within ~100 km (along the same orbit).

representation of ACOS-GOSAT observations and the transport model (see Figure S5 in Liu et al., 2017).

We directly use observational uncertainty provided with ACOS-GOSAT b7.3 to represent the observation error statistics, **R**, in Eq 1. The uncertainty of the OCO-2 super observations is the sum of the variability of $X_{CO2}$ used to generate each individual super observation and the mean uncertainty provided in the original OCO-2 retrievals. Kulawik et al. (2019) showed that both OCO-2 and ACOS-GOSAT bias-corrected retrievals have a mean bias of -0.1 ppm when compared with $X_{CO2}$ from Total Carbon Column Observing Network (TCCON) (Wunch et al., 2011), indicating consistency between ACOS-GOSAT and OCO-2 retrievals. O'Dell et al. (2018) showed that the OCO-2 $X_{CO2}$ land nadir retrievals has RMS error of ~1.1 ppm when compared to TCCON retrievals; the differences between OCO-2 $X_{CO2}$ retrievals and surface $CO_2$ constrained model simulations are well within 1.0 ppm over most of the locations in the Northern Hemisphere (NH), where most of the surface $CO_2$ observations are located.

The magnitude of observation errors used in **R** is generally above 1.0 ppm, larger than the sum of random error and biases in the observations. The ACOS-GOSAT b7.3 observations from July 2009–June 2015 are used to optimize fluxes between 2010 and 2014, and the OCO-2 $X_{CO2}$ observations from Sep 2014–June 2019 are used to optimize fluxes between 2015 and 2018.

The observational coverage of ACOS-GOSAT and OCO-2 is spatiotemporally dependent, with more coverage during summer than winter over the NH, and more observations over mid-latitudes than over the tropics (Figure S3). The variability (i.e., standard deviation) of annual total number

**Moved up [2]:** More detailed information about OCO-2 super observations can be found in Liu et al. (2017).

**Deleted:** es

**Deleted:** against

**Formatted:** Subscript

**Formatted:** Subscript

**Formatted:** Subscript

of observations from 2010–2014 is within 4% of the annual mean number for ACOS-GOSAT. Except for a data gap in 2017 caused by a malfunction of OCO-2 instrument, the variability of annual total number of observations between 2015 and 2018 is within 8% of the annual mean number for OCO-2.

### 2.4 Uncertainty quantification

The posterior flux error covariance is the inverse Hessian, which incorporates the transport, measurement, and background errors at the 4D-Var solution (Eq. 13 in Bowman et al, 2017). Posterior flux uncertainty projected to regions can be estimated analytically based on the methods described in Fisher and Courtier (1995) and Meirink et al. (2008), using either flux singular vectors or flux increments obtained during the iterative optimization (e.g., Niwa and Fujii, 2020). In this study, we rely on a Monte Carlo approach to quantify posterior flux uncertainties following Chevallier et al. (2010) and Liu et al. (2014), which is simpler and widely used. In this approach, an ensemble of flux inversions is carried out with an ensemble of priors and simulated observations to sample the uncertainties of prior fluxes (i.e., **B** in eq. 1) and observations (**R** in Eq. 1), respectively. The magnitude of posterior flux uncertainties is a function of assumed uncertainties in prior fluxes and observations, as well as the density of observations. Since the density of GOSAT and OCO-2 observations are stable (section 2.3) within their respective data record, we characterize the posterior flux uncertainties for 2010 and 2015 only, and assume the flux uncertainties for 2011–2014 are the same as 2010 and flux uncertainties for 2016–2018 are the same as 2015.

**Deleted:** analytically

**Deleted:** For large-order systems, the posterior errors cannot be explicitly calculated. Consequently,

**Deleted:** .

### 2.5 Evaluation of posterior fluxes

Direct NBE estimates from flux towers only provide a spatial representation of roughly 1 – 3 kilometers (Running et al., 1999), not appropriate to evaluate regional NBE from top-down flux inversions. Thus, we use two methods to indirectly evaluate the posterior NBE and its uncertainties. One is to compare annual NBE anomalies and seasonal cycle to a gross primary production (GPP) product. The other is to compare posterior $CO_2$ mole fractions to independent (i.e., not assimilated in the inversion) aircraft and the NOAA MBL reference observations. The second method has been broadly used to indirectly evaluate posterior fluxes from top-down flux inversions (e.g., Stephens et al., 2007; Liu and Bowman, 2016; Chevallier et al., 2019; Crowell et al., 2019). In addition to these two methods, we also compare the NBE seasonal cycles to three publicly available top-down NBE estimates that are constrained by surface $CO_2$ observations (Tables 3 and 7).

**Deleted:** of a few

**Deleted:** observations

**Deleted:** (i.e., not assimilated in the inversion)

**Formatted:** Subscript

### 2.5.1 Evaluation against independent gross primary production (GPP) product

NBE is a small residual difference between two large terms: total ecosystem respiration (TER) and GPP, plus fire. A positive NBE anomaly (i.e., less uptake from the atmosphere) has been shown to correspond to reduced GPP caused by climate anomalies (e.g., Bastos et al., 2018), and the magnitude of net uptake is proportional to GPP in most biomes observed by flux tower observations (e.g., Falk et al., 2008). Since NBE is related not only to GPP, the comparison to GPP only serves as a qualitative measure of the NBE quality. For example, we would expect that the posterior NBE seasonality to be anti-correlated with GPP in the temperate and high latitudes. In this study, we use FLUXSAT GPP (Joiner et al., 2018), which is an upscaled GPP product based on flux tower GPP observations and satellite-based geometry adjusted reflectance from the MODerate-resolution Imaging Spectroradiometer (MODIS) and solar-induced chlorophyll fluorescence observations from Global Ozone Monitoring Experiment – 2 (GOME-2) (Joiner et al., 2013). Joiner et al. (2018) show that the agreement between FLUXSAT-GPP and GPP from flux towers is better than other available upscaled GPP products.

### 2.5.2 Evaluation against aircraft and the NOAA marine boundary layer (MBL) reference $CO_2$ observations

The aircraft observations used in this study include those published in OCO-2 MIP ObsPack August 2019 (CarbonTracker team, 2019), which include regular vertical profiles from flask samples collected on light aircraft by NOAA (Sweeney et al., 2015) and other laboratories, regular (two to four weekly) vertical profiles from the Instituto de Pesquisas Espaciais (INPE) over tropical South America (SA) (Gatti et al., 2014), and from the Atmospheric Tomography (ATom, Wofsy et al., 2018), HIAPER Pole-to-Pole (HIPPO, Wofsy et al., 2011), and the $O_2/N_2$ Ratio and $CO_2$ airborne Southern Ocean Study (ORCAS) (Stephens et al., 2017) aircraft campaigns (Table 3). Figure 2 shows the aircraft observation coverage and density between 2010 and 2018. Most of the aircraft observations are concentrated over NA. ATom had four (1–4) campaigns between August 2016 to May 2018, spanning four seasons over the Pacific and Atlantic Ocean. HIPPO had five (1–5) campaigns over the Pacific, but only HIPPO 3–5 occurred between 2010 and 2011. HIPPO 1–2 occurred in 2009. Based on the spatial distribution of aircraft observations, we divide the comparison into nine regions: Alaska, mid-latitude NA, Europe, East Asia, South Asia, Africa, Australia, Southern Ocean, and South America (Table 4 and Figure 2).

**Deleted:** aircraft campaigns from

**Deleted:** and

**Deleted:** regular (two to four weekly) vertical profiles from the Instituto de Pesquisas Espaciais (INPE) over tropical South America (SA) (Gatti et al., 2014),

**Deleted:** (ORCAS)

**Deleted:** aircraft campaign

**Deleted:** and

We calculate several quantities to evaluate the posterior fluxes and their uncertainty with aircraft observations. One is the monthly mean differences between posterior and aircraft $CO_2$ mole fractions. The second is the monthly root mean square errors (RMSE) over each of nine sub-regions, which is defined as:

**Deleted:** its

$$RMSE = \left(\frac{1}{n}\sum_{i=1}^{n}(y^{o}_{aircraft} - y^{b}_{aircraft})_i^2\right)^{\frac{1}{2}} \quad (2)$$

where $y^{o}_{aircraft}$ is the $i^{th}$ aircraft observation, $y^{b}_{aircraft}$ is the corresponding posterior $CO_2$ mole fraction sampled at the $i^{th}$ aircraft location, and $n$ is the number of aircraft observations over each region. The RMSE is computed over the $n$ aircraft observations within one of the nine sub-regions. The mean differences indicate the magnitude of the mean posterior $CO_2$ bias, while the RMSE includes both random and systematic errors in posterior $CO_2$. The bias and RMSE could be due to errors in posterior fluxes, transport, and initial $CO_2$ concentrations. When errors in transport and initial $CO_2$ concentrations are smaller than the errors in the posterior fluxes, the magnitude of biases and *RMSE* indicates the accuracy of the posterior fluxes.

To evaluate the magnitude of posterior flux uncertainty estimates, we compare *RMSE* against the standard deviation of ensemble simulated aircraft observations (equation 3) from the Monte Carlo method (*RMSE<sub>MC</sub>*). The quantity $RMSE_{MC}$ can be written as:

$$RMSE_{MC} = \left[\frac{1}{nens}\sum_{iens=1}^{nens}((y^{b(MC)}_{aircraft})_{iens} - y^{b(MC)}_{aircraft})^2\right]^{\frac{1}{2}} \quad (3)$$

The variable $(y^{b(MC)}_{aircraft})_{iens}$ is the $i^{th}$ ensemble member of simulated aircraft observations from Monte Carlo ensemble simulations, $y^{b(MC)}_{aircraft}$ is the mean, and *nens* is the total number of ensemble members. For simplicity, in equation (3), we drop the indices for the aircraft observations used in equation (2). In the absence of errors in transport and initial $CO_2$ concentrations, when the estimated posterior flux uncertainty reflects the "*true*" posterior flux uncertainty, we show in the *Appendix* that:

$$RMSE^2 = R_{aircraft} + RMSE_{MC}^{\ 2} \qquad (4)$$

**Field Code Changed**

**Deleted:** s

**Deleted:** s

**Deleted:** either

**Deleted:** or

**Formatted:** Subscript

**Deleted:** or both

**Deleted:** transport errors

**Formatted:** Subscript

**Deleted:** transport errors

where $R_{aircraft}$ is the aircraft observation error variance, which could be neglected on regional scale.

Deleted: s

We further calculate the ratio *r* between *RMSE* and $RMSE_{MC}$:

$$r = \frac{RMSE}{RMSE_{MC}} \qquad (5)$$

A ratio close to one indicates that the posterior flux uncertainty reflects the true uncertainty in the posterior fluxes when the transport errors are small.

The presence of transport errors will make the comparison between *RMSE* and $RMSE_{MC}$ potentially difficult to interpret. Even when $RMSE_{MC}$ represents the actual uncertainty in posterior fluxes, the *RMSE* could be larger than $RMSE_{MC}$, since the differences between aircraft observations and model simulated posterior mole fractions *RMSE* could be due to errors in both transport and the posterior fluxes, while $RMSE_{MC}$ only reflects the impact of posterior flux uncertainty on simulated aircraft observations. In this study, we assume the primary sources of *RMSE* come from errors in posterior fluxes.

The *RMSE* and $RMSE_{MC}$ comparison only shows differences in $CO_2$ space. We further calculate the sensitivity of the *RMSE* to the posterior flux using the GEOS-Chem adjoint. We first define a cost function *J* as:

Deleted:

$$J = RMSE^2 \qquad (6)$$

The sensitivity of the mean-square error to a flux, *x*, at location *i* and month *j* is

$$w_{i,j} = \frac{\partial J}{\partial x_{i,j}} \times x_{i,j} \qquad (7)$$

This sensitivity is normalized by the flux magnitude. Equation 7 can be interpreted as the sensitivity of the $RMSE^2$ to a fractional change in the fluxes. We can estimate the time-integrated magnitude of the sensitivity over the entire assimilation window by calculating:

$$S_i = \frac{\sum_{j=1}^{M} |w_{i,j}|}{\sum_{k=1}^{P} \sum_{j=1}^{M} |w_{k,j}|} \quad (8)$$

where $P$ is the total number of grid points and $M$ is the total number of months from the time of the aircraft data to the beginning of the inversion. The numerator of equation (8) quantifies the absolute total sensitivity of the $RMSE^2$ to the fluxes at the $i^{th}$ grid. Normalized by the total absolute sensitivity across the globe, the quantity $S_i$ indicates the relative sensitivity of $RMSE^2$ to fluxes at the $i^{th}$ grid point. Note that $S_i$ is unitless, and it only quantifies sensitivity, not the contribution of fluxes at each grid to $RMSE^2$.

We use the NOAA MBL reference dataset (Table 7) to evaluate the $CO_2$ seasonal cycle over four latitude bands: 90ºN-60ºN, 60ºN-20ºN, 20ºN-20ºS, and 20ºS-90ºS. The MBL reference is based on a subset of sites from the NOAA Cooperative Global Air Sampling Network. Only measurements that are representative of a large volume air over a broad region are considered. In the comparison, we first remove the global mean $CO_2$ (https://www.esrl.noaa.gov/gmd/ccgg/trends/global.html ) from both the NOAA MBL reference and the posterior $CO_2$.

## 2.6 Regional masks

We provide posterior NBE from 2010 – 2018 using three sets of regional masks (Figure 3), in addition to the gridded product. The regional mask in Figure 3A is based on a combination of seven plant function types condensed from MODIS IGBP and the TransCom -3 regions (Gurney

**Formatted:** Subscript

**Formatted:** Subscript

**Formatted:** Subscript

**Deleted:** two

**Deleted:** aggregated regions

**Deleted:** , for a few selected FLUXNET tower sites

**Deleted:** and

**Deleted:** the underlying

**Deleted:**

**Deleted:** A

**Deleted:** TRANSCOM

**Deleted:** region mask

et al., 2004), which is referred as Region Mask 1 (RM1) in later description. There are 28 regions in Figure 3A: six in NA, four in SA, five in Eurasia (north of 40°N), three in tropical Asia, three in Australia, and seven in Africa. The regional mask in Figure 3B is based on latitude and continents with 13 regions in total, which is referred as Region Mask 2 (RM2) in later description. Figure 3C is the TransCom regional mask with 11 regions on land.

