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Atmospheric Chemistry and Physics Discussions

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 providing ideas and suggestions. These suggestions will be very helpful as we revise the manuscript. Below, we have listed each of the reviewer's comments (in bold) and the associated changes we plan to make to the manuscript.

- **In Figure 3 the single sounding error of OCO-2 is compared to the signal from uncertainties in biospheric CO2 fluxes. The question is if this comparison makes much sense, since the error budget of OCO-2 has a large**

random component. The impact of biospheric flux uncertainties is more coherent in space and time, i.e. has very different statistics. Because of this the signal/noise ratio could look very different after space-time averaging of the data.

  Figure 3 in the current ACPD manuscript shows the mean of all soundings in each PCTM model grid box for February and July, respectively. Reviewer 1 brought up this question as well, and we will clarify this point in the revised manuscript.

  As the reviewer points out, the signal-to-noise ratio in Fig. 3 will vary depending on space-time averaging. With that said, many inverse modeling studies report monthly CO_2 flux totals, so the monthly averaging in Fig. 3 is particularly pertinent. Furthermore, the uncertainties in top-down CO_2 flux estimates change when averaged to aggregate space-times scales, so this issue is also a consideration in inverse modeling, not just the analysis in Fig. 3.

  We will revise the discussion of Fig. 3 in several ways to account for the reviewer's suggestion. First, we will explain that the signal-to-noise ratio varies depending upon the space and time scales considered, and we will explain why this monthly scale is a particularly useful time period to examine. Second, we will emphasize that this signal-to-noise ratio provides a useful intuition or feel for the data, but we will point out that top-down inverse models leverage the signal in much more sophisticated ways. The limitations of this signal-to-noise comparison thus motivate subsequent analyses in the manuscript.

- **It is not clear to me what fraction of the flux uncertainty space is spanned by the flux patterns that are used in the regression. Probably many of the patterns are not independent, in which case it is not a surprise that many are not selected. This probably goes back to the question whether the range of estimates of the underlying models provides a fair estimate of the overall uncertainty. This is not easy to prove, but with only a single ocean pattern and a single anthropogenic emission pattern it seems conceivable that the**

uncertainty space is underestimated (by the way, how about uncertainties in land-use change?). Some discussion is needed of how such factors may influence the results, and what the implication could be for the estimated OCO-2 performance.

This factor can influence the results, and we will add a discussion of this point to the manuscript. We explore this possibility in the synthetic data experiments (Fig. 5b in the ACPD manuscript). In that experiment, we create synthetic XCO_2 observations using the SiBCASA flux model and an atmospheric transport model. We then run model selection, but we do not include SiBCASA as a possible predictor variable in the regression. In other words, model selection can include several different terrestrial biosphere models (TBMs) in the regression, but it cannot include the TBM that was used to generate the synthetic data in the first place. Fig. 5b in the current ACPD manuscript shows the result. Model selection does not select patterns in every region and every month, but it still selects flux patterns for most regions and months.

This issue also affects Bayesian inverse models. These inversions use a prior flux estimate as an initial guess for the fluxes. If the prior flux estimate is inaccurate, the prior error covariance matrix will have large variances/covariances, and the posterior uncertainties will likely be large. If the prior flux estimate is skilled, the prior error covariance matrix will have small variances/covariances, and the posterior uncertainties will be smaller. In other words, the availability and skill of prior flux models (i.e., TBMs) affects the robustness and uncertainty of the inverse modeling estimate.

- **SPECIFIC COMMENTS**

- **page 1, line 23: 'unlike previous missions' .. but this was the case also for GOSAT and SCIAMACHY.**

  We will change the text accordingly. In the revised text, we will remove the

phrase “Unlike previous missions” and briefly explain the similarities and differences among OCO-2, GOSAT, and SCIAMACHY.

- **page 2, line 12: references are needed to the recent special issue on OCO-2 in Science.**

  We will rewrite this paragraph and discuss studies from the new *Science* special issue. This special issue was published after the present ACPD manuscript, and it is now possible to reference these papers in the manuscript.

- **page 3, line 17-20: unless 'region' is defined more quantitatively these sentences are too vague.**

  We will revise these sentences accordingly. In response to feedback from reviewer 1, we plan to re-write the second half of Sect. 1 to describe the overall objectives and approach in a way that is more accessible to a broad audience. To that end, we will more concisely define the word “region”.

