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Interactive comment on "Characterizing biospheric carbon balance using CO_2 observations from the OCO-2 satellite" *by* Scot M. Miller et al.

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We would like to thank the reviewer for ideas and suggestions for the manuscript. This feedback will be very helpful for updating and improving the manuscript. Below, we have included both the reviewer's suggestions (in bold) along with the associated changes we plan to make.

- **I found it particularly difficult to follow the logic of the paper and to evaluate the soundness of the approach. As a preliminary step for publication, the authors should seriously invest in making their study accessible to the**

broad audience of ACP.

This is very helpful feedback for framing the paper and describing the components of the methodology. We plan to re-frame the paper logic in several ways to make it more accessible to a broad audience. First, we plan to expand the overall description of the paper and description of the general approach at the end of the introduction (pg. 2, line 28 to pg. 3, line 21). We will describe the paper narrative in non-technical terms to give the reader an intuitive, high-level overview of the paper logic and flow. This description would provide better intuition for a wide audience of readers, especially those readers who may skip over the more technical information in the methodology (sect. 2).

Second, we will simplify the methods section (sect. 2) so that it is accessible to a broad audience. For example, this section contains seven equations. We will move several of these equations to the SI (e.g., Eq. 4-7) and instead expand the non-technical portions of the description. In this way, the paper will still include all of the technical detail for readers who want it, but the description in the main paper will be accessible to a broader audience.

Third, we will provide more references to existing studies that use similar approaches. Readers who are interested in more details on the methodology could gain greater context using these references. We will make this change throughout the manuscript and particularly from pg. 6, line 10 to pg. 7, line 20.

- **The paper concludes to a limited utility of OCO-2 retrievals for flux estimation with current retrieval algorithms and transport model. This may be correct, but is orthogonal to the claim made by Liu et al. (2017). The disagreement should be clearly stated.**

  We will discuss this difference in the revised version of the manuscript. Liu et al. (2017) was published after this ACPD manuscript, so it is only now possible to make this comparison. Liu et al. use an atmospheric inversion to estimate

CO_2 fluxes for different tropical regions of the globe. They estimate uncertainties in their regional budget estimates, and those uncertainties are generally smaller than implied by the current ACPD manuscript.

Liu et al. (2017) use a 4DVAR approach and estimate the posterior uncertainties using a small number of Monte Carlo simulations. However, these uncertainty estimates are likely to be underestimates – due to compromises required to make the inversion computationally tractable. For example, most satellite-based inversions like Liu et al. (2017) do not fully account for error correlations or biases in the observations and atmospheric model; these studies typically use a diagonal error covariance matrix. Furthermore, Liu et al. (2017) and other studies use a small number of Monte Carlo simulations to estimate the errors (e.g., 60 simulations in Liu et al. (2014)). By contrast, Ribgy et al. (2011) and Ganesan et al. (2014) argue that 100,000 and 25,000 realizations are necessary to robustly estimate uncertainties for their particular inverse modeling problems. Note that it is not always possible to generate large numbers of realizations or fully account for error correlations in current satellite-based inverse models due to computational constraints. In the ACPD manuscript, we do not use a 4DVAR inverse model for this reason.

Consistent with this interpretation, results from the OCO-2 flux team ongoing intercomparison study indicate much larger uncertainties in estimated fluxes. The results are broadly consistent with those presented in the current ACPD manuscript (e.g., Crowell et al. 2017); preliminary results indicate that OCO-2 observations currently provide robust constraints for hemispheric regions but provide weaker constraints for individual continents or subcontinents. More specifically, recent flux team comparisons include CO_2 flux estimates from about eight different inverse modeling groups, and the level of disagreement among these estimates provides a measure of uncertainty in current top-down flux estimates that use the same version of the OCO-2 retrievals as applied in the current work

and in Liu et al. (2017). These estimates (using nadir observations) often show relatively good agreement for total hemispheric terrestrial CO_2 budgets, with the disagreement among inverse modeling estimates being smaller than the total CO_2 budget for a given hemisphere. The opposite is often true of CO_2 budgets estimated for smaller regions (e.g., Sub-Saharan Africa or Tropical Asia), with the disagreement among inverse modeling estimates usually being larger than the total budget. This ongoing work is consistent with the interpretation in the current manuscript.

- **Section 3.1 and the first part of Section 3.3 reinvent the wheel. See, e.g., Olsen and Randerson (2004) and Worden et al. (2017). Similarly, l. 23-28 are just an adaptation of an old argument (Rayner and O'Brien, 2001).**

The studies mentioned above investigate several requirements for constraining carbon budgets with satellite observations. Rayner and O'Brien (2001) explore the measurement precision required for space-based constraints on surface CO_2 fluxes. Olsen and Randerson (2004) model XCO_2 column enhancements across the globe due to surface CO_2 fluxes and compare them with surface enhancements. Lastly, Worden et al. (2017) estimate the errors in OCO-2 XCO_2 observations.

