

Interactive comment on “The impact of improved satellite retrievals on estimates of biospheric carbon balance” by S. M. Miller and A. M. Michalak

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We thank the referees for their comments and suggestions on the manuscript. Below, we have included the referee’s point-by-point suggestions and the associated changes we have made to the manuscript.

- “It is interesting that the retrieval bias reductions from Version 7 to 8 helped so much with the biospheric flux constraint at the biome-scale. It would be nice for the authors to comment a little more on subtle differences between versions 8 and 9. Looks like the constraint went down in some regions, e.g. the drylands and dry monsoon areas. Why is that?”

We have added text to the revised manuscript to clarify these differences. These

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small differences are due to the stochastic nature of the statistical model. The regression model used in this manuscript requires an estimate of error variances and estimates of the error correlation length and correlation time. We estimate these variances and covariances using a randomized sub-selection of the observations, described in the preceding companion paper; there are too many OCO-2 observations over a year to use all of the observations in that estimation process. Hence, the results of the regression analysis exhibit a small amount of stochasticity depending upon precisely which observations were randomly selected for the variance and covariance estimation. For example, for the simulations shown in the manuscript, we obtained a slightly higher error variance for version 9 ($(0.90 \text{ ppm})^2$) than version 8 ($(0.87)^2 \text{ ppm}^2$) and a slightly longer decorrelation length. This resulted in model selection results for version 9 in which slightly fewer months were selected relative to version 8. We subsequently reran the analysis and then obtained a slightly lower error variance for version 9 relative to version 8 ($(0.83 \text{ ppm})^2$ versus $(0.87)^2 \text{ ppm}^2$). This resulted in model selection results for version 9 in which slightly more months were selected relative to version 8. We have added a brief description of this point in the revised manuscript.

- “Did you try estimating any sub-biome scale regions? Given that the biomes tend to be multi-continental, it would be interesting to see the results using smaller regions that are (mostly) spatially contiguous within a given continent, especially with Versions 8–9.”

It could be interesting to examine sub-biome scale regions. However, the overall motivation of this study was to compare apples-to-apples with the preceding companion paper. In that study, we did not examine smaller regions because we had limited success in constraining fluxes across biome-sized regions. In the present manuscript, by contrast, we were able to detect spatiotemporal variations in CO_2 fluxes within many of these biome-sized regions, a large improvement over re-

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sults using version 7 of the observations.

- “The statement on p. 3, lines 8-10 sounds somewhat misleading: ‘We begin with large, hemispheric regions and then decrease the size of those regions until we are no longer able to detect any variations in biospheric CO₂ sources and sinks.’ It looks like you could potentially go to even finer spatial scales in the tropical grasslands/ forests and drylands/ dry monsoon biomes with Version 8 9 retrievals.”

The reviewer raises a good point, and reviewer #1 made a similar suggestion. We have revised this statement in the manuscript accordingly.

- “This may not be the focus of your study, but I was very curious to see the results of your model selection and estimated betas from the regression with the selected bio models (and anthro/ biomass burning/ ocean fluxes). Which biospheric models were selected in different region/ month combinations? When was just one model selected vs. multiple models? Can these results help to inform which models are performing best in which regions? Does the ‘best’ model for a given month change as a function of spatial scale? This could be potentially useful information for biospheric model developers. Also, I don’t see a supplemental material, but do you list anywhere which bio models went into the model selection algorithm?”

We agree; model selection can be a useful tool to help identify patterns in CO₂ fluxes that are or are not consistent with atmospheric observations. A number of studies have used model selection to explore which flux patterns and which biosphere models are best able to reproduce atmospheric observations. For example, Fang et al. (2014) and Fang and Michalak (2015) explore these questions using in situ CO₂ observations. We agree that these are interesting questions but feel that these questions are beyond the scope of the current study and would be better answered in a separate future, study. Adding that analysis to the present

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study would arguably complicate or distract from the framing and messaging of the current manuscript.

- “Not clear why you would include or exclude glint observations. It looks like in Miller et al, 2018, you exclude glint observations from results shown in the main manuscript. Why? How has the quality of these observations improved in Versions 8 and 9? And why are glint observations helping especially in tropical regions? Are they able to improve the density of observations in cloud-covered areas, or is a single glint measurement more informative than a single nadir or target measurement in these regions? Please don’t assume too much satellite-based knowledge on the part of the reader!”