## 3 Dataset description

We present the fluxes as globally, latitudinally, and regionally aggregated time series. We show the nine-year average fluxes aggregated into RM1, RM2, and TransCom regions (Figure 3). The aggregations are geographic (latitude and continent) and bio-climatic (biome by continent). For each region in the geographic and biome aggregations, we show nine-year mean annual net fluxes and uncertainties, and then the annual fluxes for each region as a set of time-series plots. The month-by-month fluxes and uncertainties are available in tabular format, so the actual aggregated fluxes may be readily compared to bottom-up extrapolated fluxes and Earth System models. Users can also aggregate the gridded fluxes and uncertainties based on their own defined regional masks. Table 5 provides a complete list of all data products available in the dataset. In section 4, we describe the major characteristics of the dataset.

## 4 Characteristics of the dataset

### 4.1 Global fluxes

The annual atmospheric $CO_2$ growth rate, which is the sum of fossil fuel emissions and total annual sink over land and ocean, is well-observed by the NOAA surface $CO_2$ observing network (https://www.esrl.noaa.gov/gmd/ccgg/ggrn.php). We compare the global total flux estimates constrained by GOSAT and OCO-2 with the NOAA $CO_2$ growth rate from 2010–2018, and discuss the mean

**Deleted:** , and there are

**Deleted:** l.

**Deleted:** gridded

**Deleted:** 28 and 13 geographic

**Deleted:**

**Deleted:** ,

**Deleted:** ), and flux-oriented (for a set of selected flux sites

**Deleted:**

**Deleted:** (Freidlingstein et al., 2019) carbon sink over land and ocean. Over these nine years, the satellite-constrained atmospheric $CO_2$ growth rate agrees with the NOAA observed $CO_2$ growth rate within the uncertainty of the posterior fluxes (Figure 4). The mean annual global surface $CO_2$ fluxes (in Gt C/yr) are derived from the NOAA observed $CO_2$ growth rate (in ppm/yr) using a conversion factor of 2.124 GtC/ppm (Le Quéré et al., 2018). The estimated growth rate has the largest discrepancy with the NOAA observed growth rate in 2014, which may be due to a failure of one of the two solar paddles of GOSAT in May 2014 (Kuze et al., 2016). Over the nine years, the estimated total accumulated carbon in the atmosphere is 41.5 ± 2.4 GtC, which is slightly lower than the accumulated carbon based on the NOAA $CO_2$ growth rate (45.2 ± 0.4 GtC). On average, the land sink is 20 ± 8% of fossil fuel emissions, and the ocean sink is 30 ± 1% of fossil fuel emissions (Figure 4). These numbers are within the ranges of the corresponding estimates from GCP 2019 (Freidlingstein et al., 2019). The mean NBE and ocean sink from GCP 2019 are 21 ± 10% (~1.0 GtC estimated residual NBE uncertainty) and 26 ± 5% (~0.5 GtC estimated ocean flux uncertainty) of fossil fuel emissions respectively between 2010–2018. The GCP NBE here is calculated as the residual differences between fossil fuel, ocean fluxes, and atmospheric $CO_2$ growth rate, and it is also equivalent to the sum of carbon fluxes from land use changes, land sink, and residual balance reported by GCP. Over these nine years, we estimate that the land sink ranges from 37% of fossil fuel emissions in 2011 (a La Niña year) to only 5% in 2015 (an El Niño year), consistent with the range estimated by GCP of 35% in 2011 to 7% in 2015. We estimate that the ocean sinks range from 39% in 2015 to 23% of fossil fuel emissions in 2012, larger than the GCP estimated ocean flux ranges of 25% to 28% of fossil fuel emissions (Freidlingstein et al., 2019).

### 4.2 Mean regional fluxes and uncertainties

**Deleted:** is

**Deleted:** estimated range

Figure 5 shows the nine-year mean regional annual fluxes, uncertainty, and its variability between 2010–2018. Table 6 shows an example of the dataset corresponding to Figure 5 A, D, and G. It shows that large net carbon uptake occurs over Eurasia, NA, and the Southern Hemisphere (SH) mid-latitudes. The largest net carbon uptake is over the eastern US (-0.4 ± 0.1 GtC (1σ uncertainty)) and high latitude Eurasia (-0.5 ± 0.1 GtC) (Figure 5A, B). We estimate a net land carbon sink of 2.5 ± 0.3 GtC/year between 2010–2013 over the NH mid to high latitudes, which agrees with 2.4 ± 0.6 GtC estimates over the same time periods based on a two-box model (Ciais et al., 2019). Net uptake in the tropics ranges from close-to-neutral in tropical South America (0.1 ± 0.1 GtC) to a net source in northern Africa (0.6 ± 0.2 GtC) (Figure 5A, B). The tropics exhibit both large uncertainty and large variability. The NBE interannual variability over northern Africa and tropical SA are 0.5 GtC and 0.3 GtC respectively, larger than the 0.2 GtC and 0.1 GtC uncertainty (Figure 5D, E). We also find collocation of regions with large NBE and GPP interannual variability (Figure S4). The availability of flux estimates over the broadly used TransCom regions make it easy to compare to previous studies. For example, we estimate that the annual net carbon uptake over North America is 0.7 ± 0.1 GtC/year with 0.2 GtC variability between 2010 and 2018, which agrees with 0.7 ± 0.5 GtC/year estimates based on surface $CO_2$ observations between 1996-2007 (Peylin et al., 2013).

**Deleted:** C

**Deleted:** E

**Deleted:** 4

**Deleted:** 0

**Deleted:** 5C

**Deleted:** D

**Formatted:** Subscript

### 4.3 Interannual variabilities and uncertainties

Here we present hemispheric and regional NBE interannual variabilities and corresponding uncertainties (Figures 6 and 7, and corresponding tabular data files). In Figure 6, we further divide the globe into three large latitude bands: tropics (20°S–20°N), NH extra-tropics (20°N–85°N), and SH extra-tropics (60°S–20°S). The tropical NBE contributes 90% to the global NBE interannual variability (IAV). The IAV of NBE over the extra-tropics is only about one-third of that over the tropics. The dominant role of tropical NBE in the global IAV of NBE agrees with Figure 4 in Sellers et al. (2018). The top-down global annual NBE anomaly is within the 1.0 GtC/yr uncertainty of residual NBE (i.e., fossil fuel – atmospheric growth – ocean sink) calculated from GCP-2019 (Friedlinston et al., 2019) (Figure 6).

Figure 7 shows the annual NBE anomalies and uncertainties over a few selected regions based on RM1. Positive NBE indicates reduced net uptake relative to the 2010–2018 mean, and vice versa. Also shown in Figure 7 are GPP anomalies estimated from FLUXSAT. Positive GPP indicates increased productivity, and vice versa. GPP drives NBE in years where anomalies are inversely correlated (e.g., positive NBE and negative GPP), and TER drives NBE in years where anomalies of GPP and NBE have the same sign or are weakly correlated. Over tropical SA evergreen broadleaf forest, the largest positive NBE anomalies occur during the 2015–2016 El Niño, corresponding to large reductions in productively, consistent with Liu et al. (2017). In 2017, the region sees increased net uptake and increased productivity, implying a recovery from the 2015–2016 El Niño event. The variability in GPP explains 80% of NBE variability over this region over the nine-year period. In Australian shrubland, our inversion captures the increased net uptake in 2010 and 2011 due to increased precipitation (Poulter et al., 2014) and increased productivity. The variability in GPP explains 70% of the interannual variability in NBE. Over tropical south America savanna, the NBE interannual variability also shows strong negative correlations with GPP, with GPP explaining 40% of NBE interannual variability. Over the mid-latitude regions where the IAV is small, the $R^2$ between GPP and NBE is also small (0.0–0.5) as expected. But the increased net uptake generally corresponds to increased productivity. We also do not expect perfect negative

**Deleted:** Savanna

correlation between NBE anomalies and GPP anomalies, as discussed in section 2.5. The comparison between NBE and GPP provides insight into when and where net fluxes are likely dominated by productivity.

### 4.4 Seasonal cycle

We provide the regional mean NBE seasonal cycle, its variability, and uncertainty based on the three regional masks (Table 5). Here we briefly describe the characteristics of the NBE seasonal cycle over the 11 TransCom regions, and its comparison to three independent top-down inversion results based on surface $CO_2$, which are CT-Europe (e.g., van der Laan-Luijkx et al., 2017) CAMS (Chevallier et al., 2005), and Jena CarbonScope (Rödenbeck et al., 2003). CMS-Flux-NBE differs the most from surface-$CO_2$ based inversions over the South American Tropical, Northern Africa, tropical Asia, and NH boreal regions. The CMS-Flux NBE has a larger seasonal cycle amplitude over tropical Asia and Northern Africa, where the surface $CO_2$ constraint is weak, while it has a smaller seasonal cycle amplitude over the boreal region; this may be due to the sparse satellite observations over the high latitudes and weaker seasonal amplitude of the prior CARDAMOM fluxes. The comparison to FluxSat GPP can only qualitatively evaluate the NBE seasonal cycle, but cannot differentiate among different estimates. In general, the months that have larger productivity corresponds to months with a net uptake of carbon from the atmosphere, especially over the NH (Figure 8). More research is still needed to understand the seasonal cycles of NBE, including its phase (i.e., transition from source to sink) and amplitude (peak-to-trough difference), and its relationships with GPP and respiration.

## 5 Evaluation against independent aircraft $CO_2$ observations

**Deleted:** a top-down $CO_2$ constrained

**Deleted:** and

**Deleted:** and

**Moved down [3]:** The seasonal cycle of NBE, including its phase (i.e., transition from source to sink) and amplitude (peak-to-trough difference), have large uncertainties, not only over the less-observed tropical regions, but also over the extra-tropics (e.g., Yang et al., 2007; Keppel-Aleks et al., 2012).

**Formatted:** Subscript

**Deleted:** Figure 8 shows NBE and GPP seasonal cycles for six selected regions.

**Formatted:** Subscript

**Formatted:** Subscript

**Deleted:** .

**Deleted:** The NH mid-to-high latitudes have larger seasonal cycle amplitudes (Figure 8A, B) compared to the other regions, and their NBE seasonalities are more closely linked to that of GPP ($R^2$ = 0.9). In the tropics, the relationship between NBE and GPP seasonality is less clear partially due to the weak seasonality of NBE (Figure 8E, F). The variability and uncertainty of monthly mean fluxes are larger over the tropics and the SH extratropics than over the NH extratropics. The

**Moved (insertion) [3]**

**Deleted:** , have large uncertainties, not only over the less-observed tropical regions, but also over the extra-tropics (e.g., Yang et al., 2007; Keppel-Aleks et al., 2012)

### 5.1 Comparison to aircraft observations over nine sub-regions

In this section, we evaluate posterior $CO_2$ against aircraft observations over the nine sub-regions listed in Table 4 and Figure 2. We compare the posterior $CO_2$ to aircraft $CO_2$ mole fractions above the planetary boundary layer and up to mid troposphere (1–5 km) at the locations and time of aircraft observations, and then calculate the monthly mean error statistics between 1–5 km. The aircraft observations between 1–5 km are more sensitive to regional fluxes (Liu et al., 2015; Liu and Bowman, 2016). Scatter plots in the left column of Figure 9 show regional monthly mean de-trended aircraft $CO_2$ observations (x-axis) versus the simulated detrended posterior $CO_2$ (y-axis). We used the NOAA global $CO_2$ trend to detrend both the observations and model simulated mole fractions (ftp://aftp.cmdl.noaa.gov/products/trends/co2/co2_trend_gl.txt). Over the NH regions (A, B, C, D) and Africa (F), the $R^2$ is greater than or equal to 0.9, which indicates that the posterior $CO_2$ captures the observed seasonality. The low $R^2$ (0.7) value in South Asia is caused by one outlier. Over the Southern Ocean, Australia, and SA, the $R^2$ is between 0.2 and 0.4, reflecting weaker $CO_2$ seasonality over these regions and possible bias in ocean flux estimates (see discussions later).

The right panel of Figure 9 shows the monthly mean differences between posterior $CO_2$ and aircraft observations (black), *RMSE* (equation 2) (blue line), and $RMSE_{MC}$ (equation 3) (red line). The magnitude of the mean differences between the posterior $CO_2$ and aircraft observations is less than 0.5 ppm except over the Southern Ocean, which has a -0.8 ppm bias. The mean differences between posterior $CO_2$ and aircraft observations are primarily caused by errors in transport and biases in assimilated satellite observations, while $RMSE_{MC}$ is 'internal flux error' projected into mole fraction space. With the exception of the Southern Ocean, for all regions mean bias is significantly

**Formatted:** Subscript

**Deleted:** or above

**Deleted:** the number of aircraft observations (blue bar, right y-axis),

**Deleted:**

less than $RMSE_{MC}$, which suggests that transport and data bias in satellite observations may be much smaller than the internal flux errors. Note that $RMSE_{MC}$ is smaller than *RMSE* over the first ~six months of simulation, which may indicate a dominant impact of errors in transport and initial $CO_2$ concentration on posterior $CO_2$ *RMSE*.

Deleted: ¶

As demonstrated in section 2.5, comparing *RMSE* and $RMSE_{MC}$ is a test of the accuracy of posterior flux uncertainty estimate. Over all the regions, the differences between *RMSE* and $RMSE_{MC}$ are smaller than 0.3 ppm, which indicates a comparable magnitude between empirical posterior flux uncertainty estimates from the Monte Carlo method and the actual posterior flux uncertainty over the regions that these aircraft observations are sensitive to. These aircraft observations are sensitive to fluxes over a broad region as shown in Figure S5.

**5.2 Comparison to aircraft observations from ATom and HIPPO aircraft campaigns**

Figures 10 and 11 show comparisons to aircraft $CO_2$ from ATom 1–4 campaigns spanning four seasons, and HIPPO 3–5 over the Pacific Ocean between 1–5 km. The vertical curtain comparisons are shown in Figure S6 and S7. The mean differences between posterior $CO_2$ and aircraft $CO_2$ are quite uniform (within 0.5 ppm) throughout the column except over the Atlantic Ocean during ATom 1–2 and the Southern Ocean during ATom 1 (Figures S6 and S7). Also shown in Figures 10 and 11 are *RMSE* of each aircraft campaign (middle column) and the ratio between *RMSE* and $RMSE_{MC}$ (right column). A ratio larger than one between *RMSE* and $RMSE_{MC}$ indicates errors in either transport or underestimation of the posterior flux uncertainty (section 2.5).