As the reviewer points out, the concepts used in Sects. 3.1 and 3.3 are, in part, built on these earlier approaches. However, the purpose of this section is not to develop new concepts. Rather, we build on existing concepts to assess real OCO-2 data. Rayner and O'Brien (2001) and Olsen and Randerson (2004), by contrast, did not have any real XCO_2 observations at their disposal, only simulations of possible future observations. Furthermore, we feel that these sections provide useful context and improve the manuscript narrative. Much of the manuscript presents the results of statistical experiments. These experiments use, as inputs, XCO_2 observations from OCO-2 and estimates of atmospheric transport and satellite retrieval errors. Sect. 3.1 provides visualizations of those inputs.

In the revised manuscript, we will cite the studies listed above, clarify that we use concepts from the studies, and explain that we apply those concepts to real observations from OCO-2. We will also compare the retrieval errors in Sect. 3.1 against those in Worden et al. (2017). Lastly, we will shorten the first part of Sect. 3.3. That section presents the synthetic study results with no errors; these results serve as a baseline for subsequent results that do include simulated errors.

- **The retrieval error simulations of Fig. 3 look overly optimistic in comparison to the validation results of Wunch et al. (2017).**

  Wunch et al. (2017) compare OCO-2 XCO_2 retrievals against XCO_2 observations at TCCON sites (the Total Column Observing Network). They report an average site bias of 0.22 ppm for comparisons between land nadir retrievals and TCCON sites. They also report an average root mean squared error of 1.31 ppm for the land nadir and TCCON comparisons (Table 3 in Wunch et al. 2017).

  The errors in Fig. 3c-3f do appear slightly smaller than the numbers reported above. However, the errors in Fig. 3 are the mean of individual sounding errors in February and July, respectively – meaned within each PCTM grid box for an entire month. Hence, the errors displayed in this plot will be somewhat smaller than the errors on individual soundings (as reported in Wunch et al. 2017). By contrast, Fig. 1 shows the standard deviation of the estimated retrieval errors (instead of the mean as in Fig. 3). These standard deviations are larger than the mean and broadly consistent with the errors estimated by Wunch et al. (2017).

  In the revised manuscript, we will clarify that the errors displayed in Fig. 3 are monthly means. Furthermore, we will compare and contrast the estimated errors with those estimated in Wunch et al. (2017) and in Worden et al. (2017).

- **Section 3.2 looks for flux patterns in XCO_2. Most top-down studies from OCO-2 would use a Bayesian approach where flux-error patterns are looked**

for. This is more challenging because the signal is even smaller (while the paragraph in-between p. 5 and p. 6 suggests that the two approaches are rather equivalent with respect to the measurement information content). One should therefore discuss this limitation and further tone down the conclusions of the paper.

The reviewer makes a great point, and we will add a discussion of this point to Sects. 2.2 (pgs. 5-6) and 3.2. The approach used here searches for flux patterns as they manifest in XCO_2. Phrased differently, the approach examines s as seen through the OCO-2 observations, where s are the fluxes. A Bayesian approach, by contrast, estimates $s - s_p$, where s_p is the prior flux estimate. This residual flux ($s - s_p$) is presumably smaller than the total flux (s). As a result, inversions essentially estimate a smaller flux signal than the flux signal examined in this study.

The reviewer's argument could therefore imply more pessimistic results than presented in the current manuscript – that the CO_2 flux constraint is weaker than reported in the present study. This issue, however, may also be more nuanced. If the prior estimate is poor, the residual flux ($s - s_p$) will be large. These large flux patterns should be relatively easy to detect using XCO_2 observations, but the inversion will need to rely heavily on the XCO_2 observations (and not on the prior) to make a robust posterior estimate. By contrast, if the prior estimate is very accurate, the residual flux ($s - s_p$) will be small. The inversion will need to estimate a small flux signal, a signal that may be difficult to parse using XCO_2 observations. However, the posterior flux estimate will still be relatively robust due to the accurate prior.

Furthermore, this issue is specific to the setup of each individual inverse model. For example, existing CO_2 inversions use a wide variety of prior flux models. Mueller et al. (2008) use a non-informative prior (i.e., a flat prior) that contributes little information on the fluxes. In addition, many geostatistical inverse modeling studies use environmental driver data in place of a tradition prior flux estimate (e.g., Gourdji et al. 2008; 2012). These studies choose environmental driver data using a model selection approach in a manner that is somewhat akin to the current ACPD manuscript. In the present study, we instead try to examine more fundamental questions about the robustness of the flux constraint, questions that are independent of subjective choices specific to each inverse model setup.

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