The reviewer makes a really good point about not assuming too much satellite-based knowledge on the part of the reader. We have added more explanation on this topic in the revised manuscript. In brief, glint observations have historically had much higher error variances and larger biases relative to nadir observations. For example, land glint observations in version 7 had a ~0.5ppm offset compared to land nadir observations (e.g., O’Dell et al. 2018). Until recently, it was arguably very challenging to include both types of observations in an inverse model because one type had a fundamentally different magnitude relative to the other. In the preceding companion paper (Miller et al. 2018), we included results using glint observations within the SI, but we did not put great emphasis on these results with glint observations because of their known biases.

By contrast, the accuracy of the glint observations greatly improved markedly with version 8 of the observations. In fact, the largest improvements between versions 7 and 8 of the observations was to the glint observations, and these improvements greatly reduced the bias between land nadir and land glint observations (O’Dell et al. 2018). These improvements arguably make it feasible to assimilate land nadir and land glint observations in the same top-down framework or inverse model.

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We have also included more explanation in the revised manuscript about the improvements tropical biomes versus mid- and high-latitude biomes. The results using versions 7 and 8 show the greatest differences across tropical biomes. This feature is most likely because there is a large signal-to-noise ratio in many tropical biomes throughout the year, whereas the signal-to-noise ratio in mid- and high-latitudes is only large during northern hemisphere summer. Phrased differently, there is a consistent flux signal from many tropical regions throughout the year, and hence we are able to detect variations in fluxes from tropical regions across different seasons using version 8 of the observations. By contrast, net ecosystem exchange (NEE) in northern mid- and high-latitudes has the largest absolute magnitude during northern hemisphere summer. As a result, we see a large improvement in the flux constraint in mid-latitudes in northern hemisphere summer but not in other times of year when the absolute magnitude of NEE is smaller. Furthermore, there are far fewer land nadir and land glint observations in northern mid- and high-latitudes in northern hemisphere winter.

- “* P. 3, lines 31-33: it might be nice to put an equation or diagram or even table here showing the potential inputs that go into the model selection and your regressions. Do you run model selection on all months simultaneously? That’s what it sounds like, but please make that more clear.”

We have added text to the revised manuscript to clarify. We do run all months simultaneously. We have also added an equation to the manuscript to summarize the regression:

$$z = h(\mathbf{X})\beta + b + \epsilon$$

where z are the OCO-2 observations, \mathbf{X} the different predictor variables, $h()$ an atmospheric transport model (in this case PCTM), β the coefficients estimated in the regression, b the model spinup or CO₂ mixing ratios at the beginning of the experiments, and ϵ the model–data residuals. Note that there are different columns of \mathbf{X} corresponding to each biospheric flux model in each different month and

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each different biome. Model selection will determine which columns of \mathbf{X} can best reproduce the OCO-2 observations without overfitting those observations.

This equation and the associated explanation is also included in the preceding companion paper.

- “* P. 4, lines 4 and 8: please replace the terms ‘former’ and ‘latter’ with something more descriptive, e.g. biospheric model output and constant fluxes.”

We have edited the text accordingly. We have replaced the word “former” with “some of the model outputs that use a flux model or vegetation index,” and we have removed the word “latter.”

- “* P. 4, line 19: ‘to avoid potentially biasing the results’. This is true, but please make clear that XCO₂ reflects the contributions of all these different types of fluxes (ocean/ FF/ BB/ terrestrial bio), so you need to account for the non-bio fluxes in order to isolate the signal of the bio in the regression. Can also comment that the uncertainty on the FF/ ocean/ BB fluxes is thought to be much smaller than that on the terrestrial bio fluxes (with reference).”

The reviewer makes a great point, and we have edited the text accordingly.

We have also added text to the manuscript explaining that biospheric fluxes are thought to be more uncertain than other CO₂ source types. For example, we have cited the National Academy of Science Report on fossil fuel CO₂ emissions (NAS 2010) and have cited a biosphere flux model intercomparison paper (Huntzinger et al. 2012) and a Global Carbon Project assessment (Le Quéré et al. 2018) as evidence of these differing uncertainties.

- “* P. 5, line 13: ‘in about half of all months in the tropics’, but didn’t you say on line 10 that ‘variations in CO₂ fluxes are detectable across tropical biomes much of the year?’ In Version 9, it looks like you can constrain bio fluxes in the tropical grasslands and forests for 8 and 9 months of the year, respectively”

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The reviewer is correct – the number cited in the manuscript should be two thirds, not one half. That is an error on our part. We have updated the text accordingly.

- “P. 6, line 17: please add references for the ACOS retrievals and bias correction, and also for OCO-3 and GeoCarb.”

We have added references to this line accordingly. We have added citations to O'Dell et al. (2012) and O'Dell et al. (2018) for the ACOS retrieval, Eldering et al. (2019) for OCO-3, and Polonsky et al. (2014) for GEOCarb.

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