Deleted: low

Deleted: estimates

Over most of the flight tracks during ATom 1–4, the posterior $CO_2$ errors are between -0.5 and 0.5 ppm, the *RMSE* is smaller than 0.5 ppm, and the ratio between *RMSE* and $RMSE_{MC}$ is smaller than or equal to 1. However, off the coast of Africa during ATOM -1 and -2 and over the Southern Ocean during ATOM-1, the mean differences between posterior $CO_2$ and aircraft observations are larger than 0.5 ppm. During ATOM-1 (29 July – 23 Aug 2016), the mean differences between posterior $CO_2$ and aircraft $CO_2$ show large negative biases, while during ATOM-2 (26 Jan 2017–21 Feb 2017), it has large positive biases off the coast of Africa. The ratio between *RMSE* and $RMSE_{MC}$ is significantly larger than one over these regions, which indicates an underestimation of posterior flux uncertainty or large magnitude of transport errors during that time period.

We further run adjoint sensitivity analyses over the three regions with ratios significantly larger than one to identify the posterior fluxes that could contribute to the large differences between posterior $CO_2$ and aircraft observations during ATOM 1–2. We run the adjoint model backward for three months from the observation time and calculate $S_i$ as defined in equation (7). The adjoint sensitivity analysis indicates that the large mismatch between aircraft observations and model simulations during ATOM-1 and -2 off the coast of Africa could be potentially driven by errors in posterior fluxes over tropical Africa (Figure S8). The large posterior $CO_2$ errors and large ratio between *RMSE* and $RMSE_{MC}$ over the Southern Ocean during ATOM-1 are driven by flux errors in oceanic fluxes around 30°S and over Australia (Figure S9), which also contribute to the large errors in comparison to aircraft observations over the Southern Ocean shown in Figure 9 H.

During the HIPPO aircraft campaigns, the absolute errors in posterior $CO_2$ across the Pacific are less than 0.5 ppm except over the Arctic Ocean and over Alaska in summer (Figure 11), consistent

**Deleted:** A

**Deleted:** These

**Deleted:**

**Deleted:** .

with Figure 10A. The large errors over the Arctic Ocean may be related to both transport errors and the accuracy of high latitude fluxes. Byrne et al. (2020) provide a brief summary of the challenges in simulating $CO_2$ over high latitudes using a transport model with 4° x 5° resolution. Increasing the resolution of the transport model may reduce transport errors over high latitudes.

**Deleted:** these

**Deleted:** transport model

We run adjoint sensitivity analysis over the high-latitude regions where the differences between posterior $CO_2$ and aircraft observations are large (Figure 11). The adjoint sensitivity analysis (Figure S10) shows that the large errors over these regions could be driven by errors in fluxes over Alaska as well as broad NH mid-latitude regions.

### 5.3 Comparison to MBL reference sites

**Formatted:** Font: Bold

Since MBL reference sites sample air over broad regions, the comparison to detrended MBL observations indirectly evaluates the NBE over large regions. Figure 12 shows the comparison over four latitude bands. The uncertainty of posterior $CO_2$ concentration is from the MC method. Except over 90°S-20°S, the differences between observations and posterior $CO_2$ are within posterior $CO_2$ uncertainty estimates. Over 90°S-20°S, the posterior $CO_2$ has positive bias in 2013 and 2014 and negative bias and much weaker seasonality between Jan 2015 – Dec 2018 compared to observations, which indicates possible biases in Southern Ocean flux estimates. The low bias over Southern Ocean is consistent with aircraft comparison during OCO-2 period (Figures 9 and 10). The posterior $CO_2$ have smallest bias and random errors over the tropical latitude band. The $R^2$ is above 0.9 over NH mid to high latitudes, consistent with Figure 9.

**Formatted:** Subscript

**Formatted:** Subscript

**Formatted:** Subscript

## 6 Discussion

Evaluation of posterior flux uncertainty estimates by comparing posterior $CO_2$ error statistics (*RMSE,* Equation 2) with the standard deviation of ensemble simulated $CO_2$ from Monte Carlo uncertainty quantification method ($RMSE_{MC}$, equation 3) has its limitations. A comparable *RMSE* and $RMSE_{MC}$ indicates a small magnitude of transport errors and reasonable posterior uncertainty estimates. A much larger *RMSE* than $RMSE_{MC}$ could be due to errors in either transport or underestimation of the posterior flux uncertainty or both. The presence of transport errors makes the interpretation of the *RMSE* and $RMSE_{MC}$ complex. A better, independent quantification of transport errors is needed in the future in order to rigorously use the comparison statistics between aircraft observations and posterior $CO_2$ to diagnose flux errors.

**Deleted:** When

**Deleted:** are similar in magnitude, this

Comparison to aircraft observations shows regionally-dependent accuracy in posterior fluxes. ATom observations show seasonally-dependent biases over the Atlantic, implying possible seasonally dependent errors in posterior fluxes over northern to central Africa. Therefore, we recommend combining NBE with other ancillary variables, e.g., GPP, to better understand carbon dynamics. Combining NBE with component carbon fluxes can shed light on the processes controlling the changes of NBE (e.g., Bowman et al, 2017; Liu et al., 2017). NBE can be written as:

NBE= TER + fire - GPP   (8)

where TER is total ecosystem respiration (TER) (Figure 1). Satellite carbon monoxide (CO) observations provide constraints on fire emissions (Arellano et al, 2006, van der Werf, 2008; Jones et al, 2009; Jiang et al., 2015, Bowman et al, 2017; Liu et al., 2017). In addition to the FLUXSAT-GPP product used here, solar induced chlorophyll fluorescence (SIF) can be directly used as a

**Deleted:** to

proxy for GPP (e.g., Parazoo et al, 2014). Once NBE, fire, and GPP carbon fluxes are quantified, TER can be calculated as a residual (e.g., Bowman et al, 2017; Liu et al., 2017, 2018).

Because of the diffusive manner of atmospheric transport and the limited observation coverage, the gridded flux values are not independent from each other. The errors and uncertainties of the fluxes at each individual grid point are larger than regional aggregated fluxes. Interpreting NBE at each individual grid point requires caution. But at the same time, satellite $CO_2$ constrained NBE can potentially resolve fluxes at spatial scales smaller than the traditional TransCom regions. Here, we provide regional fluxes at two predefined regions in addition to TransCom. We encourage data users to use the data at propriate regional scales.

**Deleted:** relative

**Deleted:** For the same reason, comparing

**Deleted:** with flux tower observations needs

**Deleted:** , though we provide NBE at a few flux tower sites

**Formatted:** Subscript

**Deleted:** ¶

The variability and changes are more robust than the mean NBE fluxes from top-down flux inversions in general (Baker et al., 2006b). The errors in transport and potential biases in observations are mostly stable in time, so biases in the mean fluxes tend to cancel out when computing interannual variability and year-to-year changes (Schuh et al., 2019; Crowell et al., 2019).

The global fossil fuel emissions have ~5% uncertainty (GCP, 2019). However, they are regionally inhomogeneous. We neglect the uncertainties in fossil fuel emissions, which will introduce additional error in regions of rapid fossil fuel growth or in areas with noisier statistics (Yin et al., 2019). In the future, we will account for uncertainties in fossil fuel emissions.

The posterior NBE includes all types of land fluxes except fossil fuel emissions, which is equivalent to the sum of land use change fluxes and land sinks published by the GCP. The sum of regional NBE and fossil fuel emissions is an index of the contribution of any specific region to the changes of the atmospheric $CO_2$ growth rate. Even over the continental US, where fossil fuel emissions are ~1.5 GtC/year, the changes of regional NBE can significantly modify contributions to the changes of atmospheric $CO_2$ (Liu et al., 2018). Since NBE has high variability and its predicted changes in the future are likely to have large uncertainties, quantifying regional NBE is critical to monitoring regional contributions to atmospheric $CO_2$ growth rate, and ultimately to guide mitigation to limit warming to 1.5°C above pre-industrial levels (IPCC, AR6).

## 7 Summary

Terrestrial biosphere carbon fluxes are the largest contributor to the interannual variability of the atmospheric $CO_2$ growth rate. Therefore, monitoring its change at regional scales is essential for understanding how it responds to $CO_2$, climate and land use. Here, we present the longest terrestrial flux estimates and their uncertainties constrained by $X_{CO2}$ from 2010–2018 on self-consistent global and regional scales (CMS-Flux NBE 2020). We qualitatively evaluate the net flux estimates by comparing its variability with GPP variability, and provide comprehensive evaluation of posterior fluxes and the uncertainties by comparing posterior $CO_2$ with independent $CO_2$ observations from aircraft and the NOAA MBL reference sites. The estimated posterior flux uncertainty agrees with the expected uncertainty in the posterior fluxes based on the comparison to aircraft $CO_2$ observations. This dataset can be used in understanding controls on regional NBE interannual variability, evaluating biogeochemical models, and supporting the monitoring of regional contributions to changes in atmospheric $CO_2$.

**Deleted:** $CO_2$

**Deleted:** provide support

**Deleted:** the

**Deleted:** of the

**Deleted:** the

## 8 Data availability and future update

The CMS-Flux NBE 2020 data are available at: https://doi.org/10.25966/4v02-c391 (Liu et al., 2020). The regional aggregated fluxes are provided as *csv* files with file size ~10MB, and the gridded data is provided in NetCDF format with file size ~1.4 GB. The full ensemble of posterior fluxes used to estimate posterior flux uncertainties are provided in NetCDF format with file size ~30MB. Table 7 lists the sources of the data used in producing and evaluating the CMS-Flux NBE 2020 data product.

**Deleted:** is

**Deleted:** 10MB

**Deleted:** 20MB

The quality of $X_{CO2}$ from satellite observations is continually improving. The OCO-2 v10 $X_{CO2}$ has been released in June 2020 along with the full GOSAT record (June 2009–Jan 2020) processed by the same retrieval algorithm as OCO-2. Continuing to improving the quality of satellite observations and extending the NBE estimates beyond 2018 in the future will help us better understand interactions between terrestrial biosphere carbon cycle and climate and provide support in monitoring the regional contributions to the changes of atmospheric $CO_2$. Thus, we plan a future update of the dataset on an annual basis, with a goal to support current scientific research and policy making.

**Deleted:** will be

**Deleted:**

**Deleted:** , and

**Deleted:** by

**Deleted:** will be released around the same time

## 9 Author contributions

JL designed the study and led the writing of the paper in close collaboration with KB and DS. LB helped generate the plots and created all the data files. AAB provided the prior of the terrestrial biosphere carbon fluxes. NP helped interpret the GPP evaluation. DM and DC generated the prior ocean carbon fluxes. TO generated the ODIAC fossil fuel emissions. JJ provided the FLUXSAT GPP product. BD and SW provided and contributed to the interpretation of HIPPO aircraft $CO_2$

observation comparisons. BS, KM, and CS provided ORCAS aircraft $CO_2$ observations and contributed interpretation of aircraft $CO_2$ observation comparisons. LVG and JM provided INPE aircraft $CO_2$ observations and contributed interpretation of aircraft $CO_2$ observation comparisons. CS and KM provided ATom and the NOAA aircraft CO2 observations and contributed interpretation of aircraft $CO_2$ observation comparisons. We furthermore acknowledge funding from the EU for the ERC project "ASICA" (grant number 649087) to Wouter Peters (Groningen University) and EU and NERC (UK) funding to Emanuel Gloor (University of Leeds), which contributed to the INPE Amazon greenhouse sampling program. All authors contributed to the writing, and have reviewed and approved the paper.

## 10 Competing interest

The authors declare that they have no conflict of interest.

## Acknowledgement

Resources supporting this work were provided by the NASA High-End Computing (HEC) Program through the NASA Advanced Supercomputing (NAS) division at Ames Research Center. We acknowledge the funding support from NASA OCO-2/3 Science Team, Carbon Monitoring System (CMS), and Making Earth Science Data Records for Use in Research Environments (MEaSUREs) programs. Tomohiro Oda is supported by the NASA Carbon Cycle Science program (grant no. NNX14AM76G). We acknowledge EU and NERC (UK) funding to Emanuel Gloor, University of Leeds which substantially contributed to the INPE Amazon greenhouse sampling program. CarbonTracker Europe results provided by Wageningen University in collaboration with the ObsPack partners (http://www.carbontracker.eu). Part of the research was carried out at Jet Propulsion Laboratory, Caltech.

**Formatted:** Font: 12 pt

**Formatted:** Font: (Default) Times New Roman

**Formatted:** Hyperlink, Font: (Default) Times New Roman, Font color: Auto

**Formatted:** Font: (Default) Times New Roman

**Field Code Changed**

## Appendix

As shown in Kalnay (2003):

$$RMSE^2 = R_{aircraft} + HP^aH^T \quad (A.1)$$

where $R_{aircraft}$ is the aircraft observation error variance, and $P^a$ is the posterior flux error covariance. The $H$ is linearized observation operator, which transfers posterior flux errors to aircraft observation space, and $H^T$ is its adjoint. In the Monte Carlo method, the posterior flux error covariance $P^a$ is approximated by:

$$P^a = \frac{1}{nens} X^a {X^a}^T \quad (A.2)$$

where $X^a$ is the ensemble perturbations written as:

$$X^a = x^a - \boldsymbol{x}^a \quad (A.3)$$

where $x^a$ is the ensemble posterior fluxes from Monte Carlo, and $\boldsymbol{x}^a$ is the mean.

Therefore, $HP^aH^T$ can be written as:

$$HP^aH^T = \frac{1}{nens}[h(x^a) - h(\boldsymbol{x}^a)][h(x^a) - h(\boldsymbol{x}^a)]^T \quad (A.4)$$

The right hand side is the same as the definiation of $RMSE_{MC}$ in the main text.

Therefore, when the posterior flux uncertainty estimated by Monte Carlo method represents the actual uncertainty in posterior fluxes, equation (A.1) can be written as:

$$RMSE^2 = R_{aircraft} + RMSE_{MC}^2 \quad (A.5).$$

It is the same as equation (3) in the main text.

Deleted:

Deleted: i

References

Arellano Jr, A.F., Kasibhatla, P.S., Giglio, L., Van der Werf, G.R., Randerson, J.T., and Collatz, G.J.: Time-dependent inversion estimates of global biomass-burning CO emissions using Measurement of Pollution in the Troposphere (MOPITT) measurements, J. Geophys. Res: Atmos., 111, D09303, https://doi.org/10.1029/2005JD006613, 2006.

Baker, D.F., Doney, S.C., and Schimel, D.S.: Variational data assimilation for atmospheric CO2, Tellus B: Chem. Phys. Meteorol., 58, 359-365, https://doi.org/10.1111/j.1600-0889.2006.00218.x, 2006a.

Baker, D.F., Law, R.M., Gurney, K.R., Rayner, P., Peylin, P., Denning, A.S., Bousquet, P., Bruhwiler, L., Chen, Y.H., Ciais, P., and Fung, I.Y.: TransCom 3 inversion intercomparison: Impact of transport model errors on the interannual variability of regional CO2 fluxes, 1988–2003, Global Biogeochem. Cy., 20, GB1002, https://doi.org/10.1029/2004GB002439, 2006b.