- **page 3, line 19-23: Explain the motivation for this second approach? Is one considered to be more realistic than the other?**

  We will clarify the text in this paragraph. We do not consider one approach to be more accurate than another per se. Rather, it is challenging to estimate realistic retrieval errors because these errors are unknown (except possibly at TCCON sites). We asked several colleagues for advice on how to estimate these errors, and different colleagues recommended different approaches that produce different retrieval error estimates. As a result, we decided to use two different retrieval error estimates – to ensure that the results were not contingent upon the specific method used.

- **page 5, line 9: the constant fluxes need to be defined more quantitatively. What did you use? The same flux for each region and month? Are they**

estimated per region? Does it mean that the regressed flux patterns have zero mean? If so please mention.

We will clarify this topic in the manuscript, and we will define these constant terms more quantitatively.

The constant flux is estimated for each region and each month. This constant flux is included as a predictor variable in the regression, and the regression framework scales the magnitude of the constant flux in each region and month to match the observations.

Equations 1 and 2 in the manuscript describe the overall regression and illustrate these relationships quantitatively:

$\mathrm{Y} = h(\mathbf{X})$

$z = \mathbf{Y}\beta + \epsilon$

where $\mathbf{X}$ are the predictor variables in the regression, $h()$ is the atmospheric transport model, z are the observations, β are the coefficients estimated by the regression, and ϵ are the regression residuals. In this setup, the constant flux terms are individual columns in $\mathbf{X}$. Each column has a value of one in a given region and month and has values of zero elsewhere. Phrased differently, these constant flux terms are analogous to the y-intercept terms in the regression. Also of note, the regression residuals ϵ have a mean of zero, but the regressed flux patterns will not have a zero mean.

We will make several changes to clarify this topic in the manuscript. We will move Eqs. 1-2 earlier in Sect. 2.2 and describe these equations alongside the description of the constant or intercept terms. In response to reviewer 1, we will move several equations to the SI and simplify the description in Sect. 2.2. Instead, we will dedicate more description to Eqs. 1-2 and will explain how the different predictor variables (including the constant or intercept terms) fit into these equations.

- **page 7, line 25: should we conclude that OCO-2's glint mode retrievals do not provide significant independent information?**

  We will provide additional discussion of this point in the manuscript. The statement above may be too bold to make in the manuscript, especially in context of the reviewer's next suggestion below. Furthermore, the OCO-2 nadir and glint observations have different biases in the version 7 OCO-2 data product (the product used in this manuscript), and these differing biases make it difficult to use both types of observations in the same analysis. For example, there is a step change in the XCO_2 observations at the coastline in some locations (e.g., in parts of Africa). In these cases, the nadir mode observations may be sensitive to flux patterns, and the glint mode observations might be sensitive to flux patterns. However, an inverse model that uses both observation types together might produce unrealistic flux patterns due to the step change in XCO_2 at the coastline.

- **page 8, line 18: I would argue that the ocean is too strongly constraint by allowing only a single pattern to be adjusted in the regression. If more degrees of freedom would be assigned to the ocean, wouldn't that influence OCO-2's flux resolving performance over land?**

  We will add this caveat to the manuscript. If there are large, unresolved CO_2 fluxes from the ocean, it could influence top-down inferences of terrestrial biospheric fluxes. With that said, ocean fluxes on sub-daily time scales are much smaller than terrestrial fluxes, and the spatial patterns in these fluxes are much more diffuse than in most terrestrial regions. As a result, small errors in the distribution of marine CO_2 fluxes should not dramatically change the detectability of terrestrial fluxes.

- **page 8, line 21: this means that the biospheric flux patterns are specified per region and month, or?**

  This is correct. We tag CO_2 fluxes from each region and each month in the

PCTM atmospheric transport model. In other words, we incorporate flux patterns into PCTM at the PCTM model resolution; the model ingests CO_2 fluxes at a 1° latitude by 1.25° longitude spatial resolution and 3-hourly time resolution (Sect. 2.4 of the current ACPD manuscript). We then run the PCTM model once for each region and each month of interest. For each of these PCTM runs, we input flux patterns for the region and month of interest and zero out CO_2 fluxes for other regions and months. We will clarify that point in the associated paragraph of the revised manuscript.