Bastos, A., Friedlingstein, P., Sitch, S., Chen, C., Mialon, A., Wigneron, J.-P., Arora, V. K., Briggs, P. R., Canadell, J. G., and Ciais, P.: Impact of the 2015/2016 El Niño on the terrestrial carbon cycle constrained by bottom-up and top-down approaches. Philos. Trans. R Soc. Lond. B. Biol. Sci., 373, 1760, https://doi.org/10.1098/rstb.2017.0304, 2018.

Bloom, A.A., Exbrayat, J.F., van der Velde, I.R., Feng, L., and Williams, M.: The decadal state of the terrestrial carbon cycle: Global retrievals of terrestrial carbon allocation, pools, and residence times. Proc. Natl Acad. Sci., 113, 1285-1290, 2016.

Bloom, A. A., Bowman, K. W., Liu, J., Konings, A. G., Worden, J. R., Parazoo, N. C., Meyer, V., Reager, J. T., Worden, H. M., Jiang, Z., Quetin, G. R., Smallman, T. L., Exbrayat, J.-F., Yin, Y., Saatchi, S. S., Williams, M., and Schimel, D. S.: Lagged effects dominate the inter-annual variability of the 2010–2015 tropical carbon balance, Biogeosciences Discuss., https://doi.org/10.5194/bg-2019-459, in review, 2020.

Bowman, K.W., Liu, J., Bloom, A.A., Parazoo, N.C., Lee, M., Jiang, Z., Menemenlis, D., Gierach, M.M., Collatz, G.J., Gurney, K.R., and Wunch, D.: Global and Brazilian carbon response to El Niño Modoki 2011–2010, Earth Space Sci., 4, 637-660, https://doi.org/10.1002/2016EA000204, 2017.

Brix, H., Menemenlis, D., Hill, C., Dutkiewicz, S., Jahn, O., Wang, D., Bowman, K., and Zhang, H.: Using Green's Functions to initialize and adjust a global, eddying ocean biogeochemistry general circulation model, Ocean Model., 95, 1-14, https://doi.org/10.1016/j.ocemod.2015.07.008, 2015.

Byrd, R.H., Nocedal, J., and Schnabel, R.B.: Representations of quasi-Newton matrices and their use in limited memory methods, Math. Program., 63, 129-156, https://doi.org/10.1007/BF01582063, 1994.

Byrne, B., Liu, J., et al.: Improved constraints on northern extratropical CO2 fluxes obtained by combining surface-based and space-based atmospheric CO2 measurements, *JGR-Atmosphere*, (*minor revision*), 2020

Carroll, D., Menemenlis, D., Adkins, J. F., Bowman, K. W., Brix, H., Dutkiewicz, S., et al.: The ECCO-Darwin Data-assimilative Global Ocean Biogeochemistry Model: Estimates of Seasonal to Multi-decadal Surface Ocean $pCO_2$ and Air-sea $CO_2$ Flux. *Journal of Advances in Modeling Earth Systems*, 12, e2019MS001888. https://doi.org/10.1029/2019MS001888.2020

**Formatted:** Justified

**Deleted:** Carroll, D., Menemenlis, D., Adkins, J.:

**Deleted:** The ECCO-Darwin Data-assimilative Global Ocean Biogeochemistry Model: Estimates of Seasonal to Multi-decadal Surface Ocean pCO2 and Air-sea CO2 Flux. *Journal of Advances in Modeling Earth Systems* (*minor revision*), 2020

Carbontracker Team; (2019) : Compilation of near real time atmospheric carbon dioxide data; obspack_co2_1_NRT_v5.0_2019-08-13; NOAA Earth System Research Laboratory, Global Monitoring Division. http://doi.org/10.25925/20190813

Chevallier, F., Fisher, M., Peylin, P., Serrar, S., Bousquet, P., Bréon, F.M., Chédin, A., and Ciais, P.: Inferring CO2 sources and sinks from satellite observations: Method and application to TOVS data, J. Geophys. Res.-Atmos., 110, D24309, https://doi.org/10.1029/2005JD006390, 2005.

Chevallier, F., Ciais, P., Conway, T.J., Aalto, T., Anderson, B.E., Bousquet, P., Brunke, E.G., Ciattaglia, L., Esaki, Y., Fröhlich, M., and Gomez, A.: $CO_2$ surface fluxes at grid point scale estimated from a global 21 year reanalysis of atmospheric measurements, J. Geophys. Res., 115, D21307, https://doi.org/10.1029/2010JD013887, 2010.

Chevallier, F., Remaud, M., O'Dell, C. W., Baker, D., Peylin, P., and Cozic, A.: Objective evaluation of surface- and satellite-driven carbon dioxide atmospheric inversions, Atmos. Chem. Phys., 19, 14233–14251, https://doi.org/10.5194/acp-19-14233-2019, 2019.

Ciais, P., Tan, J., Wang, X., Roedenbeck, C., Chevallier, F., Piao, S.L., Moriarty, R., Broquet, G., Le Quéré, C., Canadell, J.G., and Peng, S.: Five decades of northern land carbon uptake revealed by the interhemispheric CO 2 gradient, Nature, 568, 221-225, https://doi.org/10.1038/s41586-019-1078-6, 2019.

Conway, T. J., Tans, P. P., Waterman, L. S., Thoning, K. W., Kitzis, D. R., Masarie, K. A., and Zhang, N. (1994), Evidence for interannual variability of the carbon cycle from the National Oceanic and Atmospheric Administration/Climate Monitoring and Diagnostics Laboratory Global Air Sampling Network, *J. Geophys. Res.*, 99( D11), 22831– 22855, doi:10.1029/94JD01951.

Crisp, D., Fisher, B. M., O'Dell, C., Frankenberg, C., Basilio, R., Bösch, H., Brown, L. R., Castano, R., Connor, B., Deutscher, N. M., Eldering, A., Griffith, D., Gunson, M., Kuze, A., Mandrake, L., McDuffie, J., Messerschmidt, J., Miller, C. E., Morino, I., Natraj, V., Notholt, J., O'Brien, D. M., Oyafuso, F., Polonsky, I., Robinson, J., Salawitch, R., Sherlock, V., Smyth, M., Suto, H., Taylor, T. E., Thompson, D. R., Wennberg, P. O., Wunch, D., and Yung, Y. L.: The ACOS $CO_2$ retrieval algorithm – Part II: Global $X_{CO2}$ data characterization, Atmos. Meas. Tech., 5, 687–707, https://doi.org/10.5194/amt-5-687-2012, 2012.

Crisp, D., Pollock, H. R., Rosenberg, R., Chapsky, L., Lee, R. A. M., Oyafuso, F. A., Frankenberg, C., O'Dell, C. W., Bruegge, C. J., Doran, G. B., Eldering, A., Fisher, B. M., Fu, D., Gunson, M. R., Mandrake, L., Osterman, G. B., Schwandner, F. M., Sun, K., Taylor, T. E., Wennberg, P. O., and Wunch, D.: The on-orbit performance of the Orbiting Carbon Observatory-2 (OCO-2) instrument and its radiometrically calibrated products, Atmos. Meas. Tech., 10, 59–81, https://doi.org/10.5194/amt-10-59-2017, 2017.

Crowell, S., Baker, D., Schuh, A., Basu, S., Jacobson, A. R., Chevallier, F., Liu, J., Deng, F., Feng, L., McKain, K., Chatterjee, A., Miller, J. B., Stephens, B. B., Eldering, A., Crisp, D., Schimel, D., Nassar, R., O'Dell, C. W., Oda, T., Sweeney, C., Palmer, P. I., and Jones, D. B. A.: The 2015–

**Deleted:** ¶

**Formatted:** Font: (Default) Times New Roman, 12 pt

**Formatted:** Justified

**Formatted:** Font: (Default) Times New Roman, 12 pt

2016 carbon cycle as seen from OCO-2 and the global in situ network, Atmos. Chem. Phys., 19, 9797–9831, https://doi.org/10.5194/acp-19-9797-2019, 2019.

Falk, M., Wharton, S., Schroeder, M., Ustin, S., and U, K.T.P.: Flux partitioning in an old-growth forest: seasonal and interannual dynamics. Tree Physiol., 28, 509-520, https://doi.org/10.1093/treephys/28.4.509, 2008.

Fisher, M. and Courtier, P. (1995) Estimating the covariance matrices of analysis and forecast error in variational data assimilation. Technical Memorandum 220. Reading, UK: ECMWF.

Friedlingstein, P., Meinshausen, M., Arora, V.K., Jones, C.D., Anav, A., Liddicoat, S.K., and Knutti, R.: Uncertainties in CMIP5 climate projections due to carbon cycle feedbacks, J. Clim., 27, 511-526, https://doi.org/10.1175/JCLI-D-12-00579.1, 2014.

Friedlingstein, P., Jones, M., O'Sullivan, M., Andrew, R., Hauck, J., Peters, G., Peters, W., Pongratz, J., Sitch, S., Le Quéré, C., and DBakker, O.: Global carbon budget 2019, Earth Syst. Sci. Data, 11, 1783-1838, https://doi.org/10.3929/ethz-b-000385668, 2019.

Gatti, L.V., Gloor, M., Miller, J.B., Doughty, C.E., Malhi, Y., Domingues, L.G., Basso, L.S., Martinewski, A., Correia, C.S.C., Borges, V.F., and Freitas, S., 2014, Drought sensitivity of Amazonian carbon balance revealed by atmospheric measurements, Nature, 506, 76-80, https://doi.org/10.1038/nature12957, 2014.

Gaubert, B., Stephens, B. B., Basu, S., Chevallier, F., Deng, F., Kort, E. A., Patra, P. K., Peters, W., Rödenbeck, C., Saeki, T., Schimel, D., Van der Laan-Luijkx, I., Wofsy, S., and Yin, Y.: Global atmospheric $CO_2$ inverse models converging on neutral tropical land exchange, but disagreeing on fossil fuel and atmospheric growth rate, Biogeosciences, 16, 117–134, https://doi.org/10.5194/bg-16-117-2019, 2019.

Gurney, K.R., Law, R.M., Denning, A.S., Rayner, P.J., Pak, B.C., Baker, D., Bousquet, P., Bruhwiler, L., Chen, Y.H., Ciais, P., and Fung, I.Y.: Transcom 3 inversion intercomparison: Model mean results for the estimation of seasonal carbon sources and sinks, Global Biogeochem. Cycles, 18, GB1010, https://doi.org/10.1029/2003GB002111, 2004.

Henze, D. K., Hakami, A., and Seinfeld, J. H.: Development of the adjoint of GEOS-Chem, Atmos. Chem. Phys., 7, 2413–2433, https://doi.org/10.5194/acp-7-2413-2007, 2007.

Jiang, Z., Worden, J. R., Worden, H., Deeter, M., Jones, D. B. A., Arellano, A. F., and Henze, D. K.: A 15-year record of CO emissions constrained by MOPITT CO observations, Atmos. Chem. Phys., 17, 4565–4583, https://doi.org/10.5194/acp-17-4565-2017, 2017.

Joiner, J., Guanter, L., Lindstrot, R., Voigt, M., Vasilkov, A. P., Middleton, E. M., Huemmrich, K. F., Yoshida, Y., and Frankenberg, C.: Global monitoring of terrestrial chlorophyll fluorescence from moderate-spectral-resolution near-infrared satellite measurements: methodology,

**Formatted:** Font: (Default) Times New Roman, 12 pt

**Formatted:** Font: (Default) Times New Roman, 12 pt, Not Italic

**Formatted:** Font: (Default) Times New Roman, 12 pt

simulations, and application to GOME-2, Atmos. Meas. Tech., 6, 2803–2823, https://doi.org/10.5194/amt-6-2803-2013, 2013.

Joiner, J., Yoshida, Y., Zhang, Y., Duveiller, G., Jung, M., Lyapustin, A., Wang, Y., & Tucker, C.: Estimation of terrestrial global gross primary production (GPP) with satellite data-driven models and eddy covariance flux data. *Remote Sensing*, **10**(9), 1346. https://doi.org/10.3390/rs10091346. 2018.

Jones, D. B. A., Bowman, K. W., Logan, J. A., Heald, C. L., Liu, J., Luo, M., Worden, J., and Drummond, J.: The zonal structure of tropical $O_3$ and CO as observed by the Tropospheric Emission Spectrometer in November 2004 – Part 1: Inverse modeling of CO emissions, Atmos. Chem. Phys., 9, 3547–3562, https://*doi*.org/*10.5194*/*acp-9-3547-2009* , 2009.

Kiel, M., O'Dell, C. W., Fisher, B., Eldering, A., Nassar, R., MacDonald, C. G., and Wennberg, P. O.: How bias correction goes wrong: measurement of $X_{CO2}$ affected by erroneous surface pressure estimates, Atmos. Meas. Tech., 12, 2241–2259, https://doi.org/10.5194/amt-12-2241-2019, 2019.

Konings, A. G., Bloom, A. A., Liu, J., Parazoo, N. C., Schimel, D. S., and Bowman, K. W.: Global satellite-driven estimates of heterotrophic respiration, Biogeosciences, 16, 2269–2284, https://doi.org/10.5194/bg-16-2269-2019, 2019.

Kulawik, S. S., Crowell, S., Baker, D., Liu, J., McKain, K., Sweeney, C., Biraud, S. C., Wofsy, S., O'Dell, C. W., Wennberg, P. O., Wunch, D., Roehl, C. M., Deutscher, N. M., Kiel, M., Griffith, D. W. T., Velazco, V. A., Notholt, J., Warneke, T., Petri, C., De Mazière, M., Sha, M. K., Sussmann, R., Rettinger, M., Pollard, D. F., Morino, I., Uchino, O., Hase, F., Feist, D. G., Roche, S., Strong, K., Kivi, R., Iraci, L., Shiomi, K., Dubey, M. K., Sepulveda, E., Rodriguez, O. E. G., Té, Y., Jeseck, P., Heikkinen, P., Dlugokencky, E. J., Gunson, M. R., Eldering, A., Crisp, D., Fisher, B., and Osterman, G. B.: Characterization of OCO-2 and ACOS-GOSAT biases and errors for $CO_2$ flux estimates, Atmos. Meas. Tech. Discuss., https://doi.org/10.5194/amt-2019-257, in review, 2019.

Kuze, A., Suto, H., Shiomi, K., Kawakami, S., Tanaka, M., Ueda, Y., Deguchi, A., Yoshida, J., Yamamoto, Y., Kataoka, F., Taylor, T. E., and Buijs, H. L.: Update on GOSAT TANSO-FTS performance, operations, and data products after more than 6 years in space, Atmos. Meas. Tech., 9, 2445–2461, https://doi.org/10.5194/amt-9-2445-2016, 2016.

Le Quéré, C., Andrew, R. M., Friedlingstein, P., Sitch, S., Pongratz, J., Manning, A. C., Korsbakken, J. I., Peters, G. P., Canadell, J. G., Jackson, R. B., Boden, T. A., Tans, P. P., Andrews, O. D., Arora, V. K., Bakker, D. C. E., Barbero, L., Becker, M., Betts, R. A., Bopp, L., Chevallier, F., Chini, L. P., Ciais, P., Cosca, C. E., Cross, J., Currie, K., Gasser, T., Harris, I., Hauck, J., Haverd, V., Houghton, R. A., Hunt, C. W., Hurtt, G., Ilyina, T., Jain, A. K., Kato, E., Kautz, M., Keeling, R. F., Klein Goldewijk, K., Körtzinger, A., Landschützer, P., Lefèvre, N., Lenton, A., Lienert, S., Lima, I., Lombardozzi, D., Metzl, N., Millero, F., Monteiro, P. M. S., Munro, D. R., Nabel, J. E. M. S., Nakaoka, S., Nojiri, Y., Padin, X. A., Peregon, A., Pfeil, B., Pierrot, D., Poulter, B., Rehder, G., Reimer, J., Rödenbeck, C., Schwinger, J., Séférian, R., Skjelvan, I., Stocker, B. D., Tian, H., Tilbrook, B., Tubiello, F. N., van der Laan-Luijkx, I. T., van der Werf, G. R., van Heuven, S.,

**Deleted:**
Keppel-Aleks, G., Wennberg, P. O., Washenfelder, R. A., Wunch, D., Schneider, T., Toon, G. C., Andres, R. J., Blavier, J.-F., Connor, B., Davis, K. J., Desai, A. R., Messerschmidt, J., Notholt, J., Roehl, C. M., Sherlock, V., Stephens, B. B., Vay, S. A., and Wofsy, S. C.: The imprint of surface fluxes and transport on variations in total column carbon dioxide, Biogeosciences, 9, 875–891, https://doi.org/10.5194/bg-9-875-2012, 2012.

Viovy, N., Vuichard, N., Walker, A. P., Watson, A. J., Wiltshire, A. J., Zaehle, S., and Zhu, D.: Global Carbon Budget 2017, Earth Syst. Sci. Data, 10, 405–448, https://doi.org/10.5194/essd-10-405-2018, 2018.

Liu, J., Baskarran, L., Bowman, K., Schimel, D., Bloom, A. A., Parazoo, N., Oda, T., Carrol, D., Menemenlis, D., Joiner, J., Commane, R., Daube, B., Gatti, L. V., McKain, K., Miller, J., Stephens, B. B., Sweeney, C., & Wofsy, S. (2020). *CMS-Flux NBE 2020* [Data set]. NASA. https://doi.org/10.25966/4V02-C391

Liu, J. and Bowman, K.: A method for independent validation of surface fluxes from atmospheric inversion: Application to CO2, Geophys. Res. Lett., 43, 3502-3508, https://doi.org/10.1002/2016GL067828, 2016.

Liu, J., Bowman, K. W., and Henze, D. K.: Source-receptor relationships of column-average $CO_2$and implications for the impact of observations on flux inversions. *J. Geophys. Res. Atmos.*, 120, 5214– 5236. doi: 10.1002/2014JD022914, 2015

Liu, J., Bowman, K.W., Lee, M., Henze, D.K., Bousserez, N., Brix, H., James Collatz, G., Menemenlis, D., Ott, L., Pawson, S., and Jones, D.: Carbon monitoring system flux estimation and attribution: impact of ACOS-GOSAT XCO2 sampling on the inference of terrestrial biospheric sources and sinks. Tellus B Chem. Phys. Meteorol. B., 66, 22486, http://dx.doi.org/10.3402/tellusb.v66.22486, 2014.

Liu, J., Bowman, K.W., Schimel, D.S., Parazoo, N.C., Jiang, Z., Lee, M., Bloom, A.A., Wunch, D., Frankenberg, C., Sun, Y., and O'Dell, C.W.: Contrasting carbon cycle responses of the tropical continents to the 2015–2016 El Niño. Science, 358, eaam5690, https://doi.org/10.1126/science.aam5690, 2017.

Liu, J., Bowman, K., Parazoo, N.C., Bloom, A.A., Wunch, D., Jiang, Z., Gurney, K.R., and Schimel, D.: Detecting drought impact on terrestrial biosphere carbon fluxes over contiguous US with satellite observations. Environ. Res. Lett., 13, 095003, https://doi.org/10.1088/1748-9326/aad5ef, 2018.

Liu, Z.-Q. and Rabier, F. (2003), The potential of high-density observations for numerical weather prediction: A study with simulated observations. Q.J.R. Meteorol. Soc., 129: 3013-3035. doi:10.1256/qj.02.170

Lorenc, A. C., 1981: A Global Three-Dimensional Multivariate Statistical Interpolation Scheme. *Mon. Wea. Rev.*, **109**, 701–721

Lovenduski, N.S. and Bonan, G.B.: Reducing uncertainty in projections of terrestrial carbon uptake, Environ. Res. Lett., 12, 044020, https://doi.org/10.1088/1748-9326/aa66b8, 2017.

**Formatted:** Font: (Default) Times New Roman, 12 pt

**Formatted:** Font: (Default) Times New Roman, 12 pt

**Formatted:** Font: Times New Roman

**Deleted:** ¶

Meirink, J.F., Bergamaschi, P. and Krol, M.C. (2008) Four-dimensional variational data assimilation for inverse modelling of atmospheric methane emissions: method and comparison with synthesis inversion, Atmos. *Chem. Phys.*, **8**, 6341– 6353, https://doi.org/10.5194/acp-8-6341-2008.

Nassar, R., Jones, D.B., Suntharalingam, P., Chen, J.M., Andres, R.J., Wecht, K.J., Yantosca, R.M., Kulawik, S.S., Bowman, K.W., Worden, J.R., and Machida, T.: Modeling global atmospheric CO2 with improved emission inventories and CO2 production from the oxidation of other carbon species. Geosci. Model Dev., 3, 689-716, https://doi.org/10.5194/gmd-3-689-2010, 2010.

Niwa, Y, Fujii, Y. A conjugate BFGS method for accurate estimation of a posterior error covariance matrix in a linear inverse problem. *Q J R Meteorol Soc*. 2020; 1– 26. https://doi.org/10.1002/qj.3838

Oda, T., Maksyutov, S., and Andres, R. J.: The Open-source Data Inventory for Anthropogenic $CO_2$, version 2016 (ODIAC2016): a global monthly fossil fuel $CO_2$ gridded emissions data product for tracer transport simulations and surface flux inversions, Earth Syst. Sci. Data, 10, 87–107, https://doi.org/10.5194/essd-10-87-2018, 2018.

O'Dell, C. W., Connor, B., Bösch, H., O'Brien, D., Frankenberg, C., Castano, R., Christi, M., Eldering, D., Fisher, B., Gunson, M., McDuffie, J., Miller, C. E., Natraj, V., Oyafuso, F., Polonsky, I., Smyth, M., Taylor, T., Toon, G. C., Wennberg, P. O., and Wunch, D.: The ACOS $CO_2$ retrieval algorithm – Part 1: Description and validation against synthetic observations, Atmos. Meas. Tech., 5, 99–121, https://doi.org/10.5194/amt-5-99-2012, 2012.

O'Dell, C., Eldering, A., Wennberg, P.O., Crisp, D., Gunson, M., Fisher, B., Frankenberg, C., Kiel, M., Lindqvist, H., Mandrake, L., and Merrelli, A.: Improved retrievals of carbon dioxide from Orbiting Carbon Observatory-2 with the version 8 ACOS algorithm, Atmos. Meas. Tech., 11, 6539–6576, https://doi.org/10.5194/amt-11-6539-2018, 2018.

Olsen, S.C. and Randerson, J.T.: Differences between surface and column atmospheric CO2 and implications for carbon cycle research, J. Geophys. Res: Atmos., 109, D02301, https://doi.org/10.1029/2003JD003968, 2004.

Parazoo, N.C., Bowman, K., Fisher, J.B., Frankenberg, C., Jones, D.B.A., Cescatti, A., Pérez-Priego, Ó., Wohlfahrt, G. and Montagnani, L.: Terrestrial gross primary production inferred from satellite fluorescence and vegetation models. Glob Change Biol, 20: 3103-3121. doi:10.1111/gcb.12652. 2014.

Peylin, P., Law, R. M., Gurney, K. R., Chevallier, F., Jacobson, A. R., Maki, T., Niwa, Y., Patra, P. K., Peters, W., Rayner, P. J., Rödenbeck, C., van der Laan-Luijkx, I. T., and Zhang, X.: Global atmospheric carbon budget: results from an ensemble of atmospheric $CO_2$ inversions, Biogeosciences, 10, 6699–6720, https://doi.org/10.5194/bg-10-6699-2013, 2013.

**Formatted:** Font: (Default) Times New Roman, 12 pt

**Formatted:** Justified

**Formatted:** Font: (Default) Times New Roman, 12 pt

**Formatted:** Justified

**Formatted:** Font: (Default) Times New Roman, 12 pt

**Formatted:** Font: Times New Roman, 12 pt

**Formatted:** Justified

Peters, W., et al. (2007), An atmospheric perspective on North American carbon dioxide exchange: CarbonTracker, *Proc. Natl. Acad. Sci. U. S. A.*, **104**(48), 18,925– 18,930, doi:10.1073/pnas.0708986104.

Peters, W., Krol, M. C., Van Der Werf, G.R., et al, 2010, Seven years of recent European net terrestrial carbon dioxide exchange constrained by atmospheric observations. Global Change Biology, 16: 1317-1337. doi:10.1111/j.1365-2486.2009.02078.x

Poulter, B., Frank, D., Ciais, P., Myneni, R.B., Andela, N., Bi, J., Broquet, G., Canadell, J.G., Chevallier, F., Liu, Y.Y., and Running, S.W.: Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle, Nature, 509, 600-603, https://doi.org/10.1038/nature13376, 2014.

Quetin, G., Bloom, A. A., Bowman, K. W., & Konings, A.: Carbon flux variability from a relatively simple ecosystem model with assimilated data is consistent with terrestrial biosphere model estimates. *Journal of Advances in Modeling Earth Systems*, 12, e2019MS001889. https://doi.org/10.1029/2019MS001889, 2020

Randerson, J.T., Van Der Werf, G.R., Giglio, L., Collatz, G.J., and Kasibhatla, P.S.: Global Fire Emissions Database, Version 4.1 (GFEDv4), ORNL DAAC, Oak Ridge, Tennessee, USA, https://doi.org/10.3334/ORNLDAAC/1293, 2018.

Rienecker, M.M., Suarez, M.J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., Bosilovich, M.G., Schubert, S.D., Takacs, L., Kim, G.K., and Bloom, S.: MERRA: NASA's modern-era retrospective analysis for research and applications, J. Clim., 24, 3624-3648, https://doi.org/10.1175/JCLI-D-11-00015.1, 2011.

Rödenbeck, C., Houweling, S., Gloor, M., and Heimann, M.: $CO_2$ flux history 1982–2001 inferred from atmospheric data using a global inversion of atmospheric transport, Atmos. Chem. Phys., 3, 1919–1964, https://doi.org/10.5194/acp-3-1919-2003, 2003.

Running, S.W., Baldocchi, D.D., Turner, D.P., Gower, S.T., Bakwin, P.S., and Hibbard, K.A.: A global terrestrial monitoring network integrating tower fluxes, flask sampling, ecosystem modeling and EOS satellite data, Remote Sens. Environ., 70, 108-127, https://doi.org/10.1016/S0034-4257(99)00061-9, 1999.

Schuh, A.E., Jacobson, A.R., Basu, S., Weir, B., Baker, D., Bowman, K., Chevallier, F., Crowell, S., Davis, K.J., Deng, F., and Denning, S.: Quantifying the impact of atmospheric transport uncertainty on CO2 surface flux estimates, Global Biogeochem. Cy., 33, 484-500, https://doi.org/10.1029/2018GB006086, 2019.

Sellers, P.J., Schimel, D.S., Moore, B., Liu, J., and Eldering, A.: Observing carbon cycle–climate feedbacks from space, PNAS, 115, 7860-7868, https://doi.org/10.1073/pnas.1716613115, 2018.

**Formatted:** Font: (Default) Times New Roman, 12 pt
**Formatted:** Justified
**Formatted:** Font: (Default) Times New Roman, 12 pt
**Formatted:** Font: (Default) Times New Roman, 12 pt
**Formatted:** Font: (Default) Times New Roman
**Formatted:** Font: (Default) Times New Roman
**Formatted:** Font: (Default) Times New Roman, 12 pt
**Formatted:** Font: (Default) Times New Roman, 12 pt
**Formatted:** Font: Times New Roman, 12 pt
**Formatted:** Justified

Stephens, B.B., Gurney, K. R., Tans, P. P., *et al.*:. Weak northern and strong tropical land carbon uptake from vertical profiles of atmospheric $CO_2$. *Science* **316**: 1732– 35, doi:10.1126/science.1137004. 2007

Stephens, B., et al. 2017. ORCAS Airborne Oxygen Instrument. Version 1.0. UCAR/NCAR - Earth Observing Laboratory. https://doi.org/10.5065/D6N29VC6.

Sweeney, C., Karion, A., Wolter, S., et al.: Seasonal climatology of $CO_2$ across North America from aircraft measurements in the NOAA/ESRL Global Greenhouse Gas Reference Network. *J. Geophys. Res. Atmos.*, 120, 5155– 5190. doi: 10.1002/2014JD022591. 2015

Suntharalingam, P., Jacob, D.J., Palmer, P.I., Logan, J.A., Yantosca, R.M., Xiao, Y., Evans, M.J., Streets, D.G., Vay, S.L., and Sachse, G.W.: Improved quantification of Chinese carbon fluxes using CO2/CO correlations in Asian outflow, J. Geophys. Res.: Atmos., 109, D18S18, https://doi.org/10.1029/2003JD004362, 2004.