- **page 8, line 27: 'stringent' in what sense? (I'd say they are rather less well contraint)**

  We agree that "stringent" is not be the best or most descriptive word here. We will replace the word "stringent" with the following phrase: "This case is more demanding of the observations than the two and four region cases; it is more difficult to obtain a robust constraint for seven regions than for two or four global regions."

- **page 8, line 31: Would this goal be achieved if the 7 biomes could be resolved by OCO- 2? Some quantitative information on how to relate surface and satellite measurements is needed here.**

  We will remove this sentence from the revised manuscript. Fang et al. (2014) examine CO_2 fluxes for North American biomes while the present ACPD manuscript focuses on global biomes. Hence, the two studies are not equivalent.

- **page 9, line 26-32: Should the reader conclude from this that we don't know whether the signal/noise analysis in figure 3 means anything?**

  We think that interpretation would be too bold. We feel that the signal/noise analysis provides useful context; it is useful to show the reader what the biospheric XCO_2 signal looks like, how it varies across the globe, and how it varies by month.

The results in Sect. 3.2 and 3.3 are based on a statistical model, and we wanted to provide an intuitive illustration of the signal and noise before presenting statistical results that use those inputs.

- **page 10, line 16: 'scales smaller than hemispheric in about half of the cases'. How can you infer information about hemispheres from a split between Tropics and Extra Tropics? The way I look at it only a single pattern is selected in 3 out of 4 seasons. Is that sufficient to resolve two pieces of information? The text suggests that OCO-2 does better than 2 ...**

  The reviewer makes a good point. A pattern is selected in approximately half of the regions and months. However, in three of the four seasons, not a single pattern is selected for one of the two hemispheres. We will add this description to the text to better represent the results.

- **page 10, line 18: 'we choose flux patterns ...' does this mean 1 or more?**

  This statement is correct. We will revise this paragraph accordingly by changing "flux patterns" to "at least one flux pattern."

- **page 10, line 32: Why is n* going down with the number of regions? Wouldn't you expect the residuals to become more random when fitting more regions? Shouldn't that make V more diagonal?**

  There are more unexplained flux patterns in the 7-region case – because model selection selects fewer variables than in the two or four region cases. As a result, the regression residuals have large covariances, and $\mathbf{V}$ is less diagonal. The variable n^* is smaller as a result.

  A brief overview of the regression helps elucidate why this is the case. The regression is iterative. We make an initial guess for n^*, run the regression with model selection, adjust n^*, and rerun the regression with model selection. We continue iterating until n^* and the regression converge – until they stop changing from one iteration to the next. As a result, the estimate for n^* depends on which variables are included in the regression. We select a relatively small number of variables in the 7-region case, so there are many unexplained patterns in the residuals. The estimate for n^* is smaller as a result.

- **page 11, line 31: Or underestimate noise? Is there a factor in the synthetic experiments that accounts for retrieval noise?**

  The reviewer makes a great point; the estimated retrieval errors could overestimate the covariances but underestimate the variances (i.e., white noise). We will add a sentence to the paragraph explaining this point.

- **page 11, line 33: It doesn't really become clear what is mean by this "salient role". Can this be seen in the presented results?**

  This statement references the synthetic data experiments in Fig. 5. In the revised manuscript, we will specifically reference the synthetic data experiments and Fig. 5.

- **page 12, line 19: Does the relative role of transport and measurement uncertainty follow from the results of this study, or is this just speculation? It seems to me that the study should provide information on this.**

  We will clarify this result in the revised manuscript. We explore the relative roles of transport and measurement/retrieval uncertainty in the synthetic data experiments (e.g., Fig. 5 in the current ACPD manuscript). In the revised manuscript, we will make reference to the figure here and explicitly tie this statement back to the synthetic data experiments.

- **page S4, line 141: 'Consistency check'. What potential inconsistency is checked? Do you mean sensitivity or robustness check?**

  We agree that it is better to use the term "sensitivity" or "robustness" instead of "consistency." We will change the text accordingly.

- **TECHNICAL CORRECTIONS**

- **page 2, line 7: 'the the'**

  Thank you for pointing out this typo. We will correct it in the revised manuscript.

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