Tramontana, G., Jung, M., Schwalm, C. R., Ichii, K., Camps-Valls, G., Ráduly, B., Reichstein, M., Arain, M. A., Cescatti, A., Kiely, G., Merbold, L., Serrano-Ortiz, P., Sickert, S., Wolf, S., and Papale, D.: Predicting carbon dioxide and energy fluxes across global FLUXNET sites with regression algorithms, Biogeosciences, 13, 4291–4313, https://doi.org/10.5194/bg-13-4291-2016, 2016.

van der Laan-Luijkx et al, 2017, "The CarbonTracker Data Assimilation Shell (CTDAS) v1.0: implementation and global carbon balance 2001-2015", Geosci. Model Dev., 10, 2785-2800,

van der Werf, G. R., Randerson, J. T., Giglio, L., Gobron, N., and Dolman, A. J.: Climate controls on the variability of fires in the tropics and subtropics, *Global Biogeochem. Cycles*, 22, GB3028, doi:10.1029/2007GB003122. 2008

Wofsy, S. C.: HIAPER Pole-to-Pole Observations (HIPPO): Fine-grained, global-scale measurements of climatically important atmospheric gases and aerosols, Philos. Trans. R. Soc. A-Math. Phys. Eng. Sci., 369, 2073– 2086, https://doi.org/10.1098/rsta.2010.0313, 2011.

Wofsy, S.C., Afshar, S., Allen, H.M., Apel, E., Asher, E.C., Barletta, B., Bent, J., Bian, H., Biggs, B.C., Blake, D.R., and Blake, N.: ATom: Merged Atmospheric Chemistry, Trace Gases, and Aerosols, ORNL DAAC, Oak Ridge, Tennessee, USA, https://doi.org/10.3334/ORNLDAAC/1581, 2018.

Wunch, D., Toon, G.C., Blavier, J.F.L., Washenfelder, R.A., Notholt, J., Connor, B.J., Griffith, D.W., Sherlock, V., and Wennberg, P.O.: The total carbon column observing network, Philos. Trans. R. Soc. A, 369, 2087-2112, https://doi.org/10.1098/rsta.2010.0240, 2011.

**Formatted:** Font: (Default) Times New Roman

**Formatted:** Justified

**Formatted:** Font: (Default) Times New Roman, Not Bold

Yin, Y., Bowman, K., Bloom, A.A., and Worden, J.: Detection of fossil fuel emission trends in the presence of natural carbon cycle variability, Environ. Res. Lett., 14, 084050, https://doi.org/10.1088/1748-9326/ab2dd7, 2019.

Zhu, C., Byrd, R.H., Lu, P., and Nocedal, J.: Algorithm 778: L-BFGS-B: Fortran subroutines for large-scale bound-constrained optimization, ACM Trans. Math. Softw., 23, 550-560, https://doi.org/10.1145/279232.279236, 1997.

**Deleted:** Yang, Z., Washenfelder, R. A., Keppel-Aleks, G., Krakauer, N. Y., Randerson, J. T., Tans, P. P., Sweeney, C., and Wennberg, P. O.: New constraints on Northern Hemisphere growing season net flux, Geophys. Res. Lett., 34, L12807, https://doi.org/10.1029/2007GL029742, 2007.¶
¶

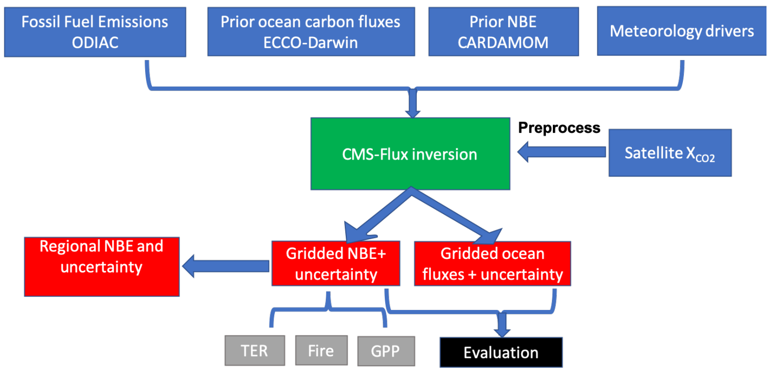



**Figure: 1 Data flow diagram with the main processing steps to generate regional net biosphere change (NBE). TER: total ecosystem respiration; GPP: gross primary production. The green box is the inversion system. The blue boxes are the inputs for the inversion system. The red boxes are the data outputs from the system. The black box is the evaluation step, and the grey boxes are the future additions to the product.**

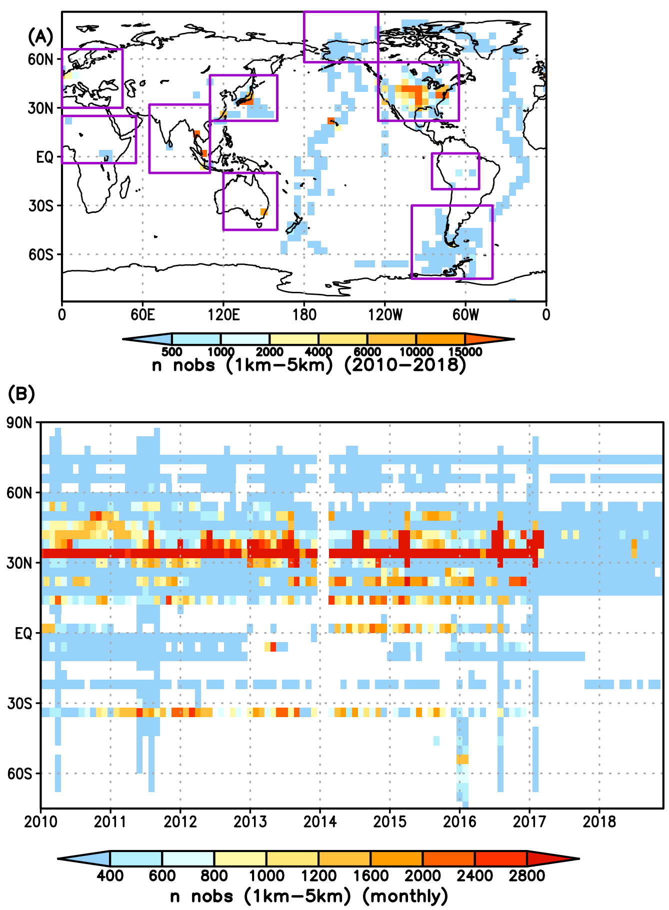



**Figure: 2 The spatial and temporal distributions of aircraft observations used in evaluation of posterior NBE. (A) The total number of aircraft observations between 1–5 km between 2010–2018 at each 4° x 5°grid point. The rectangle boxes show the range of the nine sub regions. (B) The total number of monthly aircraft observations at each longitude as a function of time**.

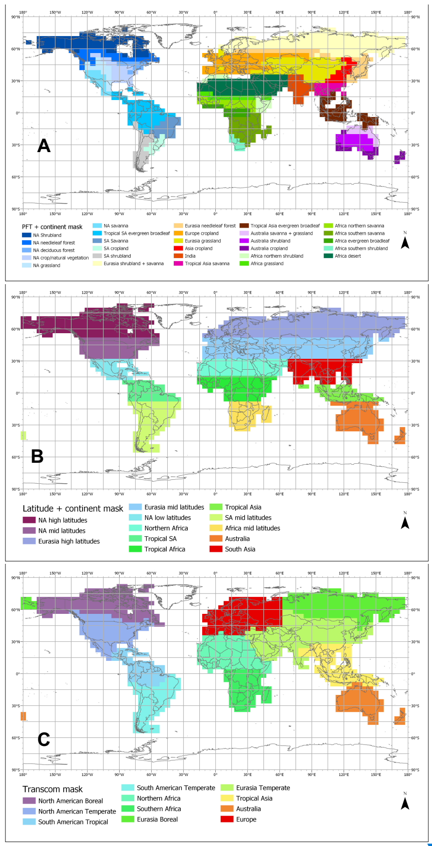
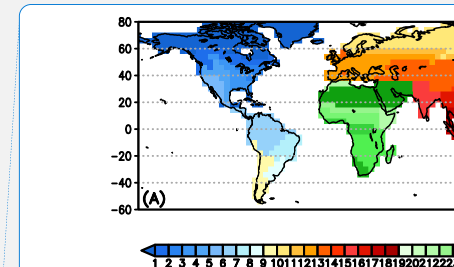



Figure: 3 Three types of regional masks used in calculating regional fluxes. The mask in the top panel is based on a combination of condensed seven MODIS IGBP plant functional types, TRANCOM-3 regions (Gurney et al., 2004), and continents. The mask in the middle panel is based on latitude and continents. The mask in the bottom panel is the TransCom region mask.




Deleted:

Formatted: Centered

Deleted: Two

Deleted: (A)

Deleted: (B)

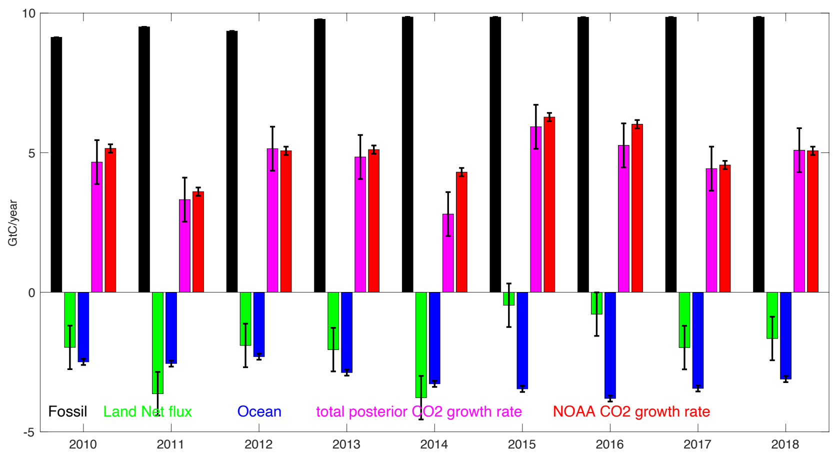



**Figure: 4 Global flux estimation and uncertainties from 2010 –2018 (black: fossil fuel; green: posterior land fluxes; blue: ocean fluxes; magenta: estimated $CO_2$ growth rate; red: the NOAA $CO_2$ growth rate).**

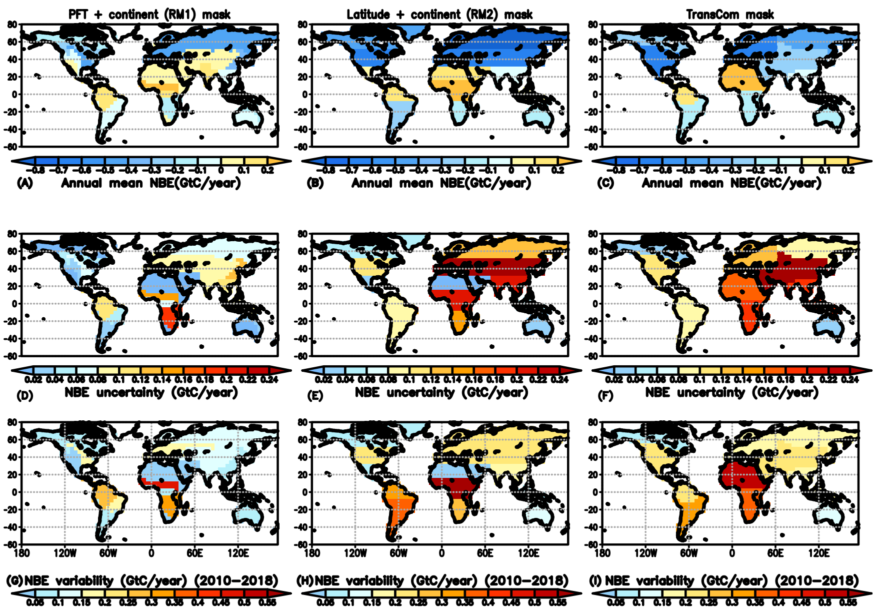



**Figure: 5 Mean annual regional NBE (A, B, and C), uncertainty (D, E, and F), and variability between 2010–2018 (G, H, and I) with the three types of regional masks (Figure 3). The first column uses a region mask based on PFT and continents (RM1). The second column uses a region mask based latitude and continents (RM2), and the third column uses TransCom mask.**

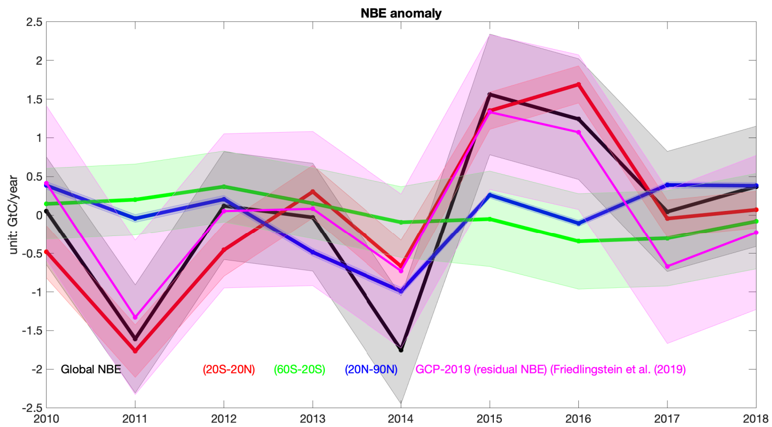
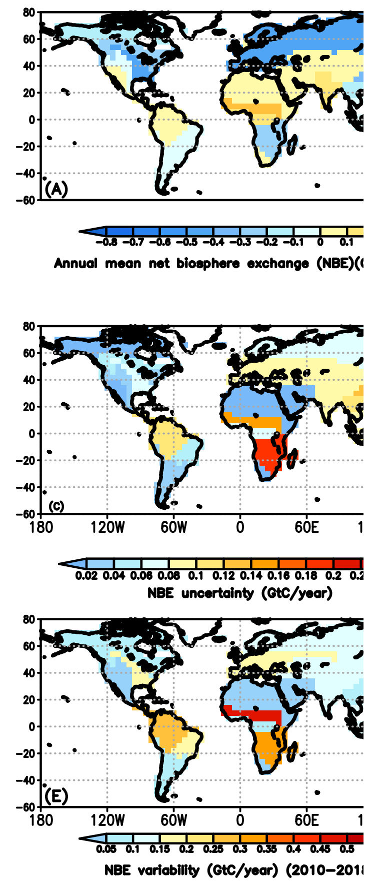



**Figure: 6 The NBE interannual variability over the globe (black), the tropics (20°S–20°N), SH mid-latitudes (60°S–20°S), and NH mid-latitudes (20°N–9°0N). For reference, the residual net land carbon sink from GCP (Friedlingstein et al., 2019) and its uncertainty is also shown (magenta).**




**Deleted:**
**Figure: 5 Mean annual regional NBE (A and B), uncertainty (C and D), and variability between 2010–2018 (E and F) with two types of regional masks.**

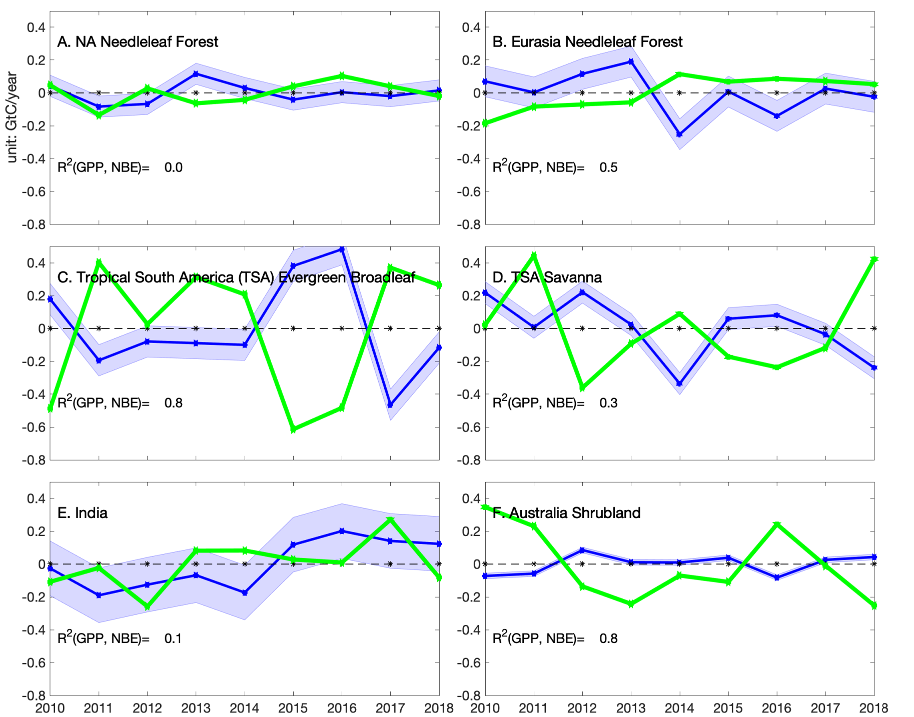
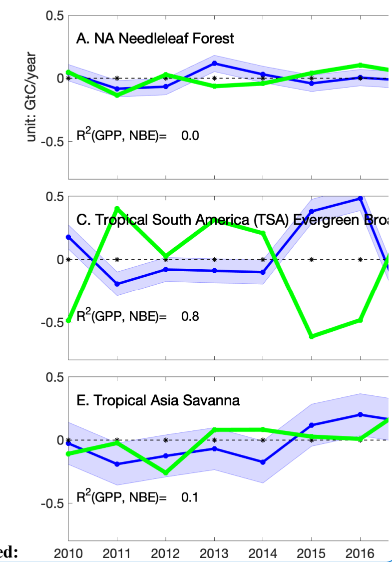



**Figure: 7 The NBE interannual variability over six selected regions. Blue: annual NBE anomaly and its uncertainties. Green: annual GPP anomaly based on FLUXSAT.**

**Deleted:**



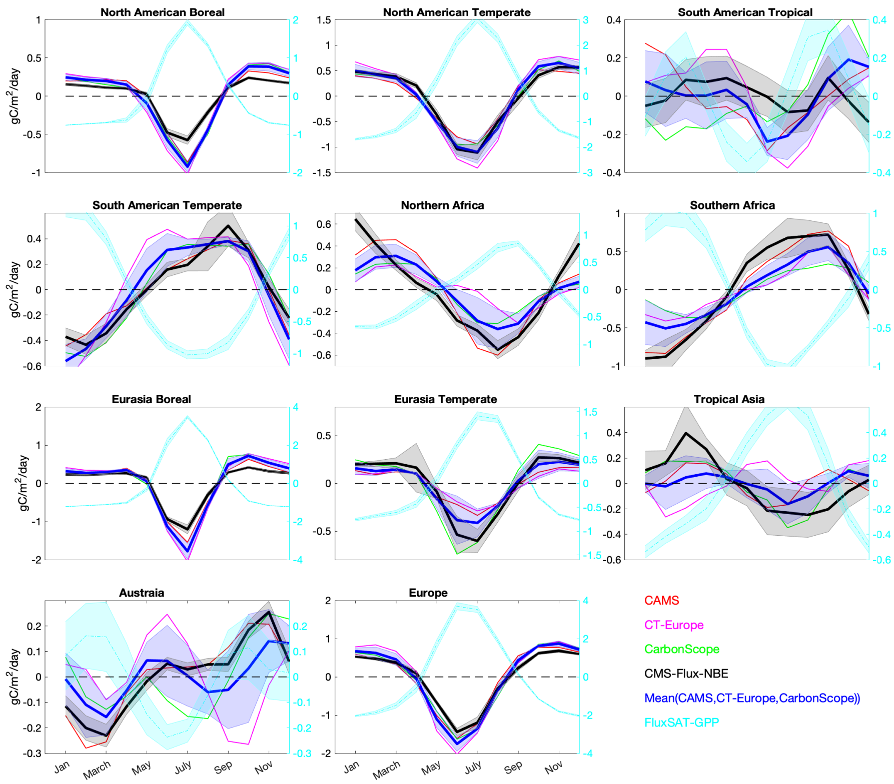
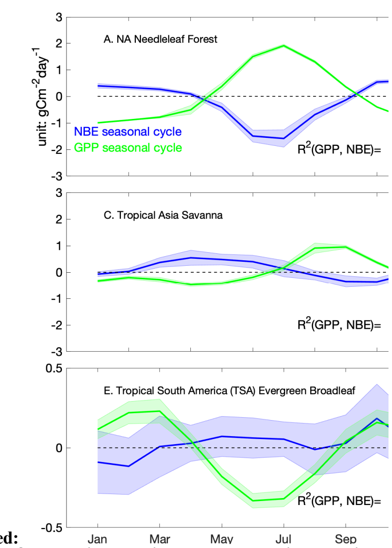



**Figure: 8 The NBE climatological seasonality over TransCom regions. The seasonal cycle is calculated over 2010-2017 since CT-Europe only covers till 2017. Black: CMS-Flux-NBE and its uncertainty; blue shaded: mean NBE seasonality based on surface $CO_2$ inversion results from CAMS, CT-Europe, and Jena CarbonScope; red: CAMS; magenta: CT-Europe; green: Jena CarbonScope. The names of each region are shown on individual subplots.**




**Deleted: Figure: 8 Blue: climatological NBE seasonality over six selected regions shown in Figure 3A; blue shaded: NBE monthly uncertainty and variability (1-sigma) over nine years. Green and shaded: monthly mean GPP and its variability (1-sigma) over nine years. The names of each region are shown on individual subplots.¶**

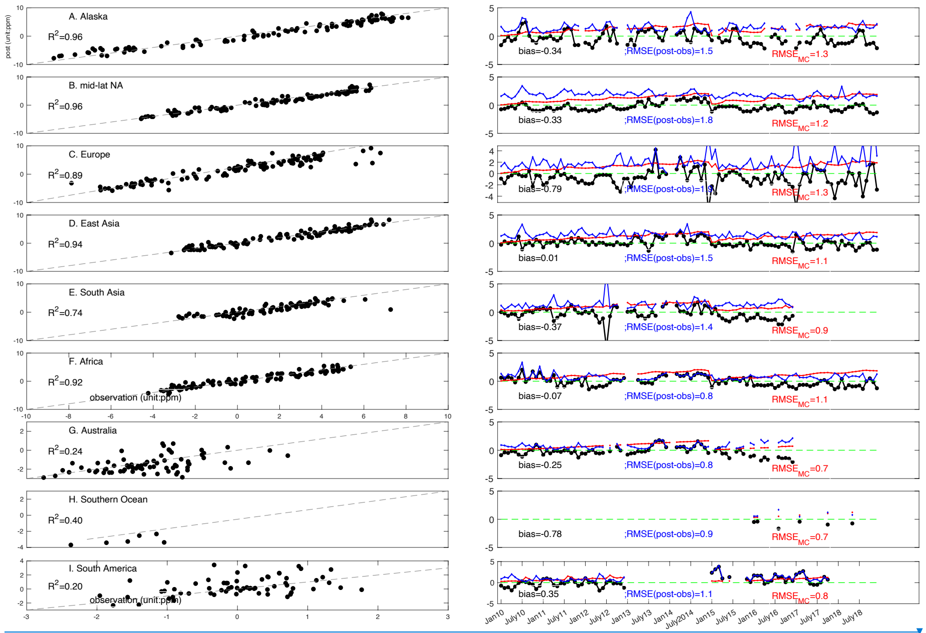
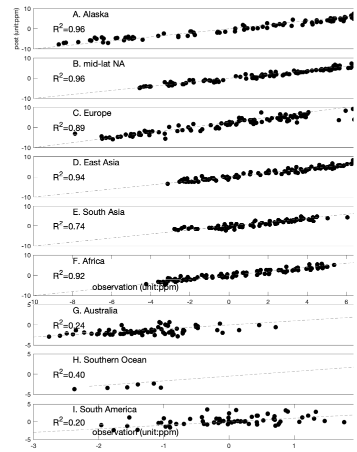



**Figure: 9 Comparison between posterior $CO_2$ mole fraction and aircraft observations. Left panel: detrended posterior $CO_2$ (y-axis) vs. detrended aircraft $CO_2$ (x-axis) over nine regions. The dashed line is 1:1 line; right panel: black: the differences between posterior $CO_2$ and aircraft $CO_2$ as a function of time; blue: RMSE (unit: ppm); red: $RMSE_{MC}$.**

**Deleted:**




**Deleted: The blue bar shows the number of aircraft observations (log scale) as a function of month.**

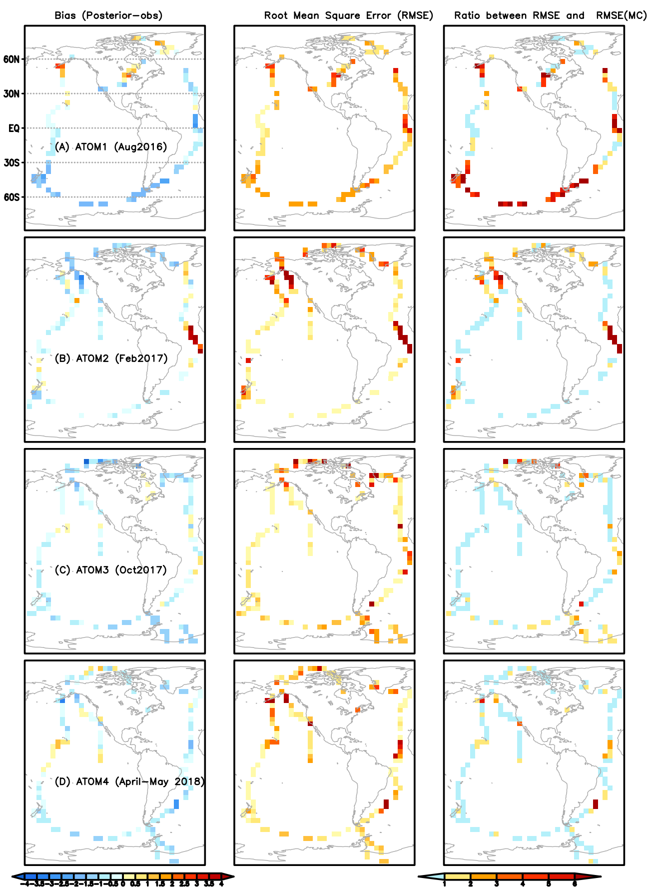
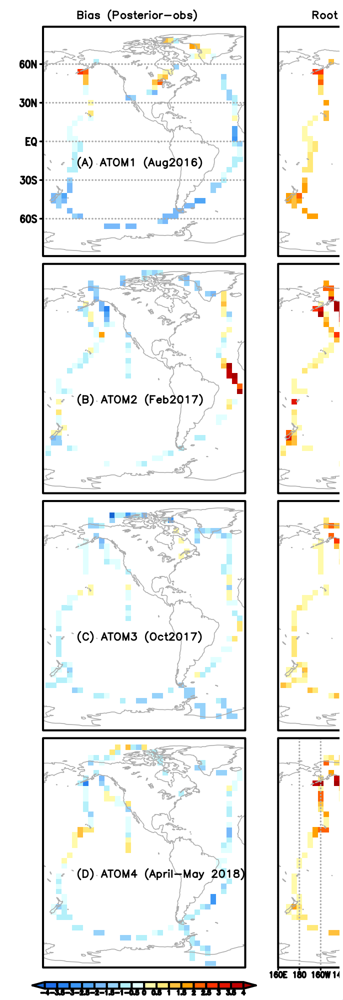
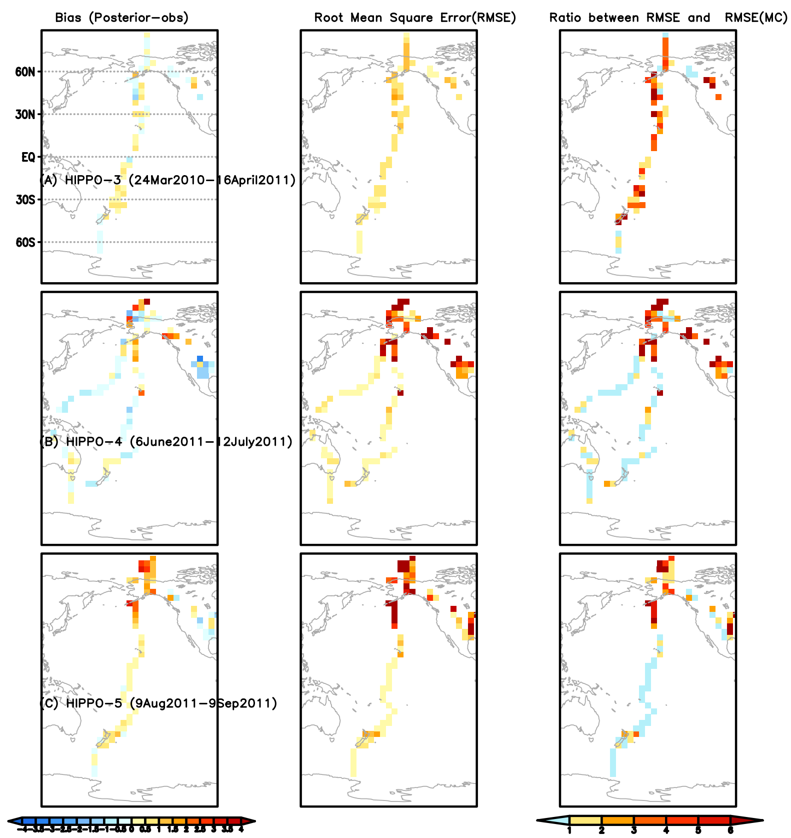



**Figure: 10 Left column: the mean differences between posterior $CO_2$ and aircraft observations from ATOM 1–4 aircraft campaigns between 1–5 km (A–D). Middle column: the Root Mean Square Errors (RMSE) between aircraft observations and posterior $CO_2$ between 1–5 km. The color bar is the same as the left column. Right column: the ratio between RMSE and $RMES_{MC}$ based on ensemble $CO_2$ from the Monte Carlo uncertainty estimation method.**

**Deleted:**






Deleted:

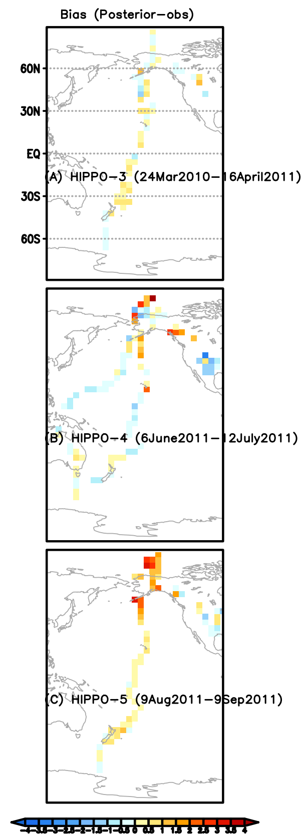



**Figure: 11 Left column: the mean differences between posterior $CO_2$ and aircraft observations from HIPPO 3-5 aircraft campaigns between 1–5 km (A–C) (unit: ppm). (unit: ppm). The time frame of each campaign is in the figure. Middle column: the Root Mean Square Errors (RMSE) between aircraft observations and posterior $CO_2$ between 1–5 km (unit: ppm). The color bar is the same as the left column. Right column: the ratio between RMSE and $RMSE_{MC}$ based on ensemble $CO_2$ from the Monte Carlo method.**

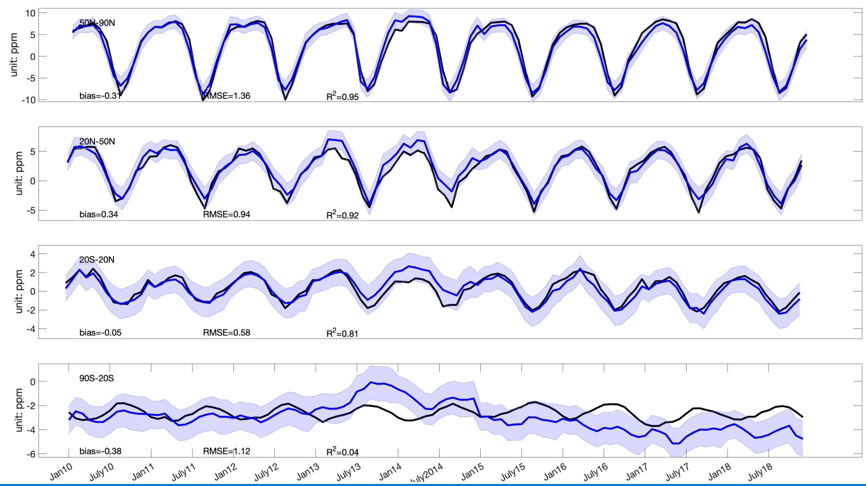



**Figure: 12 Comparison between posterior $CO_2$ and the NOAA marine boundary layer (MBL) reference sites. Black: observations averaged over each latitude bands; blue and shaded area: posterior $CO_2$ and its uncertainty. The global mean $CO_2$ (https://www.esrl.noaa.gov/gmd/ccgg/trends/global.html ) was subtracted from both the NOAA MBL reference and posterior $CO_2$ before the comparison.**

**Formatted:** Justified

**Table: 1 Configurations of the CMS-Flux atmospheric inversion system**

| | Model setup | Configuration | Reference |
|---|---|---|---|
| **Inversion general setup** | Spatial scale | Global | -- |
| | Spatial resolution | 4° latitude x 5° longitude | |
| | Time resolution | monthly | |
| | Minimizer of cost function | L-BFGS | Byrd et al., 1994; Zhu et al., 1997 |
| | Control vector | Monthly net terrestrial biosphere fluxes and ocean fluxes | |
| **Transport model** | Model name | GEOS-Chem and its adjoint | Suntharalingam et al., 2004<br>Nassar et al., 2010<br>Henze et al., 2007 |
| | Meteorological forcing | GEOS-5 (2010–2014) and GEOS-FP (2015–2019) | Rienecker et al., 2008 |

**Table: 2 Description of the prior fluxes and assumed uncertainties in the inversion system**

| Prior fluxes | Terrestrial biosphere fluxes | Ocean fluxes | Fossil fuel emissions |
|---|---|---|---|
| **Model name** | CARDAMOM-v1 | ECCO-Darwin | ODIAC 2018 |
| **Spatial resolution** | 4° x 5° | 0.5° | 1° x 1° |
| **Frequency** | 3-hourly | 3-hourly | hourly |
| **Uncertainty** | Estimated from CARDAMOM | 100% same as Liu et al. (2017) | No uncertainty |
| **References** | Bloom et al., 2006; 2020 | Brix et al, 2015; Carroll et al., 2020 | Oda et al., 2016; 2018 |

**Table: 3 Description of observation and evaluation dataset. Data sources are listed in Table 7.**

| | Dataset name and version | References |
|---|---|---|
| Satellite $X_{CO2}$ | ACOS-GOSAT v7.3 | O'Dell et al., (2012) |
| | OCO-2 v9 | O'Dell et al., (2018) |
| Aircraft $CO_2$ observations | ObsPack OCO-2 MIP | CarbonTracker team (2019) |
| | HIPPO 3-5 | Wofsy et al. (2011) |
| | ATom 1-4 | Wofsy et al. (2018) |
| | INPE | Gatti et al., (2014) |
| | ORCAS | Stephens et al. (2017) |
| NOAA marine boundary layer (MBL) reference | NOAA MBL reference | Conway et al., 1994 |
| GPP | FLUXSAT-GPP | Joiner et al., (2018) |
| Top-down NBE estimates constrained by surface $CO_2$ | CarbonTracker-Europe | van der Laan-Luijkx et al. (2017)<br>Peters et al., (2010)<br>Peters et al. (2007) |
| | Jena CarbonScope s10oc_v2020 | Rödenbeck et al., 2003 |
| | CAMS v18r1 | Chevallier et al., 2005 |

**Table: 4 Latitude and longitude ranges for seven sub regions.**

| Region | Alaska | Mid-lat NA | Europe | East Asia | South Asia |
|---|---|---|---|---|---|
| **Longitude range** | 180°W–125° W | 125°W–65°W | 5°W–45°E | 110°E–160°E | 65°E–110°E |
| **Latitude range** | 58°N–89°N | 22°N-58°N | 30°N–66°N | 22°N–50°N | 10°S–32°N |
| **Region** | Africa | South America | Australia | Southern Ocean | |
| **Longitude range** | 5°W–55°E | 95°W–50°W | 120°E–160°E | 110°W–40°E | |
| **Latitude range** | 2°N–18°N | 20°S–2°N | 45°S–10°S | 80°S–30°S | |

**Deleted: Table: 3 Description of observation and evaluation dataset. Data sources are listed in Table 7.** ... [1]

**Table: 5 List of the data products.**

Deleted: ¶

| **Product** | **Spatial resolution** | **Temporal resolution when applicable** | **Data format** | **Sample data description in the text** |
|---|---|---|---|---|
| **Total fossil fuel, ocean, and land fluxes** | Global | Annual | *csv* | Figure 4 (section 4.1) |
| **Climatology mean NBE, variability, and uncertainties** | PFT and continents based 28 regions | N/A | *csv* | Figure 5 (section 4.2) |
| | Geographic-based 13 regions | | *csv* | |
| | TransCom regions | | *csv* | |
| **Hemispheric NBE and uncertainties** | NH (20°N-90°N), tropics (20°S-20°N), and SH (60°S-20°S) | Annual | *csv* | Figure 6 (section 4.3) |
| **NBE variability and uncertainties** | PFT and continents based 28 regions | Annual | *csv* | Figure 7 (section 4.3) |
| | Geographic -based 13 regions | | *csv* | |
| | TransCom regions | | *csv* | |
| **NBE seasonality and its uncertainties** | PFT and continents based 28 regions | Monthly | *csv* | Figure 8 (section 4.4) |
| | Geographic -based 13 regions | | *csv* | |
| | TransCom regions | | *csv* | |
| **Monthly NBE and uncertainties** | PFT and continents based 28 regions | Monthly | *csv* | N/A |
| | Geographic -based 13 regions | | *csv* | |
| | TransCom | | *csv* | |
| **Gridded posterior NBE, air-sea carbon exchanges, and uncertainties** | 4° (latitude) x 5° (longitude) | Monthly | *NetCDF* | N/A |
| **Gridded prior NBE and air-sea carbon exchanges** | 4° (latitude) x 5° (longitude) | Monthly and 3-hourly | *NetCDF* | N/A |
| **Gridded fossil fuel emissions** | 4° (latitude) x 5° (longitude) | Monthly mean and hourly | *NetCDF* | N/A |
| **Region masks** | PFT and continents based 28 regions | N/A | csv | Figure 3 (section 2.4) |
| | Geographic -based 13 regions | | | |
| | TransCom regions | | | |

**Table: 6 The nine-year mean regional annual fluxes, uncertainties, and variability. Regions are based on the mask shown in Figure 5A (Figure 5.csv). Unit: GtC/year**

| Region name (Figure4.csv) | Mean NBE | Uncertainty | Variability |
|---|---|---|---|
| NA shrubland | -0.14 | 0.02 | 0.05 |
| NA needleleaf forest | -0.22 | 0.04 | 0.06 |
| NA deciduous forest | -0.2 | 0.04 | 0.07 |
| NA crop natural vegetation | -0.41 | 0.06 | 0.18 |
| NA grassland | -0.04 | 0.03 | 0.03 |
| NA savannah | 0.03 | 0.02 | 0.03 |
| Tropical South America (SA) evergreen broadleaf | 0.04 | 0.1 | 0.28 |
| SA savannah | -0.09 | 0.06 | 0.18 |
| SA cropland | -0.07 | 0.03 | 0.07 |
| SA shrubland | -0.03 | 0.02 | 0.08 |
| Eurasia shrubland savanna | -0.44 | 0.07 | 0.14 |
| Eurasia needleleaf forest | -0.41 | 0.07 | 0.12 |
| Europe cropland | -0.46 | 0.09 | 0.16 |
| Eurasia grassland | 0.02 | 0.08 | 0.13 |
| Asia cropland | -0.37 | 0.13 | 0.08 |
| India | 0.14 | 0.09 | 0.14 |
| Tropical Asia savanna | -0.12 | 0.11 | 0.08 |
| Tropical Asia evergreen broadleaf | -0.09 | 0.09 | 0.12 |
| Australia (Aus) savannah grassland | -0.11 | 0.02 | 0.09 |
| Aus shrubland | -0.07 | 0.01 | 0.05 |
| Aus cropland | -0.01 | 0.01 | 0.03 |
| African (Afr) northern shrubland | 0.04 | 0.02 | 0.03 |
| Afr grassland | 0.03 | 0.01 | 0.01 |
| Afr northern savanna | 0.54 | 0.15 | 0.49 |
| Afr southern savanna | -0.27 | 0.18 | 0.33 |
| Afr evergreen broadleaf | 0.1 | 0.07 | 0.09 |
| Afr southern shrubland | 0.01 | 0.01 | 0.01 |
| Afr desert | 0.06 | 0.01 | 0.04 |

**Deleted: Table: 5 List of the data products.**
**Product** ... [2]

**Table: 7 Lists of data sources used in producing and evaluating posterior NBE product.**

| Data name | Data Source |
|---|---|
| ECCO-Darwin ocean fluxes | https://doi.org/10.25966/4v02-c391 |
| CARDAMOM NBE and uncertainties | https://doi.org/10.25966/4v02-c391 |
| ODIAC | http://db.cger.nies.go.jp/dataset/ODIAC/DL_odiac2019.html |
| GOSAT b7.3 | https://oco2.gesdisc.eosdis.nasa.gov/data/GOSAT_TANSO_Level2/ACOS_L2S.7.3/ |
| OCO-2 b9 | https://disc.gsfc.nasa.gov/datasets?page=1&keywords=OCO-2 |
| ObsPack | https://www.esrl.noaa.gov/gmd/ccgg/obspack/data.php |
| ATom 1-4 | https://daac.ornl.gov/ATOM/guides/ATom_merge.html |
| HIPPO 3-5 | https://www.eol.ucar.edu/field_projects/hippo |
| INPE | https://www.esrl.noaa.gov/gmd/ccgg/obspack/data.php?id=obspack_co2_1_INPE_RESTRICTED_v2.0_2018-11-13 and |
| FLUXSAT-GPP | https://gs614-avdc1-pz.gsfc.nasa.gov/pub/tmp/FluxSat_GPP/ |
| NOAA MBL reference | https://www.esrl.noaa.gov/gmd/ccgg/mbl/index.html |
| CarbonTracker-Europe NBE | https://www.carbontracker.eu/download.shtml |
| Jena CarbonScope NBE | http://www.bgc-jena.mpg.de/CarboScope/?ID=s |
| CAMS NBE | https://apps.ecmwf.int/datasets/data/cams-ghg-inversions/?date_month_slider=2009-12,2018-12&param=co2&datatype=ra&version=v17r1&frequency=mm&quantity=surface_flux |
| Posterior NBE | https://doi.org/10.25966/4v02-c391 |

Deleted:

**Table: 6 The nine-year mean regional annual fluxes, uncertainties, and variability. Regions are based on the mask shown in Figure 5A (Figure 5.csv). Unit: GtC/year**
**Region name (Figure4.csv)** ... [3]

| | | |
|---|---|---|
| **Page 55: [1] Deleted** | **Liu, Junjie (US 329G)** | **9/30/20 10:47:00 AM** |
| **Page 57: [2] Deleted** | **Liu, Junjie (US 329G)** | **9/30/20 10:48:00 AM** |
| **Page 58: [3] Deleted** | **Liu, Junjie (US 329G)** | **9/30/20 10:49:00 AM** |